Performance Evaluation of Face Recognition Using Gabor Filter, Log Gabor filter and Discrete Wavelet Transform

D Murugan[1], Dr. S Arumugam[2], K Rajalakshmi[3] and Manish T I[4]

[1]Assistant Professor, Department of CSE, Manonmaniam Sundaranar University, India
dhanushkodim@yahoo.com

[2]Chief Executive Officer, Nandha College of Engineering & Technology, Erode, India
arumugamdote@yahoo.com

[3]Assistant Professor, Department of CSE, Francis Xavier Engineering College, India
rajalakshmiji@yahoo.com

[4]PG Student, Department of CSE, Manonmaniam Sundaranar University, India
manishti2004@yahoo.com

ABSTRACT

The face recognition problem is made difficult by the great variability in head rotation and tilt, lighting intensity and angle, facial expression, aging, partial occlusion (e.g. Wearing Hats, scarves, glasses etc.), etc. The Eigenfaces algorithm has long been a mainstay in the field of face recognition and the face space has high dimension. Principal components from the face space are used for face recognition to reduce dimensionality. A multiscale representation for face recognition is done to preserve the discriminant information prior to dimensionality reduction. In this paper, three multiscale representation techniques Gabor filter; Log Gabor filter and Discrete Wavelet Transform are applied prior to dimensionality reduction. PCA is then applied on the above techniques to find the face recognition accuracy rate and to compare the results of the three methods with PCA method. The approximation coefficients in discrete wavelet transform is extracted and it is used to compute the face recognition accuracy instead of using all the coefficients.

KEYWORDS

Eigenfaces; face space; Gabor filter; Principal components; multiscale; Log Gabor filter.

1. INTRODUCTION

A newly emerging trend, claimed to achieve previously unseen accuracies, is three-dimensional face recognition. This technique uses 3-D sensors to capture information about the shape of a face. This information is then used to identify distinctive features on the surface of a face, such as the contour of the eye sockets, nose, and chin. One advantage of 3-D facial recognition is that it is not affected by changes in lighting like other techniques. It can also identify a face from a range of viewing angles, including a profile view. Even a perfect 3D matching technique could be sensitive to expressions. For that goal a group at the Technion applied tools from metric geometry to treat expressions as isometries. Face recognition is not perfect and struggles to perform under certain conditions. Despite the potential benefits of this technology, many citizens are concerned that their privacy will be invaded.

Face recognition can be applied for a wide variety of problems like image and film processing, human-computer interaction, criminal identification etc. A face image has high dimension. The Eigenfaces algorithm has long been a mainstay in the field of face recognition due to the high dimensionality of face images. While providing minimal reconstruction error, the Eigenface-based transform space de-emphasizes high-frequency information, effectively reducing the information available for classification [1].

The process of dimensionality reduction is an essential stage in face recognition tasks where the data have an intrinsically high dimensionality [8]. Principal Component Analysis (PCA) is used to reduce the dimensionality of image space [3]. Recognition is performed by projecting a new image into the subspace spanned by the eigenfaces ('face space') and then classifying the face by comparing its position in the face space with the positions of the known individuals. While trying to reduce the dimensionality of image space it can remove the information required to discriminate objects within that space [7].

In this paper, three multiscale techniques are used to partition the information contained in the frequency domain prior to dimensionality reduction [8]. In this manner, it is possible to preserve the discriminative information available for classification and, hence, increase the performance of PCA method. Gabor filters, Log Gabor filters & Discrete Wavelet Transform are applied to preserve the information content prior to PCA and face recognition accuracy is computed.

2. EIGENFACES ALGORITHM

Eigenface technique is a method used for face recognition for many years. Principal component analysis is used in eigenface method. Mathematically, Principal component analysis approach will treat every image of the training set as a vector in a very high dimensional space. The eigenvectors of the covariance matrix of these vectors would incorporate the variation amongst the face images. Now each image in the training set would have its contribution to the eigenvectors (variations).

The training data set has to be mean adjusted before calculating the covariance matrix or eigenvectors. The average face is calculated as $\Psi = (1/M)\ \Sigma 1MTi$ each image in the data set differs from the average face by the vector $\Phi = Ti - \Psi$. This is actually mean adjusted data. The high dimensional space with all the eigenfaces is called the image space (feature space). If the eigenface with small eigenvalues are neglected, then an image can be a linear combination of reduced number of these eigenfaces. Figure 1 shows the some of the training images and its eigenfaces.

The face image to be recognized (known or unknown), is projected on the face space. The Euclidean distance between the image projection and known projections is calculated. The face image is then classified as one of the faces with minimum Euclidean distance [2].

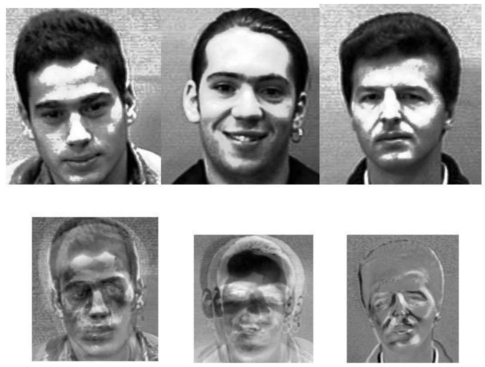


Figure 1. Row 1 shows some of the gray scale images used for training row 2 shows eigenfaces with significant eigenvectors.

2.1 GABOR FILTER APPLIED PCA

In this paper, a multiscale representation technique, Gabor filter is applied for Face Recognition. Face representation using Gabor features has attracted considerable attention in computer vision, image processing, pattern recognition etc. The principal motivation to use Gabor filters is biological relevance that the receptive field profiles of neurons in the primary visual cortex of mammals are oriented and have characteristic spatial frequencies. Gabor filters can exploit salient visual properties such as spatial localization, orientation selectivity, and spatial frequency characteristics [5]-[6].

Gabor filter works as a band pass filter for the local spatial frequency distribution, achieving an optimal resolution in both spatial and frequency domains. The 2D Gabor filter $\psi_{f,\theta}(x,y)$ can be represented as a complex sinusoidal signal modulated by a Gaussian kernel function as in equation 1.

$$\psi_{f,\theta}(x,y) = \exp\left[-\frac{1}{2}\left\{\frac{x_{\theta_n}^2}{\sigma_x^2} + \frac{y_{\theta_n}^2}{\sigma_x^2}\right\}\right]\exp(2\pi f x_{\theta_n}),$$

$$\text{where, } \begin{bmatrix} x_{\theta_n} \\ y_{\theta_n} \end{bmatrix} = \begin{bmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \qquad (1)$$

σ_x, σ_y are the standard deviations of the Gaussian envelope along the x- and y- dimensions, f is the central frequency of the sinusoidal plane wave, and θ_n .the orientation. The rotation of the x-y plane by an angle n θ will result in a Gabor filter at the orientation θ_n .The angle θ_n is defined by:

$$\theta_n = \frac{\pi}{p}(n-1), \qquad (2)$$

for $n = 1,2,\ldots,p$ and $p \in \mathbf{N}$,

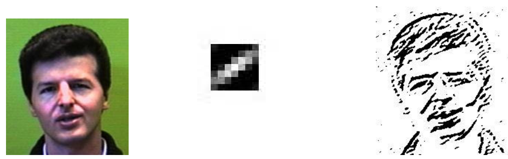
where p denotes the number of orientations.

2.1.1 Recognition using Gabor filter Approach

The Gabor representation of a face image is computed by convolving the face image with the Gabor filters. Let f(x, y) the intensity at the coordinate (x, y) in a gray scale image face image,its convolution with a Gabor filter $\psi_{f,\theta}(x, y)$ is defined as

$$g_{f,\theta}(x, y) = f(x, y) \otimes \psi_{f,\theta}(x, y) \qquad (3)$$

Where $\otimes$ denotes the convolution operator [4]. Figure 2 illustrates the convolution result of a face image with a Gabor filter. A Gabor filter applied train database is created Face recognition by applying PCA on Gabor train database.



(a) (b) (c)

Figure 2. (a)Original Image. (b)Gabor Filter. (c) Gabor filtered Image.

2.2 LOG GABOR FILTER APPLIED PCA

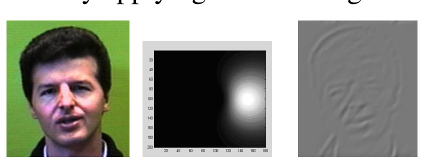
An alternative to the Gabor function is the log-Gabor function proposed by Field [9]. Field suggests that natural images are better coded by filters that have Gaussian transfer functions when viewed on the logarithmic frequency scale. Gabor functions have Gaussian transfer functions when viewed on the linear frequency scale [10]. On the linear frequency scale the log-Gabor function has a transfer function given in equation 4[11].

$$G(w)=e(-\log(w/w_0)^2)/ (2(\log (k/w_0)^2) \qquad \text{eq (4)}$$

Where w_0 is the filter's centre frequency.

2.2.1 Recognition using Log Gabor filter

The Log Gabor filter obtained in frequency domain is multiplied with original image by multiplying the Fourier transform of the original image with the centre adjusted log Gabor frequency result. Find the inverse Fourier transform of the multiplied image. Obtain the log Gabor filtered image by reshaping the inverse Fourier transform applied image. Figure 3 shows the original image and log gabber filtered applied image. A Log Gabor filter applied train database is created Face recognition by applying PCA on Log Gabor train database.



(a) (b) (c)

Figure 3. (a) Original Image. (b) Log Gabor filter (C) Log gabor filtered Image.

3. DISCRETE WAVELET TRANSFORM APPLIED PCA

Discrete wavelet transform (DWT) is a well-known signal analysis tool, widely used in feature extraction, compression and de-noising applications. In Discrete Wavelet Transform, the most prominent information in the signal appears in high amplitudes and the less prominent information appears in very low amplitudes. The wavelet transforms enables high compression ratios with good quality of reconstruction. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. The one-dimensional wavelet decomposition is first applied along the rows of the images, and then their results are further decomposed along the columns. This results in four decomposed sub images L1, H1, V1, and D1. These sub images represent different frequency localizations of the original image which refer to Low-Low, Low-High, High-Low and High-High respectively [12]. In each iterative step, only the sub image L1 is further decomposed. Haar wavelet is one of the oldest and simplest wavelet. In this paper haar wavelet is applied for decomposition at 3 levels and PCA is applied and face recognition accuracy is obtained for all the 3 levels. Figure 4 shows DWT decomposition at 3 levels.

(a) (b) (c)

Figure 4. (a) DWT 1st level decomposition (b) DWT 2nd level decomposition (c) DWT 3rd level decomposition

3.1 Approximation Coefficients Retained Discrete Wavelet Transform

Another approach used in this paper is retaining the approximation coefficients in Discrete Wavelet Transform. Apply a DWT Level 1 haar wavelet Transform on the Original Image and image size obtained is reduced by 2. The four coefficients obtained are approximation, vertical, horizontal and diagonal coefficients. Make the vertical, horizontal and diagonal coefficients all to zero. Make use of the above all coefficients and reconstruct the image to the original image by using inverse discrete wavelet transform.

This is done for level 2 discrete wavelet transform and face recognition accuracy is computed. Figure 5(a) shows the sample image in DWT LEVEL 1 haar wavelet and (b) shows the approximation coefficient retained DWT level 1 image. It shows the comparison among the two and (b) has high information content than the first one.

(a) (b)

Figure 5. (a) DWT Level 1 image (b) approximation coefficient retained DWT level 1 image

4. ANALYSIS

A database of 112 images of different subjects of size 180X 200 is taken for experimentation. The train image is limited in size (only 28 images). Test images contain images in different lighting conditions, illuminations, contrast, subjects with partial occlusions like hats, scarves etc, subjects with spectacles, subjects of different head orientations, rotations and tilt, subjects with mask, different background ,subjects of different facial expressions, subjects with different effects like tile, blurred images that contain Gaussian , motion, radial and smart blur, images with artificial noise like salt and pepper noise, Gaussian noise etc.

It was found that the face recognition rate for Eigenface approach with principal component analysis is 89% and the PCA based eigenface approach cannot recognize images with dark back grounds, flash light images and distorted images. PCA based Eigenface cannot work if the polygonal mask of the image is taken. It works well in different facial expression, artificial added noise like Gaussian noise, salt and pepper etc, blurred images, wearing spectacles and partial occlusion conditions like wearing scarves, hats etc.

The Gabor filter bank recognition is not affected by the above conditions and it recognize images that contain only masks. It recognizes images even under strong lights. The sample images that are recognized by Gabor filter and not by PCA eigenface is shown in Figure 6. Hence the recognition rate is more when compared with Eigen face approach. Gabor filter recognition achieves up to 92% accuracy with 112 test images.

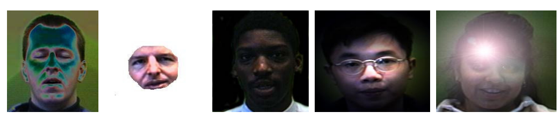


Figure 6. Sample images that are recognized by Gabor PCA and not by PCA

The log Gabor filter based PCA has a face recognition accuracy of 83% for the same test database. The log gabor filter cannot recognize images that have blurring effects like motion blur, radial blur, Gaussian blur, smart blur, spot lens lighting effects, solarize effects, shift in positions of image, mask of face image etc. It can recognize images with various expressions; diffuse glow effect, dark faces, dark backgrounds, images with wearing glasses, images with partial occlusions etc.

It was found that 2 D discrete wavelet transform haar at level 1 has 95 correct matches (84.8%) with image size 90 × 100. The wavelet transform is sensitive to strong lighting conditions. It can’t recognize strong light images, enhanced images, subjects with hats, images with dark back grounds, solorize effect etc. Like Gabor filters it can recognize mask of face images. DWT Level 2 has less information and its recognition accuracy is less than Level 1. The image size taken is 45 × 50. Out of 112 images 88 images are correctly recognized (78.6%). DWT Level 3 has less information and its recognition accuracy is less than Level 2. The image size taken is 22 × 25. Out of 112 images 79 images are correctly recognized (70.5%).

The algorithm proposed for approximation coefficients retained for both level 1 and level 2 has improved face recognition rate. With DWT level 1 95 images are correctly recognized (84.8 %). Whereas with approximation coefficients retained DWT level 1 96 images are correctly recognized (85.7%). With DWT level 2 88 images are correctly recognized (78.6%). Whereas with approximation coefficients retained DWT level 2 95 images are correctly recognized (84.8%).Table I shows the face recognition techniques accuracy in %. Table 2 shows the Face recognition accuracy using discrete wavelet transform applied PCA at 3 levels.

TABLE 1. FACE RECOGNITION TECHNIQUES ACCURACY IN %

Total No. of test Images	**Face Recognition Techniques**		
	PCA	***Gabor filter appked PCA***	***Log Gabor filter applied PCA***
112	100	103	93
Recognition Accuracy %	89 %	92 %	83 %

TABLE 2. FACE RECOGNITION ACCURACY USING DISCRETE WAVELET TRANSFORMS 3 LEVELS IN %

Total No. of test Images	**Discrete Wavelet Transforms Levels**		
	DWT Level 1	***DWT Level 2***	***DWT Level 3***
112	95	88	79
Recognition Accuracy %	84.8 %	78.6 %	70.5 %

Table 3 shows comparison result of Face recognition using DWT and approximation coefficient applied DWT. It shows the second one has better results than first one.

TABLE 3. COMPARISON OF SIMPLE DWT AND APPROXIMATION COEFFICIENT RETAINED DWT

Total No. of test Images	**Discrete Wavelet Transforms Levels**			
	DWT Level 1	***DWT Level 1 Approx. retained***	***DWT Level 2***	***DWT Level 2 Approx. retained***
112	95	96	88	95
Recognition Accuracy %	84.8%	85.7%	78.6%	84.8%

5. CONCLUSION

Image-based face recognition is still a very challenging topic after decades of exploration. A number of typical algorithms are presented, being categorized into appearance-based and model-based schemes. Sensitivity to variations in pose and different lighting conditions is still a challenging problem.

In this paper, Eigenface technique using principal component analysis for face recognition is discussed and PCA based image is shown. A multiscale representation technique for face recognition is demonstrated using gabor filter and Log gabor filter. Face recognition is done by using both gabor filtered image and log gabor filtered image and applying PCA on it. Experimentation is done using PCA, Gabor based PCA and Log Gabor based PCA approach. It has been shown that Gabor PCA method outperforms PCA based Eigenface method. Log gabor based PCA is sensitive to artificially applied effects, blur etc. Log Gabor filter method can improve its recognition accuracy by dividing the face image into sub regions [11].

Face recognition is done using DWT applied PCA. Up to 3 levels the face recognition accuracy is tested. Face recognition using DWT is also done by retaining the approximation coefficients and zeroing all the other coefficients. It was found that face recognition accuracy rate is increased than DWT method. Most facial recognition applications today use 2-dimensional technology, which measures height, width and distance between feature points to make identification. This technique introduces a advantage since faces are 3-dimensional, with irregularly shaped features - noses, lips, ears, hair - that change in appearance as the face turns. Faces also reflect light and produce shadows, essentially creating new and different images. With 2-dimensional technology, failure rates rise with changes in pose or expression or variable lighting.

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Authors

D Murugan received engineering and masters at Madurai Kamaraj University and doing PhD at Manonmaniam Sundaranar University. He is currently working as assistant professor in dept of computer science at Manonmaniam Sundaranar University with 12 years of teaching experience. His main research topics are face recognition and Image processing.

Manish T I studied computer science engineering at Bharathiyar University, Coimbatore, India from 2000 to 2004, and doing M.E. degree in computer science engineering from Manonmaniam Sundaranar University, India. His main research topics are biometric-pervasive hybrid models and cryptography.

Dr. S Arumugam received PhD from Anna University. Formally Worked as professor, principal and additional director of Anna university. He is currently working as chief executive officer at Nandha college of engineering, erode, India. Institutions. His main research topics are Image Processing, Applied Electronics, and Embedded system.

K. Rajalakshmi received engineering and masters at Manonmaniam Sundaranar University and doing PhD at Manonmaniam Sundaranar University. She is currently working as assistant professor in dept of computer science at Francis Xavier Engineering College Her research interests include Image processing, Fuzzy logic and remote sensing.