ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Issue 01, January 2018

Sharp Gabor Features for Subspace Based Face Recognition System

Kailash S. Sharma[1], Ramchandra R. Manthalkar[2]

Ph.D Scholor, E & Tc Engineering Department, SGGSIET, Nanded, India [1]

Asso. Professor, E & Tc Engineering Department, SGGSIET, Nanded, India[2]

3

Abstract: In this research paper we proposed a novel approach to design a face recognition system based on the findings in the psychophysics & neuroscience related to the human face. Gabor wavelet – as it is proved work more similar to human cortex system, is used to get the discriminative features from a face image. Another finding related to the human processing of the inputs through the linear discriminant analysis of face images. The novelty of the approach is in the use of different Gaussian widths along the x and y axis. Based on the fact that the variations in the human face in vertical direction has comparatively more variations and with more sharpness as compared to the variations along the horizontal direction. Followed by the linear discriminant analysis applied on the reduced feature dimensionality through the eignespace approach.

Keywords: Gabor wavelet; linear discriminant analysis; feature descriptor; sharpness; dimensionality reduction

I. INTRODUCTION

A fundamental problem which spans over different disciplines is face recognition. Number of different disciplines such as Neuroscience, Psychophysics, computer vision, image processing, patter recognition etc. are involved in face recognition related research. Psychological studies have shown that the faces can be recognised from single view of face image. Some particular orientation of faces plays vital role in recognising faces. The familiar faces can be recognized from low resolution image compared to less familiar faces. According to psychological data, there is existence of single canonical view termed as ¾ view. Whereas according to physiological data, two canonical forms- frontal and profile exists. Before designing the computational model for building face recognition system, every researcher in this area must know about some findings in psychophysics and neuroscience which is directly related with face recognition. An experimental study on human being for recognising faces is carried out. This study revealed that, human can recognize familiar faces with low resolution also, the noise can be tolerated for the familiar faces. Pigmentation, shape of the face components and motion are important in face recognition. 'Eyebrows' are most important for face recognition. Psychophysics & neuroscience findings revealed that the Gabor wavelets work similar to the human cortex system. After capturing the image through the human sensory organ-eyes, it is processed by the human nervous system. The availability of different technological tools in the form of software and hardware make this task relatively easy [1], [2] [3].

In [4] the review of the early most popular techniques based on the Gabor wavelet including dynamic link architecture (DLA) and elastic bunch graph matching (EBGM) is given. In this a rectangular grid of fiducial points is formed and kept over the faces. At these fiducial point, number of Gabor wavelets with different orientation and scale are applied. They are referred as Gabor Jet. These Gabor Jet represents the features of the image and are used in retrieving the image from the database which is close to the query image. The equation for the 2D Gabor wavelet is also went through some modification. Here we are using the equation given by [5]. The equation along with additional algorithms is implemented and made available publicly through Matlab based PhD Toolbox [6], [7]. This Toolbox contains different demo applications including Gabor wavelet processing, principal component analysis (PCA), Kernel PCA, linear discriminant analysis (LDA), kernel LDA etc alongwith different utility functions useful in the performance analysis of the system.

In [8] multiscale Gabor wavelets are used to process the input image. A Gabor wavelet with different scales and orientations will cover entire frequencies present in the face image. Generally 5 scales with 8 orientations are used. In [9], local patterns of Gabor magnitude and phase are fused together using local Gabor XOR pattern (LGXP) and block based Fisher's linear discriminant (BFLD). The BFLD is used to reduce the dimensionality of the features and to improve the discrimination power of these features. In [10] a similar approach is further extended - natural and Gabor faces are combined to form the face feature descriptor. A statistical model based on Gabor filter for locating the effective feature points on the face is suggested by [11]. A neural network using Back propagation algorithm is used in [12]. The neural network is trained with the features obtained by processing the face image with a set of Gabor wavelets using different scales and orientations. Here the features from the face are extracted using reduced Gabor filter bank. The radial basis function network used in [13], [14], [15] is good at approximation and works well for the small data problem. For the training data it will give good recognition set but for different data in the testing set the performance degrades due to the high dimensionality of the input image feature vector. [16].

In all the work mentioned above, the efforts are made to build a system which will work in the direction of recognising the human face that will further strengthen the finding in the Psychophysics & Neuroscience. The features extracted through the Gabor filter bank are increasing the dimensionality of the face image. To reduce the dimensionality PCA [17] and to further improving the discriminability LDA [18], [23] are commonly used. In [24] the Gabor features are further processed locally by taking the histograms of the intensity values for forming the feature vector.

In the last three decades considerable progress is achieved in the field of face recognition system through various face recognition evaluation tests, grand challenges[1], the availability of face images is made through the standard databases like AT&T [19], extended YaleB [20] etc. The different parameters used in any pattern recognition system and in particular in the biometric system is available in [21], [22].

The contribution made by the paper includes the use of Gabor filter bank with different Gaussian widths in the x and y direction, with increasing the sharpness particularly in the vertical direction. This will improve the extraction of discriminative features.

The rest of the paper is organized as follows. In section II we describe Gabor wavelet along with its mathematical modelling. Section III describes the LDA. System architecture is explained in Section IV. Experiments performed & results along with discussion are given in Section V. Finally we conclude along with the future scope in section VI.

II. Gabor Wavelet

Gabor wavelet works similar to the human cortex system. As the human eyes capture the image and process it through the use of rods and cones, Gabor wavelet can determine the fine details in the images. They are able to extract the illumination invariant features from the image of a complex face structure. The complex face image have different frequency components, distributed spatially, to process it Gabor wavelet with multiple filters (filter bank) are used. The Gabor filter gives optimal resolution in both frequency and spatial domain [4].

To analyse an image with 2D Gabor functions, commonly the following steps are performed:

1) Discrete Fourier transform of the image is taken to convert the image into frequency domain
2) It is multiplied with Gaussian window representing the narrow band of frequencies
3) The inverse Fourier transform of the product is taken which represents the information content in the original image which falls in the frequency ranges limited by the Gaussian window.

An image is converted into frequency domain. Then it is passed through a narrow band filter bank. The filter bank is such that all the possible frequencies in the image will be filtered out with the respective band filter in the filter bank. This is done through Gaussian envelopes centered at each band using the magnitude function. Each envelope is multiplied with the Fourier transform of the whole image.

This process effectively eliminates the frequencies outside the selected frequency band, keeping the frequencies inside the selected band intact. After this an inverse Fourier transform of all images is taken one by one, the results are images which contain only frequencies in the selected band. These images, tells us which parts of the original image contain frequencies in this band. The part which does not contain the frequencies in the particular band will be dark. So, at the end we have stack of images.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Issue 01, January 2018

When using Gaussian windows, the frequency plane is tessellated using biologically inspired polar co-ordinates. It has been observed that the 2D receptive field profiles of the simple cells in the mammalian visual cortex may be modelled by 2D Gabor functions defined at various orientations and various radian frequencies. Alternatively, we often use bands that are narrower for higher frequencies and broader for low frequencies because the information content for discrimination are associated with high frequencies rather than low frequencies.

The 2D Gabor wavelet in spatial domain ($\psi(x,y)$) and frequency domain $\Phi(u,\upsilon)$ is given by [5]

$$\psi(x,y) = \frac{f^2}{\pi\lambda\varsigma}\exp(-(a^2x_r^2 + b^2y_r^2)).\exp(j2\pi f x_r) \qquad (1)$$

$$x_r = x.\cos\phi + y.\sin\phi \ \& \ y_r = -x.\sin\phi + y.\cos\phi$$

Where the spatial Cartesian coordinates are represented by x and y. x_r & y_r is giving the polar form representation. The Gabor filter is a product of Gaussian function with the sinusoidal function. 'f' represents the central frequency of the sinusoidal function.

$a = \frac{\sqrt{2}\,\pi f}{\sigma x}$, $b = \frac{\sqrt{2}\,\pi f}{\sigma y}$ represents the sharpness of the Gaussian function in the Gabor wavelet in x and y direction respectively. This sharpness value is directionally proportional to the central frequency in the overall Gabor filter and inversely proportional to the width of the Gaussian. Hence, if the width of the Gaussian is more, represents that sharpness is less, the slope of the curve is small. Whereas if the Gaussian width is small, the curve is steeper and hence the sharpness is more.

$\lambda = \frac{f}{a}$ represents the ratio of central frequency and sharpness in the x-direction and $\varsigma = \frac{f}{b}$ represents the ration of central frequency and sharpness in the y direction.

In our work we replace ς with log (ς). By this the ratio between the center frequency and the sharpness in y direction will decrease indicating the increase in the sharpness in the filter along vertical direction.

σ_x and σ_y are the widths of the Gaussian function representing standard deviation in x & y direction respectively.

ϕ is the orientation of the major axis of elliptical Gaussian.

$$\Phi(u,\upsilon) = e^{-\pi^2(\frac{1}{a^2}(u_r - f)^2 + \frac{1}{b^2}\upsilon_r^2)} \qquad (2)$$

Where u,v are the frequency axes in the frequency domain representation of the Gabor wavelets and u_r and v_r are the components in terms of the polar co-ordinates.

In most of the literature, it is found that the symmetric nature of Gaussian filter is used, i.e., the width of Gaussian function in both the direction is taken same. If we look at the face image, there are more sharp variations in the vertical direction due to the shape of the face. The aspect ratio indicates the dimension is more vertically compared to horizontally. We are considering different widths along x and y direction.

To filter the image with a Gabor wavelet for extracting the spatial features in particular frequency domain, input intensity image f(x,y) is convolved with the Gabor filter $\psi(x,y)$, with different scale and orientation to produce number of output intensity images representing the sharp features in the narrow band specified by the Gabor filter, using

$$g(x,y) = f(x,y) * \psi(x,y) \qquad (3)$$

The convolution operation is a complex one, which involves folding of one signal and then sliding down the other signal over it, in both the direction covering complete and partial overlap. Compared to this the frequency domain operation which involves the multiplication is simple, hence used practically. The Fourier transform of the terms on the right side of equation (3) is taken separately, then multiplied. Finally, the inverse Fourier transform of the result is taken to get the Gabor filtered image. The output represents the spatial information restricted to the frequency band of the Gabor filter, each contributing different information.

III. LINEAR DISCRIMINANT ANALYSIS

After processing the data with Gabor filter bank the dimensionality of the images is increased further by an amount multiples of the number of Gabor filters used in the bank with different scale and orientation. Even after down sapling it with a maximum allowable factor of 64, the dimensionality is still more. The main challenge in the feature extraction is to keep the dimensionality of these features as low as possible to reduce the computational and memory cost. Further while representing the data in the low dimensional space, the face images corresponding to same subject with slight variations in the poses should be near as compared to the face images of different subjects [23]. The principal component analysis (PCA) is commonly used in the literature for dimensionality reduction. It provides features that capture the main directions along which face images differ to represent the face images effectively, but fails to lower the

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Issue 01, January 2018

within-class scatter. As there is no separation in terms of the face images of the different subjects. Each face image is treated in the same way irrespective of the class to which it belongs. This drawback of PCA is overcome in [18][23] using fisherfaces, which applied the linear discriminant analysis (LDA) and use the class membership information. Further, as it works on the data projected into the eigen space, the dimensionality will be reduced. The features so obtained maximizes the between class scatter and minimizes the within class scatter.

The within class 'S_w' and between class 'S_B' scatter matrices are given respectively by

$$S_w = \sum_{i=1}^{N}(xi - \mu)(xi - u)^T \qquad (4)$$

where x_i represents images in a class and u represents the mean of that class. The scaltter matrix 'S_w' represents the mean scatter of the sample vectors of different classes around their mean vector.

$$S_B = \sum_{I=1}^{N}(m - \mu i)(m - ui)^T \qquad (5)$$

where 'μ_i' represents the mean of each class and m represents the mean of all classes. The scatter matrix 'S_B' represents the scatter of the mean vector of different classes around the mean vector of all classes.

IV. System Architecture

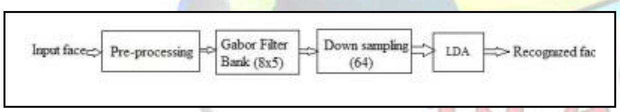

Fig 1. System architecture

The input face image is pre-processed and normalized to size of 128x128. It is then processed through a bank of Gabor filters. The filter bank with 8 rotation angles and 5 scales is used. The sharpness in the vertical direction of faces is kept more as compared to the horizontal direction, based on the observation that the variations in the vertical direction of the face are more closely spaced as compared to the horizontal.

The obtained filtered images are then down sampled separately with a factor of 64. The filtered images are get reduced to a size of 16x16. Each image is then converted into a feature vector. All such feature vectors of a single face image are then concatenated to form a feature vector of 16x16x40 dimension.

As discussed earlier these Gabor filters are representing the spatial information in the form of regional intensities and are effective enough to discriminate between the faces of different subjects. But they are redundant and will cause more computational time and memory resources. Hence to reduce the dimension we are using LDA. Considering N number of classes, we will get a feature vector of length N-1 using LDA. To process the images, we are first finding their eigen features as given by [17] using the co variance matrices of the input face images in the database. The LDA is applied on this low dimensionality space will result into a feature vector of length N-1. The projection matrix of gallery images is formed in this way and stored as a model in the memory.

The prepared model based on Gallery images using LDA is to be tested with the probe image. The probe image is also go through the similar steps as the gallery images. After pre-processing, the image is filtered with the Gabor filter bank, down sampled and projected on the LDA space to get a feature weight vector of size (N-1)x1. The feature vector obtained is checked for similarity with the feature vectors of gallery images using Mahalabonis similarity measure. Due to the application of different Gaussian width, the feature extracted becomes more discriminative. The recognition rate obtained are improved as compared with the symmetry in filters in both the direction. We also checked the same on the horizontal direction, but the recognition rate obtained is less.

V. Experiments & Results

The experiments are performed using AT&T & Extended YaleB database. The AT&T database contains 40 subjects with 10 images per subject. The images are taken with a plain background. The images are with different pose and expressions. The image size is 112x92. From the available database, first 3 images are taken for training, next 3 for evaluation and final 4 images are taken for the testing purpose or as probe images.

Fig 2. Some faces in AT&T database

For performing experiments, the PhD Toolbox by [6], [7] is used. The application to create Gabor filter bank is modified

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Issue 01, January 2018

by replacingς, the ratio of center frequency to the sharpness along vertical direction by its natural logarithm ln (ς). This will result in increasing sharpness in the vertical direction, In other words, the filters are with narrower bands in the vertical direction compared to the horizontal direction and are able to filter the high frequency information.

The experiments are performed. From the results obtained we determine the recognition rate by dividing the total recognized faces with total number of faces used as probe inputs. The product is multiplied with 100 to obtaine the percentage error rate. The Table I shows that the results obtained by our method is 1.66 % better than that of Gabor-KFA and 2.50 % better than Gabor-KFA.

TABLE I
COMPARISON RESULTS ON AT&T DATABASE

Sr. No.	Method	Recognition Rate (%)	Verification Rate (%)
1	Gabor-PCA	75.00	96.67
2	Gabor-KPCA	74.17	93.33
3	Gabor-LDA	90.83	97.50
4	Gabor-KFA	91.67	95.00
5	SharpGabor-LDA	**93.33**	96.67

The Extended Yale B database is used in the experiments as it contains images with 64 different illumination variations of 38 subjects. It is a benchmark dataset used to test the robustness of a face recognition algorithm against illumination variations. Cropped version of the Extended Yale B dataset is used in the experiments. From the available images 10 images of each subject are selected randomly. Out of these first 3 are taken as training images, next three as evaluation set and final 4 are considered as test or probe images. For performing experiments, the PhD Toolbox is used as in the previous case of AT &T.

Fig. 3 Some faces in extended Yale B database

The results obtained are shown in Table II. The results outperforms the other methods which have used Gabor wavelets for extracting features with same Gaussian width in x and y direction. Compared with the Table I, it is found that the results obtained on extended Yale B by using all methods except Gabor-KPCA, are better than that obtained on AT & T database. AT&T database has expression variation and pose variations included in it. Whereas extended Yale B database has illumination variation in it. Compared to pose variations, illumination variations are treated better by Gabor wavelets. Fig 4 shows some of the faces in extended Yale B database.

TABLE II
COMPARISON RESULTS ON EXTENDED YALE B DATABASE

Sr. No.	Method	Recognition Rate (%)	Verification Rate (%)
1	Gabor-PCA	75.83	100
2	Gabor-KPCA	63.17	74.17
3	Gabor-LDA	94.17	100
4	Gabor-KFA	95.00	100
5	SharpGabor-LDA	**95.83**	100

The first column is showing the faces, the second column is showing one of the Gabor wavelet from the wavelet bank with 1st row showing real part, second row is showing magnitude and the last row showing angle of the Gabor wavelet. The last column is showing the Gabor filtered images. Each image is showing the part of the original image which has the frequency contents as per the Gabor wavelet. The brighter part shows these frequencies and darker part shows the area where such frequencies are absent.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Issue 01, January 2018

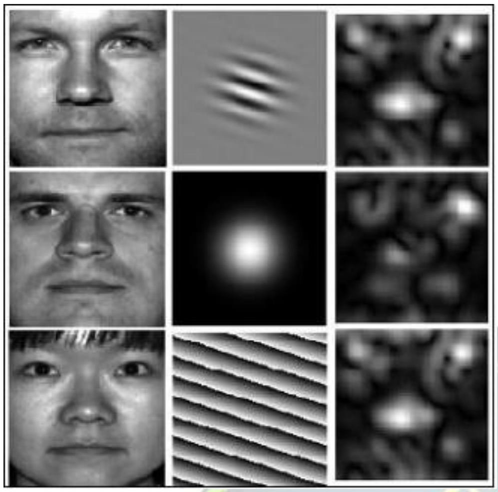

Fig 4. Face Images, Gabor filter and filtered images

VI. CONCLUSIONS

In this paper, we proposed a face recognition system using Gabor wavelets for extracting discriminative features followed by LDA to further increase the discriminability between the features and reduce the dimensionality of features using PCA. The features extracted with Gabor filter bank with the use of different sharpness along the x-axis and y-axis. Along the x-axis we are taking normal sharpness whereas along the y-axis the natural logarithmic is taken.

From the experiments performed on the different database it can be concluded that –

- The features extracted by Gabor wavelet works well even after down sampling with factor of 64.
- Linear discriminant analysis further reduces the dimensionality of the feature vector based on projecting the input over eigen faces before extracting the LDA feature vector.

In the future we would like to work to recursively accumulate the features in the multiple region through statistical averages to reduce the number of features so as to make the feature vector more compact with more discrimination power. This will reduce the online computational cost and speed up the real time processing of face images for recognition and verification purpose.

REFERENCES

[1]. W. Zhao, R. Chellappa, A. Rosenfeld, P.J. Phillips, Face Recognition: A Literature Survey, ACM Computing Surveys, 2003, pp. 399-458

[2]. P. Sinha, B. Balas, Y. Ostrovsky, R. Russell, Face Recognition by Humans: 19 Results All Computer Vision Researchers Should Know About, Proceedings of the IEEE, Vol. 94, No. 11, November 2006, pp. 1948-1962

[3]. Dominique Valentin, Hervi Abdi, Betty Edelman, "What represents a face: A computational approach for the integration of Physiological and psychological data", Perception, 1996, vol. 26

[4]. Linlin Shen & Li Bai, "A review on Gabor wavelets for Face Recognition", Pattern Analysis Application, vol. 9, 2006, pp. 273-292

[5]. Kyrki, V., Kamarainen, J.K., Kalviainen, H., Simple Gabor feature space for invariant object recognition, Pattern Recognition Letters, 25, 2004, pp. 311-318

[6]. Struc, V., Paveˇ si´c, N., "Gabor-based kernel partial-least-squares discrimination features for face recognition", Informatica (Vilnius) 20, 2009. 115–138

[7]. Struc,V.,Paveˇ, si´c,N., "The complete gabor fisher classifier for robust face recognition", EURASIP Advances in Signal Processing 2010

[8]. Lin Huang, Wenjing Zhang, "Face Recognition Using Multiscale Gabor Wavelet", PACRIM'07, 2007 IEEE, pp. 280-283

[9]. Shufu Xie, Shiguang Shan, Xilin Chen, and Jie Chen, "Fusing Local Patterns of Gabor Magnitude and Phase for Face Recognition", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 19, NO. 5, MAY 2010, pp. 1349-1361

[10]. Christian Tenllado, et. Al., "Improving face recognition by combination of natural and Gabor faces", Pattern Recognition Letters 31 (2010) 1453–1460

[11]. Sanqiang Zhao, Yongsheng Gao, Baochang Zhang, "Gabor feature constrained statistical model for efficient landmark localization and face recognition", Pattern Recognition Letters 30 (2009) 922–930

[12]. Amina Khatun and Md. Al-Amin Bhuiyan, "Neural Network based Face Recognition with Gabor Filters", IJCSNS International Journal of Computer Science and Network Security, VOL.11 No.1, January 2011, pp. 71-76

[13]. Chen, S., C.F.N. Cowan, and P.M. Grant, "Orthogonal Least Squares Learning Algorithm for Radial Basis Function Networks," IEEE Transactions on Neural Networks Vol. 2, No. 2, March 1991, pp. 302-309.

[14]. M. T. Musavi,W. Ahmed, K. H. Chan, K. B. Faris, and D. M. Hummels, "On the training of radial basis function classifiers," Neural Networks, vol. 5, pp. 595–603, 1992.

[15]. J. L. Yuan and T. L. Fine, "Neural-Network design for small training sets of high dimension," IEEE Trans. Neural Networks, vol. 9, pp. 266–280, Jan.1998.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Issue 01, January 2018

[16]. R. O. Duda, P. E. Hart, and D. G. Stork, "Pattern Classification", Second Edition, John Wiley & Sons Inc, New York, 2006, pp. 114-124, 568.

[17]. Turk, M.A., Pentland, A.P., Eigenfaces for recognition. JournaL of Cognitive Neuroscience 3, 1991, pp.71–86.

[18]. Belhumeur, P.N., Hespanha, J.P., Kriegman, D.J., Eigenfaces vs. fisherfaces: Recognitionusingclassspecificlinearprojection. IEEE Transactions on pattern analysis and machine intelligence 19, 1997, 711–720.

[19]. ORL Database: www.cl.cam.ac.uk/Research/DTG/attarchive/pub /att_faces.zip

[20]. The Extended Yale B database, http://vision.ucsd.edu/ ~iskwak/ExtYaleDatabase/ExtYaleB.html

[21]. Anil K. Jain, Arun Ross, and Salil Prabhakar "An Introduction to Biometric Recognition", IEEE Transactions on Circuits and Systems for Video Technology, Vol. 14, No. 1, January 2004, pp. 4-20

[22]. Anil K. Jain, Robert P.W. Duin, and Jianchang Mao, "Statistical Pattern Recognition: A Review", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, No. 1, January 2000, pp. 4-37

[23]. K. Etemad and R. Chellappa," Discriminant analysis for recognition of human face images", J. Opt. Soc. Am. A / Vol. 14, No. 8 / August 1997,pp. 1724-1733

[24]. Kailash S. Sharma, Ramchandra R. Manthalkar, "A Local approach to Gabor Wavelet based Face Recognition System", IJARCS, Vol. 8, No. 9, Dec. 2017, pp. 718-722

