An Efficient Method for Face Recognition based on Fusion of Global and Local Feature Extraction

E. Gomathi, K. Baskaran

Abstract: Face recognition is a process of identifying people from their face images. Face recognition technology has many applications such as ATM access, verification of credit card, video surveillance etc. In this paper, we propose a novel face recognition algorithm which exploits both local and global features for feature extraction. Local features are extracted by Gabor wavelets and for global feature extraction, contourlet transform is applied. Then statistical parameters for local and global features are calculated and both the features are combined. Finally face recognition is performed using distance classifier. This proposed algorithm is implemented using MATLAB. The experimental results on ORL face database demonstrate the efficiency of proposed method as 98.5% as against non-fusion face recognition schemes.

Index Terms : Face recognition, contourlet transform, feature extraction, local features, global features.

I. INTRODUCTION

A biometric system is a pattern recognition system in which based on a feature vector, a person is recognized. Face recognition has become popular in the area of pattern recognition and computer vision. This technology has been widely applied in identity authentication, video surveillance, ATM access, etc. The main issue of face recognition is to extract the relevant information from the face image. The challenges mainly arise due to variation in illumination, pose, facial expression, aging, occlusion, etc. Many different algorithms such as Principal Component Analysis (PCA) [1], [2], Linear Discriminant Analysis (LDA) [3], [4], Discrete Cosine Transform (DCT) [5], Hidden Markov Models (HMMs) [6], Neural Networks (NNs) [7], [8] and Support Vector Machine (SVM) [9] were developed for feature extraction and data reduction. Feature extraction can be performed by two methods: Global and Local feature extraction. Both global and local features are crucial for face representation and recognition. For efficient feature extraction, employing image transformation technique is very much useful. An image transformation means a way of representing an image. Multiresolution analysis tools such as wavelets, contourlets, ridgelets etc. were developed for effective image transformation. Because of good time-frequency characteristics [10], wavelet transform was applied in various image processing applications. Wavelets can handle point singularities well. Contourlet transform is a multiscale and multidirection image analysis tool. Since Contourlet transform offers directionality and anisotropy, it can effectively represent information than wavelet transforms [11].

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Hence it is employed to extract global features.
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Gabor wavelet is one of the most successful local feature extraction methods due to their biological relevance therefore it is employed for local feature extraction. Hence, an efficient method has been developed and studied in this paper for face recognition based on fusion of local and global extraction techniques using contourlet transform.

II. RELATED WORK

Wei-wei Yu *et al.* [12] presented a feature extraction method by combining both local (PCA) and global features (Gabor wavelet). Experimental results demonstrated that this method is robust to variations over time, expression, illumination, and pose to a certain extent. Aman *et al.* [13] proposed a face recognition scheme using Discrete Cosine Transform (DCT) for Local and Global Features. Though a high recognition rate is obtained in this study, the image is restricted to a size of 128 × 128 pixels. In [14], the authors presented a novel algorithm based on hybrid of contourlet and manifold learning. Here contourlet transform extracts effective discriminate features in face images sufficiently and the dimensionalities of the features get reduced using surprised preserve local mapping algorithm. Finally using the nearest neighbor classifier, the face image is recognized. Chitaliya *et al.* [15] proposed a face feature extraction and recognition method using Contourlet Transforms and Principal Component Analysis. The feature vector obtained after applying PCA for dimensionality reduction is used as a classifier. It is observed that higher recognition rate was obtained using this extraction and recognition method. A combined subspace method based on LDA using both global and local features for face recognition is proposed [16]. The combined space is constructed with the projection vectors corresponding to large eigenvalues of the between-class scatter matrix in each subspace. This method resulted a better recognition rate than other methods. It is understood that the recognition rate can be improved by combining global and local information. Hence, a strategy for the fusion of local and global facial feature to address the feature extraction problem is studied.

III. BACKGROUND

Contourlet transform is applied to the detected face to extract the global features. The main goal of contourlet transform is to obtain a sparse expansion for typical images having smooth contours. It can represent a smooth contour with fewer coefficients efficiently. Do *et al* [11] proposed a double filter bank structure that decomposes an image into subbands at multiple scales.
The structure is a cascade combination of laplacian pyramid and directional

filter bank. To capture point discontinuities, laplacian pyramid is used and directional filter bank is used to link point discontinuities into linear structures. The advantage of contourlets is that they can deal effectively with smooth contours at multiple resolutions because they have elongated supports at various scales, directions and aspect ratios. Also it provides multiscale and directional decomposition in frequency domain.

A. Laplacian Pyramid

Laplacian pyramid performs multiscale decomposition which was introduced by Burt and Adelson [17]. At each level, Laplacian pyramid decomposition produces a down sampled lowpass version of the original image and the difference between the original and the prediction thus results a bandpass image. Figure 1 explains one level of decomposition process. Here coarse approximation and difference between the original signal and prediction are generated. The distinguishing feature of Laplacian pyramid is that, only one band pass image which does not have scrambled frequencies generated at each pyramid level.

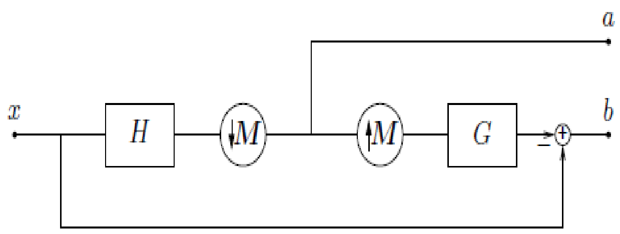


Figure 1 Decomposition Process

B. Directional Filter Bank

Bamberger and Smith proposed a 2-D Directional Filter Bank (DFB) that can achieve perfect reconstruction. The directional filter bank can be implemented by l-level tree decomposition leading to 2^l subbands. DFB is designed to capture high frequency components so that directional information can be captured efficiently. If only directional filter bank is used alone, it cannot provide sparse representation for images due to poor handling of low frequencies.

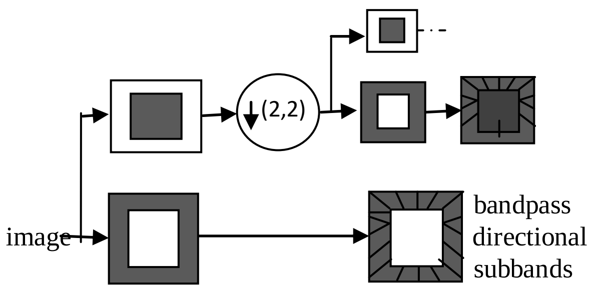


Figure 2 Multiscale and Directional Decomposition Process

Figure. 2 represents a multiscale and directional decomposition process. Multiscale decomposition is done by Laplacian pyramid then directional decomposition is done using a directional filter bank. Bandpass images generated by Laplacian pyramid are fed to a directional filter bank thus directional information can be captured. Contourlet filter bank is a double iterated filter bank that decomposes images into directional subbands at multiple scales.

C. Gabor Wavelet Transform

Among various local features, Gabor wavelets (Figure 3) is one of the most successful extraction methods for face representation due to their biological relevance. Gabor wavelets can take a variety of different forms with different scales and orientations. This can extract more information in certain facial areas such as eyes, nose and mouth, which are very important for face representation. To save more locality information, Gabor features are spatially grouped into a number of feature vectors [18].

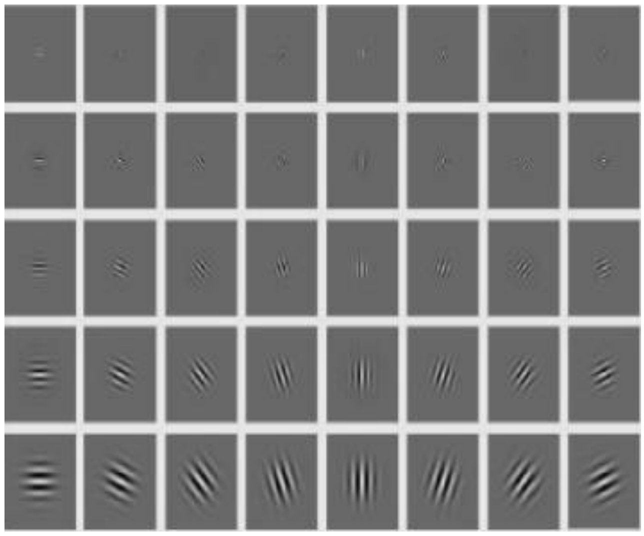
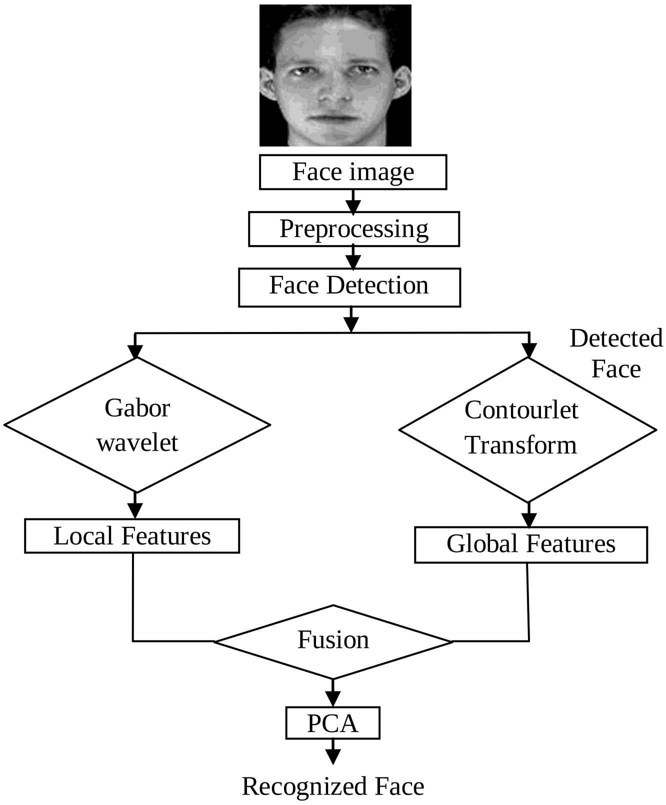


Figure 3 Gabor Wavelets with Five Scales and Eight Orientations

IV. PROPOSED METHOD

In this study, feature extraction by combining local features by gabor wavelet and global features by contourlet transform is proposed for face recognition. Initially the input face image is preprocessed using histogram equalization. After preprocessing, the image is detected. Contourlet transform is applied on the whole detected face image with pkva filter of level 2 to extract the global features. The contourlet transform decomposes the image into subbands and thereby generating contourlet coefficients in different scales and angles. These coefficients are used as global features. Similarly the local features such as eyes, mouth and nose are also extracted by applying Gabor wavelet transform. These Gabor features are spatially grouped into a number of feature vectors each of which corresponds to a local patch of the face image [18]. For global features, large number of coefficients are generated. Therefore feature dimension reduction is required and this is achieved by calculating the statistical measures. Similarly, the energy and entropy features are calculated for local features. Finally both the statistical features are reduced by PCA method since only reduced number of features can achieve high recognition rate. Using Euclidean distance, shortest Euclidean distance from the test feature and database feature is calculated to recognize the face. This process is implemented as shown in the flowchart 1.



Flowchart 1 Block Diagram of Proposed Algorithm

A. Calculation of Statistical Descriptors

Feature dimension reduction was carried out by statistical methods. Statistical measures are computed using the following equations for global as well as local features to form a feature vector.

E1 – Mean
E2 – Standard deviation
E3 – Energy
E4 – Skewness
E5 – Kurtosis

$$E1(s,k) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} W_{s,k}\ (i,j)$$

$$E2(s,k) = [1/MN\sum_{i=1}^{M}\sum_{j=1}^{N} |W_{s,k}\ (i,j) - \mu_{(s,k)}|]^{1/2}$$

$$E3(s,k) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} |W_{s,k}\ (i,j)\,|^{2}$$

$$E4(s,k) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} \frac{(W_{s,k}\ (i,j) - \mu(s,k))^{3}}{\sigma(s,k)^{3}}$$

$$E5(s,k) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} \frac{(W_{s,k}\ (i,j) - \mu(s,k))^{4}}{\sigma(s,k)^{3}}$$

where *M* and *N* denote the number of rows and columns of the subband image. s and k represents the index of scale and direction. W is the coefficient of row and column in sub-band.

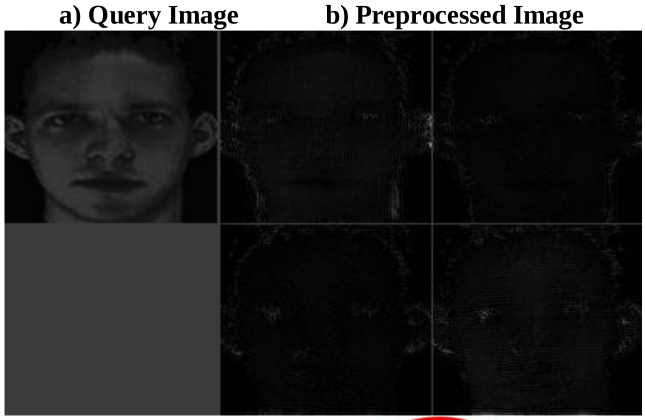
V. RESULTS AND DISCUSSIONS

The proposed algorithm is tested on a face image using three databases by MATLAB. For implementation, ORL, Iranian and own database are chosen. ORL database of faces contains a set of 10 different images of each 40 distinct subjects with variations in pose and expressions. The resolution of image is 92x112 pixels with 256 gray levels per pixel. The size of the own database is 112x112. Figure.4 represents sample of face images from ORL database. After preprocessing and detection, the image is decomposed using contourlet transform as shown in figure. 5c. and 6.c. Coefficients of low frequency and high frequency in different scales and various directions are obtained. The coefficient of contourlet transform is used as a feature vector. Decomposition of image using contourlet transform is done for level-2 using pkva filter. Local features are extracted using Gabor wavelets. Both the features are combined and statistical features are calculated and shown in table.1 and 2. Table.3 reports the performance results obtained for three databases. The recognition rates given in the table 3 indicates the better efficiency of the method in the range of 92.2% to 98.5% for all the data bases such as own, ORL and Iranian. From an overall view, the combination of local features by Gabor wavelet and global features with contourlet transform leads to best performance (98.5% recognition rate) than non-fusion schemes.

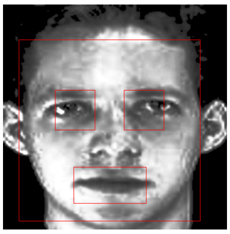
Figure 4 Sample of Face Images for One Subject

A. ORL Database

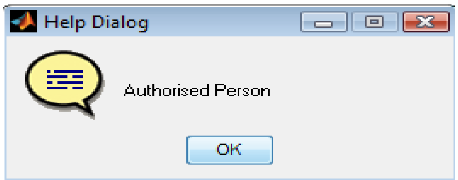
a) Query Image **b) Preprocessed Image**



c) Decomposition of Image from ORL Database using Contourlet Transform



d) Local Feature Extraction



e) Recognition

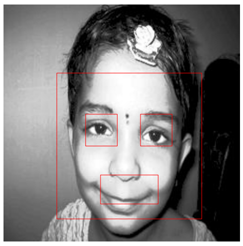
Figure 5 Fusion of Local and Global Feature Extraction and Recognition for ORL Database

B. OWN Database

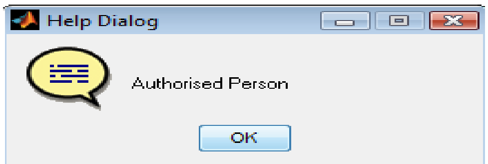
a) Query Image

b) Preprocessed Image

c) Decomposition of Image from Own Database using Contourlet Transform



d) Local Feature Extraction



e) Recognition

Figure 6 Fusion of Local and Global Feature Extraction and Recognition for Own Database

Table 1 Statistical Measures Obtained for Global Feature Image for the ORL Database and Own Database

Statistical Features	ORL	OWN
Mean	251.13	252.69
Variance	2.2019e+04	2.1696e+04
Standard deviation	148.3865	147.2953
Skew	-1.1811e-029	4.0384
Energy	251.1293	252.6913
Entropy	4.0254	4.6259

Table 2 Statistical Measures Obtained for Local Feature Image for the ORL Database and Own Database

Statistical Features	ORL	OWN
Energy (face)	150.9871	146.6782
Entropy(face)	5.4376	5.1641
Energy(mouth)	148.3865	58.4956
Entropy(mouth)	-1.1811e-029	3.9873
Energy(eye1)	251.1293	247.3984
Entropy(eye1)	4.0254	2.6298
Energy(eye2)	176.9844	230.2449
Entropy(eye2)	5.1679	3.8147
Energy(nose)	124.6806	163.0957
Entropy(nose)	4.8593	5.4401

Table 3 Comparison of Recognition Rate using Three Different Database

Database	Original Size of the Image	Size of Feature Matrix using Contourlet Transform	Size of Feature Matrix using Local features	Final Size of Feature Matrix using fusion of local and global features	Weight Matrix after applying PCA	Recognition Rate (%)

OWN	112 X 112	56*56*33	4*33	3140*33	33*33	92.2
ORL	92 X 112	56*46*51	4*51	2580*51	51*51	98.5
Iranian	120X160	60*80*62	4*62	4804*62	62*62	96.8

Comparative Analysis: The recognition rate of various methods is shown in the Table 4.

Table 4 Comparative Analysis

Method	Recognition Rate, %
Waveletface	92.5
Curveletface	94.5
Wavelet+Curvelet	97.5
Proposed method	98.5

VI. CONCLUSION

In this study, feature extraction by combining local features by gabor wavelet and global features by contourlet transform is carried out for face recognition.. After preprocessing and detection, the image is decomposed using contourlet transform. The feature vectors are obtained from contourlet transform vectors. Local features are extracted using Gabor wavelets. Experimental results demonstrated that the proposed algorithm improved the recognition rate compared with non-fusion face recognition schemes to 98.5%. This approach offers better recognition rate than using local and global features individually.

REFERENCES

1. M. Turk and A. Pentland, "Eigenfaces for recognition," Journal of Cognitive Neuroscience, vol. 3, no.1, pp. 71-86, 1991.
2. P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigen faces vs. fisher faces: recognition using class specific linear projection," IEEE Trans. on Pattern Analysis and Machine Intellignece, vol. 19, no. 7, pp. 711-720, 1997.
3. W. Zhao, R. Chellappa, and A, Krishnaswamy, "Discriminant analysis of principal components for face recognition," in Proc. of the 3rd IEEE International Conf. on Automatic Face and Gesture Recoginition, Nara, Japan, 1998, pp. 336-341.
4. Martinez, A.M.& Kak, A.C. PCA versus LDA. In IEEE Transactions (PAMI),Vol.23, No.2, 228-233, 2001
5. X.-Y. Jing and D. Zhang, "A face and palm print recognition approach based on discriminant DCT feature extraction," IEEE Trans. on System, Man, and Cybernetics-Part B: Cybernetics, vol. 34, no. 6, pp. 2405-2415, 2004.
6. H. Othman and T. Aboulnasr, "A separable low complexity 2D HMM with application to face recognition," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 25, no.10, pp. 1229-1238, 2003.
7. M. J. Er, W. Chen, and S. Wu, "High speed face recognition based on discrete cosine transform and RBF neural network," IEEE Trans. on Neural Networks, vol. 16, pp. 679-691, May 2005.
8. M. Er, S. Wu, J. Lu, and L. H. Toh, "Face recognition with radial basis function (RBF) neural networks," IEEE Trans. on Neural Networks, vol. 13, pp. 697-710, May 2002.
9. K. Lee, Y. Chung, and H. Byun, "SVM based face verification with feature set of small size," Electronic Letters, vol. 38, no.15, pp. 787-789, 2002.
10. Li, S., Wang, Y., 2000. " Multisensor image fusion using discrete multiWavelet Transform". In: Proc. 3rd International Conference on Visual Computing, pp. 93–103.
11. Do M.N., Vetterli M., "The Contourlet : An efficient directional multiresolution image representation", IEEE Transactions on Image Processing 14(12), pp. 2091 –2106, 2005.
12. Wei-wei Yu .,Xiao -long ,Teng., Chong-qing Liu ,"Face recognition fusing global and local features" ,*J. Electron. Imaging*. 15(1), 2006
13. Aman R. Chadha, Pallavi P. Vaidya, M. Mani Roja, "Face Recognition Using Discrete Cosine Transform for Global and Local Features", Proceedings of the 2011 International Conference on Recent Advancements in Electrical, Electronics and Control Engineering (IConRAEeCE) ,
14. Zhao Z. and Hao X., "Contourlet based Manifold learning for face recognition," International Conference on Uncertainty Reasoning and Knowledge Engineering, Indonesia, pp.196-199, 2012
15. N.G. Chitaliya, A.I. Trivedi, "An Efficient Method for Face Feature Extraction and Recognition based on Contourlet Transforms and Principal Component Analysis" , Procedia Computer Science 2 (2010) 52–61
16. Chunghoon K. and Oh J.Y., " Combined subspace method using global and local features for face recognition," Proceedings of IEEE International Joint Conference on Neural Networks, Montreal, vol. 4, pp. 2030 - 2035, 2005.
17. P. J. Burt and E. H. Adelson, "The Laplacian pyramid as a compact image code," IEEE Trans. Commun., vol. COM-31, no. 4, pp. 532–540, 1983
18. Yu Su, Shiguang shan, Xilin Chen and Wen Gao. "Hierarchical Ensemble of Global and Local Classifiers for Face Recognition", IEEE Trans. on image processing, vol.18, no.8, 2009.

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