Illumination Invariant Face Recognition Using Gabor Wavelet Function

Swarup Kumar Dandpat[1], Sukadev Meher[2], and Chukka Ranjith[3]
Department of Electronics and Communication Engineering
National Institute of Technology, Rourkela, India, 769008
[1]sk.dandpat@gmail.com,[2]sukadevmeher@gmail.com,[3]chukkaranjith3@gmail.com

Abstract— **Illumination variation changes the appearance of faces and makes it very difficult for accurate recognition. Face identification in an uncontrolled situation is still a challenging task for the researcher. In this paper, we propose a Fourier transform (FT) based illumination normalization and Gabor wavelets based feature extraction for perfect face representation for better classification. Implementing FT and Gabor wavelets in this method is to make the system more robust to the various constraints like illumination and noise where the performances of the other systems are degraded. Considering the phase magnitude information in the frequency domain, the illumination is compensated and using the Gabor filters noise and other unwanted disturbances like facial expressions are discarded. The extensive experimental results, on the publicly available Extended Yale-B face database, show that the proposed method outperforms the well-known face recognition methods even if on the extremely poor illumination images.**

Keywords—Illumination normalization; Fourier transform; Gabor wavelets; face recognition; feature extraction

I. INTRODUCTION

To develop a most successful algorithm for face recognition is a very challenging task in the field of pattern recognition during real time applications. Generally, face recognition system has three stages: (1) Preprocessing (2) Feature Extraction and (3) Classification as shown in the Fig. 1. The first stage includes face detection, normalization, and elimination of background and other parts of the face which may affect the recognition rate. The second stage is categorized into two groups, namely featured based and holistic based [1]. Feature based methods basically rely on facial features like eyes, nose, chin, and mouth which are analyzed and tried to identify the position and relationship between them [2]. But in the holistic approaches, images are analyzed as a whole. Due to difficulties in facial features detection, holistic methods are more frequently used [3].

In the holistic approaches, proper features are extracted considering the entire image by using deterministic or statistical transformations depending upon the databases.

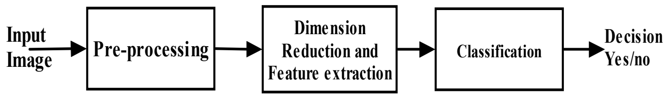


Fig. 1. Block diagram of the face recognition system.

Among the deterministic transform based approaches, Discrete Cosine Transform (DCT) [4][5], Discrete Fourier Transform (DFT) [6], and Discrete Wavelet Transform (DWT) [7] are the most important powerful transforms used in pattern recognition applications. Whereas, Principal Component Analysis (PCA) [8, 9], Linear Discriminate Analysis (LDA) [10], Independent Component Analysis (ICA) [11] and Laplacianfaces [12] are mostly used for feature extraction and dimension reduction as statistical transformation. In PCA and LDA, KL transform is employed to represent 'Eigenface' and 'Fisherface' for most efficient face representation [13]. In ICA, the higher order statistics of the image are explored for pattern recognition purposes.

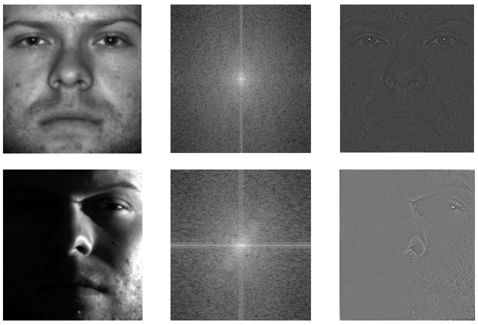
To reduce the high dimensionality 2D image signal into 1D feature vector, many dimension reduction techniques have been proposed. Some of them have some advantages and disadvantages, but it is still to be further researched. On the other hand, it is not easy to decide which features are most suitable and/or what optimal dimension should be for the better performance. It has been observed that even the best set of features for a given classifier may be suboptimal [1, 3].

In the literature, we have seen that the performances of the most efficient feature extraction methods are degraded when the prob images are having uneven illumination variations. Compensating the illumination variations effectively and efficiently is another important problem for accurate recognition in the pre-processing stage when the system works in a poor and uncontrolled environment. To normalize and compensate the illumination effect many methods have been proposed but still, the results are not satisfactory. The simple methods to normalize the lighting variations include the histogram equalization (HE), histogram matching and gamma intensity correction in the spatial domain [14]. Many other spatial domain appearance based methods are proposed in [15-20]. In the frequency domain [21-24], the illumination

978-1-5386-4303-7/18/$31.00 ©2018 IEEE.

influences are removed by selecting and modifying the low frequency coefficients in the transform domain.

In this paper, we propose a Fourier transform (FT) based illumination normalization [24] and Gabor wavelets based feature extraction [25] for face representation. As per the Fourier analysis, the magnitude components of the frequency in the transform domain under illumination are enlarged as shown in Fig. 2. The phase components of the image, which



(a) (b) (c)

Fig. 2. The magnitude and phase distributions of the image from Extended Yale B face database. (a) Frontal well-lit and illuminated images, (b) Centre shift enhanced magnitude spectrums of (a) taking phase part equal to 0, (c) Phase spectrums of (a) taking magnitude part equal to 1.

provide the shape information, are not affected by the illumination variations of the image. Hence, the magnitude parts of the image in the transform domain after transforming the image using DFT are modified. The illumination variations are attempted to be compensated by changing the distorted magnitude spectrum of the illuminated image by adding the magnitude of the frontal well-lit image in the frequency domain. To get the restored image where illuminations are eliminated, the inverse Fourier transform is performed. Then the output images which are compensated out of the illumination variations are used for the next stage of the system. The Gabor wavelet functions are applied on the restored images to extract the efficient features for face representation. The final feaure vector is obtained by down-sampling the above features for face recognition. To test the effectiveness of the proposed method two state-of-the-art feature extraction methods are employed for the comparison purposes. In the classification stage, we have used the nearest neighbor classification with simple Euclidean distance measure as the classifier though other complex classifiers are available in the literature like Neural Network (NN) [26, 27], Hidden Markov Model (HMM) [28], Support Vector Machine (SVM) [29].

The organization of the paper is as follows: In Section II, we have briefly presented the Fourier transform and about the Gabor wavelets. In Section III, the proposed method is described in details. Section IV describes the experimental set-up for face recognition system. The experimental results are presented and discussed in Section V. Finally, we concluded our presentation with some conclusions in Section VI.

II. BACKGROUND

The technique, proposed in this paper, does Fourier analysis and uses it for image restoration after the uneven illumination compensation and employs the Gabor wavelet function for feature extraction.

A. Discrete Fourier Transform

Let $f(x, y)$, represents a digital image of size $M \times N$ where $x = 0,1,2,......,M-1$ and $y = 0,1,2,.......,N-1$ in the spatial domain. This can be transformed into frequency domain by using the 2D-DFT. The 2D-DFT of $f(x, y)$ is defined by the equation

$$F(u,v) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\, e^{-j2\pi(ux/M+vy/N)} \tag{1}$$

for $u = 0,1,2,......,M-1$ and $v = 0,1,2,.......,N-1$ in the frequency domain. $F(u,v)$ is the frequency domain equivalent of $f(x, y)$ having the same size, where, u and v are the frequency variables. The first coefficient of the transform, $F(0,0)$ is the slowest varying component of the discrete Fourier transform and is equal to the MN times the average value of the image. As seen in [14], the smooth intensity variations of the image correspond to low frequency components and the edges and other components having abrupt changes in intensity level correspond to high frequency components.

As per the DFT properties, if the pixel values of the image are real, then the transform domain coefficients are complex. Let, $R(u,v)$ and $I(u,v)$ represent the real and imaginary parts of $F(u,v)$, then the Fourier magnitude spectrum of the image is defined by $|F(u,v)| = [R^2(u,v) + I^2(u,v)]^{1/2}$ and the phase angle of the transform is defined by $\phi(u,v) = \tan^{-1}[I(u,v)/R(u,v)]$. These two functions are used to express the complex function $F(u,v)$ in the polar form as

$$F(u,v) = |F(u,v)|\, e^{j\phi(u,v)} \tag{2}$$

Properties of the Fourier transform say the coefficients are conjugate symmetric about the origin in the transform domain, that is _. It is seen that the magnitude components of the transform determine the intensities of the image whereas the phase components carry the information about where desirable objects are located in the image [14]. However, the phase part gives the shape information as shown in Fig. 2c and is obtained by computing the inverse 2D-DFT of (2) using only the phase angle and taking $\left|F(u,v)\right|$ = 1. Though the intensity information has been lost, but the shape information of the image has been retained. It is seen that the visual information of the phase angle is very useful. Changes in the phase angle in the transformed domain lead to change the shape of the original image in the spatial domain. Hence, only the magnitude part of the face is modified in the transformed domain to eliminate the uneven illumination.

Figure 2 shows the magnitude and phase distributions of two face images of the same individual under different lighting conditions in the frequency domain. The high-frequencies of the lower image faded due to the uneven illumination over the wide area which contains low-frequency components. The shape information of the images is preserved by the phase spectrums of both the images.

B. Gabor Wavelets Function

The Gabor wavelets developed by Lee [30] are the extended versions of Deubenchies one dimensional wavelets. It is seen that a set of Gabor wavelets can provide a perfect representation of any image. In [25], Meshgini et al. have developed a face recognition algorithm using Gabor feature vectors derived by a family of Gabor filter bank. This filter bank is constructed by considering five different scales and eight orientations of the Gabor function. These filters are used to extract the feature vectors directly on the face image in the spatial domain itself. They have many advantages in the face recognition applications that: 1) They are invariant to rotation, scale, and translation, 2) They are very less sensitive to noise and illumination, and 3) Better classification can be done directly without any transformation.

The two dimensional Gabor filters having Gaussian Kernel function modulated by cosine and sine function is expressed by

$$g(x,y)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{x'^2+y'^2}{2\sigma^2}\right)\exp(j\omega x') \tag{3}$$

$$x'=x\cos\theta+y\sin\theta \quad \text{and} \quad y'=-x\sin\theta+y\cos\theta$$

where ω is the angular frequency of the sinusoidal plane, θ and σ are the orientation and standard deviation of the Gaussian filter. These filters are consisting of a family of kernels that are of self similar since they are generated from single mother wavelet hence called Gabor wavelets. Varying scale and orientation we could get different wavelets. The five frequencies and eight orientations are found by the equation as follow:

$$\begin{aligned}\omega_i &= \frac{\pi}{2}\times\sqrt{2}^{-i}, \quad i=0,1,\cdots,4\\ \theta_j &= \frac{\pi}{8}\times j, \quad j=0,1,\cdots,7\end{aligned} \tag{4}$$

Equation (4) gives five scales and eight orientations of the Gabor filter bank as shown in Fig. 3. After applying the Gabor filter bank on the face image using (5) the face representation can be obtained. The gabor face is obtained by convolving the image with the Gabor filter bank as below.

$$G(x,y) = I(x,y) * g(x,y) \tag{5}$$

III. PROPOSED METHOD

If the features of the original image without enhancement are directly used for classification then the performance of the system will be degraded. Thus it requires some pre-processing task before feature extraction. In this section, we describe our proposed method to get the restored image which will be the

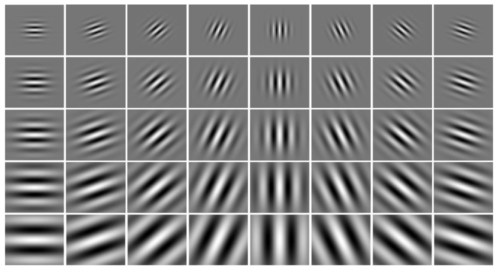


Fig. 3. Gabor filters bank.

phase components (ϕ_f) of the frequency domain are preserved which give the shape information and are important for face recognition. However, only the phase components are not sufficient for extracting suitable features for classification [25]. Fig. 2c shows that the phase spectrums of different persons are different due to different face shape of each person. But the magnitude components are similar even for dissimilar persons. This is because, the faces of all people consist of common facial features like eyes, nose, mouth, eye brows and others which have similar frequency contents and similar magnitudes. The illumination variations are compensated by compensating the magnitude spectrum $|F(u,v)|$ of the distorted image. For this purpose, any good frontal image of any class from the training database is taken without taking the average image of the database as [24]. Making the compensate magnitude $\left|F_{Frontal}(u,v)\right|$ which considers both shape and structural information of the face image [14]. Actually, the shape along with the structure gives the complete information about the image. This information gives us a new idea to prevent the illumination normalization from the images having light variations. The magnitude of the original image $F_I(u,v)$ is then substituted with the magnitude which is a weighted linear combination of the magnitude of the original image as (7). The values of parameters α and β are empirically chosen to obtain the best recognition rate. Finally, the output restored image f_P is obtained by applying the inverse 2D- DFT as per (6) given below:

$$f_P(x,y) = \frac{1}{MN}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} F_f(u,v)e^{j2\pi\phi_I(\mathrm{ux/M+vy/N})} \qquad (6)$$

where,

$$\left|F_f(u,v)\right| = \alpha\,(|\,F(u,v)|) + \beta\,(|\,\mathrm{F}_{Frontal}(u,v)|) \text{ and } (\alpha+\beta)=1. \quad (7)$$

The block diagram of the proposed method is shown in Fig. 4. The original images and their restored images by histogram equalization method [14] and the Fourier transform method [24] are shown in Fig. 5. The values of α and β are taken as 0.5.

The Gabor wavelet functions [23] are applied on these restored images. The dimension of the resulting vector is quite high, e.g., for a 100×100 image, the vector dimension is (100 ×100) × (5 × 8). As the dimension is too large we have down-sampled this by the different down sampling factors to get the best recognition rate.

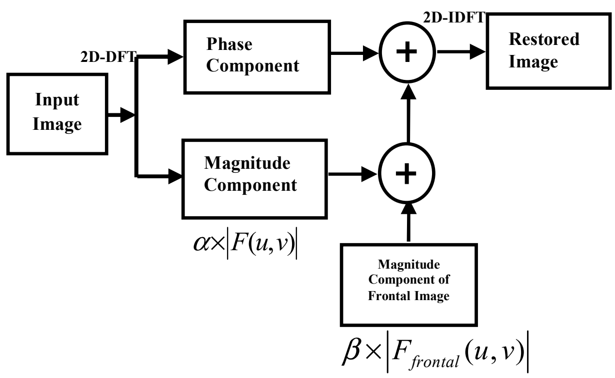


Fig. 4. Block diagram of illumination normalization method [22].

Fig. 5. Illumination normalisation images. The upper row is from Subset 4, Lower row is from Subset 5. (a) Original images; (b) Normalized by HE[14]; (c) Normalized by [24].

IV. Experimental Set Up

A. Extended Yale- B Face Database

For providing different illumination variations images with different pose variations Extended Yale-B face database is mainly designed. This database contains 2414 images of 38 individuals; each image photographed under 64 illuminations conditions for a single pose. These 64 illumination variations images of the frontal pose (Pose00) are considered. These images are subdivided into 5 subsets according to the light source directions with respect to the optical axis of the camera: Subset 1 (angle < 12 degrees), Subset 2 (13 < angle < 25 degrees), Subset 3 (26 < angle < 50 degrees), Subset 4 (51 < angle < 77 degrees) and Subset 5 (as rest of the images) as shown in Fig.6. There are 266, 456, 456, 532 and 722 numbers of images in Subset 1, 2, 3, 4, and 5, respectively, having a size of 192 x 168. The well-lit seven face images of Subset 1 are considered as training database for the classification.

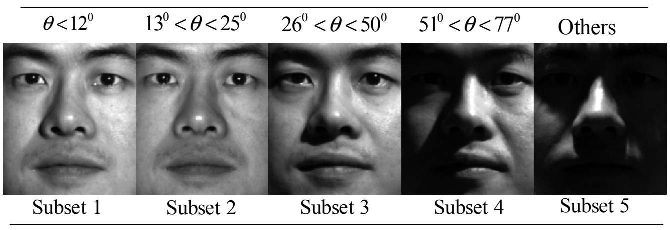


Fig.6. Sample images of different subsets of Extended Yale-B face database.

B. Classification

The classifier used for classification should be fast and should have less computational complexity [31]. In this method, the nearest neighbor classifier with L_2 norm is used for classification. It is very easy, fast and efficient algorithm where there is nothing to train and the matching process is done during testing. The L_2 norm is defined as

$$\text{L2:}\quad d = \left(\sum_{j=1}^{k}\left|f_{training,\,j} - f_{p(test),\,j}\right|^2\right)^{1/2} \qquad (8)$$

where k is the total number of features in the feature vector considered in the second stage of the system. The matching is done by comparing the test image with the entire training images previously stored in the database. The class is identified by finding the nearest distance to the test image. The class of the nearest distance image is considered as the class of the query image. If the class of the nearest image is same as the class of test image then it is counted as correct recognition, otherwise, the test is dismissed as a false identification. Similar tests have been done for thousand times and the recognition rate (RR) is calculated as the following.

$$RR(\%) = \left(\frac{No\ of\ correct\ recognition}{No\ of\ test\ performed}\right)\times 100 \qquad (9)$$

V. EXPERIMENTAL RESULTS

The experimental results, on the original images, histogram equalization images, and Fourier transform based equalized images using the bench mark deterministic transform DCT [4], statistical transform LDA [9] and Gabor wavelet function based [25] face recognition systems, are shown in the Table I. The DCT based FR method improves the recognition rate of the images of Subset 3, 4, and 5 by 10.44%, 13.16%, and 23.25%, respectively, whereas for the Subset 2 the RR is decreased as the images are somehow good images as compare to other subsets. It is observed that applying the quality improvement technique on good images decreases the pixel relation information of the original images for the use of classification. The LDA based FR method increases the recognition rate by 7.19%, 17.44%, and 21.21%, respectively, whereas for Subset 2 the RR is 100%. For the proposed Gabor based method, the RR is 100% for the Subset 2 and 3 images and there is 51.99% and 64.34% increase for the Subset 4 and Subset 5, respectively. The results of all the systems are shown in Fig. 7a and 7b for the Subset 4 and 5 for better observation. From the results, it is seen that proposed Gabor based method significantly increases the RR when the images are most corrupted due to uneven illumination. It gives the highest recognition rate in comparison to others as **100%**, **100%**, **93.42%**, and **92.94%** for Subset 2, 3, 4, and 5, respectively. It improves the performance by 125% and 224.96% for the Subset 4 and Subset 5, respectively from its values on the original image.

From the Fig. 8, it is observed that in comparison to DCT and LDA it outperforms by more than **31.84%** and **5.88%** for Subset 3, respectively. And for Subset 4 and 5, its results are **63.30%** and **66.63%** more than the DCT based and **47.04%** and **55.5%** more than the LDA based method.

VI. CONCLUSIONS

An efficient illumination normalization method based on Fourier transform and Gabor wavelet function is presented. Illumination compensation under uneven lighting conditions is An efficient illumination normalization method based on Fourier transform and Gabor wavelet function is presented. Illumination compensation under uneven lighting conditions is done by keeping the shape information intact and modifying the magnitude information of the illuminated face image in the transformed domain. The magnitude components of the distorted image are modified by adding the magnitude components of any frontal well-lit image taken from the training database. The restored image, which is used for face recognition is found by taking the inverse 2D-DFT. For feature extraction for classification, we have used the Gabor wavelet functions. Because of the useful properties of DFT and Gabor functions the efficient feature vector for classification is derived. The effectiveness of the proposed method on the Extended Yale-B database can be seen from the experimental results. It is observed that the recognition rate is deteriorated for well-lit test images after illumination normalization if proper FR method is not chosen. The proposed method yields the highest recognition rate of **100%**, **100%**, **93.42%**, and **92.94%** for Subset 2, 3, 4, and 5, respectively. In the future work, we implemented the method in other larger illumination based face databases. The efficacy of Gabor wavelet functions will be measured on differently illumination compensated images.

TABLE I. THE COMPARISON RESULTS OF DIFFERENT METHODS ON EXTENDED YALE-B DATABASE

Method	R.Image	Subset 2	Subset 3	Subset 4	Subset 5
DCT	$I_{original}$	91.10	57.72	26.96	3.06
	$I_{histogram}$	77.67	64.61	38.70	25.21
	$I_{Fourier}$	79.78	68.16	40.12	26.31
LDA	$I_{original}$	**100**	86.93	28.94	16.23
	$I_{histogram}$	**100**	90.25	42.12	32.96
	$I_{Fourier}$	**100**	94.12	46.38	37.44
Gabor wavelet	$I_{original}$	**100**	**100**	**41.43**	**28.60**
	$I_{histogram}$	**100**	**100**	**86.56**	**81.48**
	$I_{Fourier}$	**100**	**100**	**93.42**	**92.94**

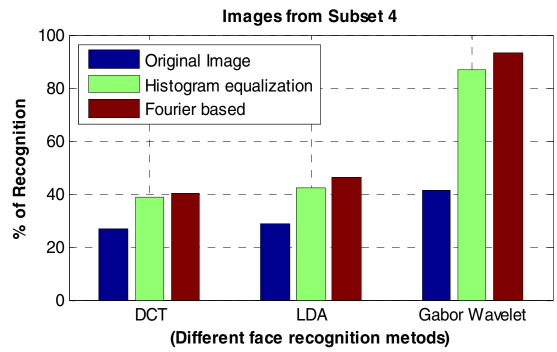


Fig. 7a. The RR of different approaches using the original images, histogram equalization images, and Fourier transform based illumination normalization images of the Subset 4.

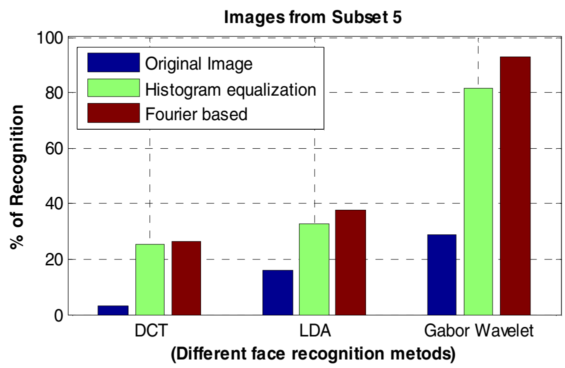


Fig. 7b. The RR of different approaches using the original images, histogram equalization images, and Fourier transform based illumination compensation images of the Subset 5.

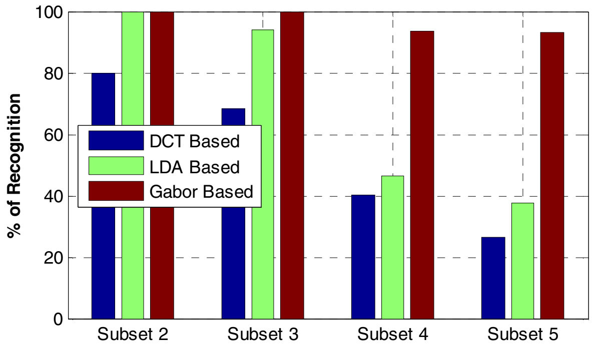


Fig. 8. Comparison of the proposed method with the other methods on the images of all subsets.

REFERENCES

[1] R. Chelleppa, C. L. Wilson, and S. Sirohey, "Human and machine recognition of faces: a survey," Proc. IEEE, vol. 83, no. 5, pp. 705-740, May 1995.

[2] L. Wiskott, J. M. Fellous, N. Kruger, and C. vonder Malsburg, "Face Recognition by Elastic Bunch Graph Matching," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 775-779, July 1997.

[3] W. Zhao, R. Chelleppa, P. J. Phillips, and A. Rosenfeld, Face recognition: a literature survey, ACM Computing Surveys 35, pp. 399–458, 2003.

[4] Z. M. Hafed and M. D. Levine, "Face recognition using the discrete cosine transform," Int. J. of Computer Vision, vol. 43, no. 3, pp. 167–188, 2001.

[5] X. Y. Jing and D. Zhang, "A face and palm print recognition approach based on discriminant DCT feature extraction," IEEE Trans. Systems, Man, and Cybernetics, vol. 34, pp. 2405–2415, 2004.

[6] Jian H. Lai, Pong C. Yuen, and Guo C. Feng, "Face recognition using holistic Fourier invariant features," Pattern Recognition, vol. 34, pp. 95-109, 2001.

[7] Chao-Chun Liu and Dao-Qing Dai, "Face Recognition Using Dual-Tree Complex Wavelet Features," IEEE Transactions on Image Processing, vol. 18, no. 11, pp. 2593-2599 Nov 2009.

[8] M. A. Turk and A. P. Pentland, "Eigenfaces for Recognition," J. Cogn. Neuroscience. vol. 3, pp. 71–6, 1991.

[9] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces versus Fisherfaces: Recognition using Class Specific Linear Projection," IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 711–720, Jul. 1997.

[10] J. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos, "Face Recognition using LDA based Algorithms, IEEE Transaction on Neural Networks 14 (1), pp 195-200, 2003.

[11] M. S. Bartlett, J. R. Movellan, and T. J. Sejnowski, "Face Recognition by Independent Component Analysis," IEEE Trans. Neural Networks, vol. 13, no. 6, pp. 1450-1464, 2002.

[12] X. F. He, S. C. Yan, Y. X. Hu, P. Niyogi, and H. J. Zhang, "Face recognition using laplacian faces," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 3, pp. 328–340, Mar. 2005.

[13] M. Kirby and L. Sirvoich, "Application of the Karhunen-Loeve Procedure for the characterization of human faces," IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 12, no. 1, pp. 103–108, Jan. 1990.

[14] Rafael C. Gonzalez and R. E. Woods, Digital Image Processing, Prentice Hall, (2002), 2nd ed.

[15] E. H. Land, and J. J. McCann, "Lightness and retinex theory", Journal of the Optical Society of America, vol. 61 pp. 1–11, 1971.

[16] D. J. Jobson, Z. Rahman, and G. A. Woodell, "Properties and Performance of a Center/Surround Retinex," IEEE Transactions on Image Processing, vol. 6, pp.451–462, 1997.

[17] D. J. Jobson, Z. Rahman and G. A. Woodell, "A multiscale retinex for bridging the gap between color images and the human observation of scenes", IEEE Transactions on Image Processing, vol. 6, pp. 965–976, 1997.

[18] H. Wang, S. Z. Li, and Y. Wang, "Face recognition under varying lighting conditions using self quotient image," in Proceedings of the Automatic Face and Gesture Recognition, pp. 819–824, 2004.

[19] R. Javier and Q. Julio, "Illumination compensation and normalization in eigenspace-based face recognition: A comparative study of different pre-processing approaches," Pattern Recognition Letter, vol. 29, no. 14, pp. 1966–1979, 2008.

[20] X. Xie and K. Lam, "An efficient illumination normalization method for face recognition," Pattern Recognition Letters, vol. 27, no. 6, pp. 609–617, 2006.

[21] W. Chen, M. J. Er, and S. Wu, "Illumination Compensation and Normalization for Face Recognition using Discrete Cosine Transform in Logarithm Domain," IEEE Transaction Systems, Man, and Cybernetics-Part B: Cybernetics, vol. 36, no. 2, pp. 458–466, 2006.

[22] D. Shan and R. Ward, "Wavelet-based Illumination Normalization for Face Recognition," vol.2, pp.954-957, 2005.

[23] T. Zhang, B. Fang, Y. Yuan, Y. Y. Tang, Z. Shang, D. Li, and F. Lang, "Multiscale facial structure representation for face recognition under varying Illumination" Pattern Recognition, vol. 42, no. 2, pp. 251 – 258, 2009.

[24] Choi S. and Jeong G, "Shadow Compensation Using Fourier Analysis With Application to Face Recognition" IEEE Signal Processing Letters, vol. 18, no. 1, pp. 23-26, 2011.

[25] S. Meshgini, A. Aghagolzadeh, and H. Seyedarabi, "Face recognition using Gabor-based direct linear discriminant analysis and support vector machine" Computers & Electrical Engineering, vol. 39, pp. 727-745, 2013

[26] Haykin, S. "Neural Networks: A Comprehensive Foundation," Prentice Hall, 0-13-273350-1, New Jersey, 1999.

[27] M. J. Er, W. Chen, and S. Wu, "High speed face recognition based on discrete cosine transform and RBF neural network", IEEE Transaction on Neural Network, vol. 16, no.3, pp. 679-691, 2005.

[28] H. Othman, and T. Aboulnasr, "A separable low complexity 2D HMM with application to face recognition", IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 25, no.10, pp. 1229-1238, 2003.

[29] K. Lee, Y. Chung, and H. Byun, "SVM based face verification with the feature set of small size", Electronic letters, vol. 38, no.15, pp. 787-789, 2002.

[30] T. S. Lee, "Image representation using 2D Gabor wavelets," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18, no. 10, pp. 959–971, 1996.

[31] Duda R, Hart P, Stork D. "Pattern Classification," 2nd edn., Wiley-Interscience, New York, 2001.