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Uneven Illumination Compensation for Unconstrained Face Recognition Using LBP

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***Abstract*— Face recognition results are degraded when the test image is having nonuniform illumination variations. Due to the lighting variations, different expressions and occlusions the facial appearance of the face changes dramatically such that recognition by the methods is quite a difficult task. Out of which the problems due to illumination variations such as shadows, under lighting, over lighting in the face are the crucial problems which are to be overcome to achieve the satisfactory results for an automatic face recognition system. In this paper, we propose an efficient illumination compensation method based on frequency analysis and multi-resolution analysis. The effect of uneven lighting variations of the test image is efficiently and effectively removed by applying the LBP image to modify the magnitude information in the frequency domain. The magnitudes of the LBP image compensate the distorted magnitudes of the original image, caused by the light variations, as well as add some structural information to the restored image. To examine the efficacy of our developed method, histogram equalization based normalization and Fourier based normalization methods are compared with the proposed method. An extensive simulation study has been carried out to measure the effectiveness of our proposed method on the images containing extreme illumination variations. For this purpose, we have used the Extended Yale-B face database. From the results, it is found that our proposed method outperforms other methods and also it works better for extremely poor illuminated images.**

***Index Terms*— Face Recognition, Discrete Fourier Transform, Local Binary Pattern, Illumination Normalization, Feature Extraction.**

I. INTRODUCTION

By understanding the human perception, modelling a robust automatic artificial system to recognize an image is a very challenging task in pattern recognition. The intensive up to date research has not developed a robust system that could be useful for solving all practical applications. Many face recognition methods have been proposed that have been better recognition rate but have some limitations [1-2]. The recognition rate of these methods is different for different face databases. The recognition rate is seriously degraded when the test image is imaged in an uncontrolled environment. During testing, accurate recognition of faces is a challenging task when the system works with uncooperative users or in poor and uncontrolled lighting conditions. In face recognition, the illumination variations create difficulty for classification as the facial appearance looks different. It is observed that the changes in facial appearance of same class images due to illumination variations is always more than the changes between the inter class variation images [3]. Almost all the well known face recognition methods either subspace methods or transformed domain methods [4-7], and also the spatial domain methods [8-9] are suffered due to varying illumination conditions. To enhance the recognition accuracy of the systems illumination compensation in the pre-processing step before the features extraction for classification is necessary [10-25].

In the approaches [10-12], it has been attempted to design a model of the luminance effect of the non uniform lighting variations. Though these methods yield better results for face recognition but to generate the model that is assembled with available different templates is very difficult. In real time applications, model based approaches need many additional information and assumptions and also require a large number of training data [10]. The Illumination compensation has been done in the spatial domain as well as in frequency domain. The simple methods to normalize the lighting variations in the spatial domain are histogram equalization (HE), histogram matching, and gamma intensity correction [13]. Considering the local information, illumination variations are compressed, preserving the image edges as well as removing the halo effects [14]. This effect is efficiently compensated by proposing a self quotient image (SQI) method in [15]. Based on SQI, a logarithm based total variation model [16] is developed. Illumination normalization methods are also developed in the frequency domain [17-20]. With the knowledge of frequency distribution of the signal in the transformed domain, illumination influences are removed by selecting and modifying the low frequency coefficients in the transformed domain [17]. In [18], the multiresolution technique is applied to downsample the degraded face image into four subbands. Some pre-processing steps are carried out on these subbands to remove the lighting effect and simultaneously to enhance the edges and other information. A similar approach with quality based illumination compensation technique using same DWT has been proposed in [19]. In [20], authors have used DFT and kept the phase components as it is i.e. the shape information of the image which is insensible to the light and modify the magnitude components to eliminate the illumination variations.

In this paper, we try to identify some of the weaknesses and there by propose an effective and efficient illumination variation method which gives better performance. In this proposed method, discrete Fourier transform (DFT) and local binary pattern (LBP) are used for illumination compensation in the transformed domain. As per the Fourier analysis, the magnitude components of the frequency coefficients in the transform domain under illumination are enlarged [13]. The phase components of the image, which provide the shape information, are not affected by the magnitude components of the image. Only the magnitude parts of the image in the transform domain after transforming the image using DFT are explored as [20]. The illumination variations are compensated by changing the distorted magnitude spectrum of the illuminated image by adding the magnitude of the LBP image in the frequency domain. We use different LBP operators to get the LBP image on any good frontal image taken from the training database. To get the restored image, after illuminations are eliminated, the inverse Fourier transform is performed. Then this output image is fed to the face recognition system for the recognition purposes. To test the effectiveness of the proposed method, histogram equalization based normalization [13] and Fourier based normalization method [20] are compared with this proposed method. An extensive simulation study has been carried out to measure the effectiveness of the proposed method on the images containing extremely illumination variations. From the results, it is found that the efficacy of this proposed method outperforms other methods.

The remainder of this presented paper is organized as follows. The DFT, LBP, and the details about the proposed illumination normalization technique are explained in Section II. In Section III, the evaluations of this paper presented here using the Extended Yale-B face database along with feature extraction and classification are briefly described. The simulation results are presented and discussed in Section IV. The conclusion of the work is drawn in Section V.

II. Proposed Method

In this proposed technique, the DFT and LBP for efficient illumination compensation are used. LDA [7] and Gabor wavelet based [21] methods are applied on the output restored images for feature extraction for classification to measure the performance.

A. Discrete Fourier Transform

The discrete Fourier transform (DFT) is a most suitable signal processing tool to analyze the signal in the transformed domain. Let $f(a,b)$ represents a digital face image of size $m \times n$, and $a = 0,1,2,\ldots,m-1$ and $b = 0,1,2,....,n-1$ are the coordinates in the spatial domain. Then this image can be transformed into frequency domain by applying the 2D-DFT. The 2D-DFT of as

$$F_f(c,d) = \sum_{a=0}^{m-1}\sum_{b=0}^{n-1} f(a,b)e^{-j2\pi(ac/\mathrm{m}+bd/\mathrm{n})} \tag{1}$$

where $c = 0,1,2,....,m-1$ and $d = 0,1,2,....,n-1$ are the frequency coordinates in the transformed domain.

It is seen that the smooth intensity variations of the image correspond to low frequency components and the edges and other components having abrupt changes in intensity level related to the high frequency coefficients [13]. Though the value of the $f(a,b)$ is real, its value in the transformed domain is complex in general.

In the complex configuration, if $R(c,d)$ and $I(c,d)$ represent the real and imaginary components of $F_f(c,d)$, then the Fourier spectrum of the face image can be expressed as $|F_f(c,d)| = [R^2(c,d)+I^2(c,d)]^{1/2}$ and the phase angle of the transform is defined by: $\phi_f(c,d) = \arctan\left[\dfrac{I(c,d)}{R(c,d)}\right]$.

These two functions can be used to express the complex function $F_f(c,d)$ in the polar form as

$$F_f(c,d) = |F_f(c,d)|e^{j\phi_f(c,d)} \tag{2}$$

As the pixel values of the image are real, the Fourier transform is conjugate symmetric about the origin. It is seen that [20] the phase components carry the information about where the desirable objects are located in the image. However, the phase part gives the shape information that is obtained by computing the inverse 2D-DFT of (2) using only phase angle and considering $F_f(c,d)$ = 1. Though the intensity information has been lost but the shape information of the image has been retained. Changes in the phase angle lead to the change in shape of the original image $f(a,b)$ in the original domain. It is observed that the visual analysis of the phase angle is not intuitive, it is just as important. The magnitude spectrum provides the information about the changes in the intensity of an image. Hence, the magnitude part of the face image has to be reconstructed to remove the illumination variations.

B. Local Binary Pattern

The Local binary pattern (LBP), developed by Ojala et al. [22], is generated by a number of binary comparisons between the gray-level value of the 3×3 neighboring pixels and its centre pixel with a uniform order as shown in Fig. 1. The mathematical derivation is expressed as:

Let f_c be the intensity value of the centre pixel and f_n, for $n = 0,1,2,.....,\mathrm{P}-1$, be the intensity value of each neighboring pixel, then the decimal value of the centre pixel of the LBP image is derived by

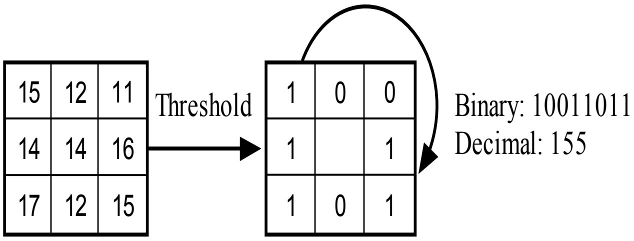

Fig. 1. LBP operator (P=8, R=1) gives a decimal number.

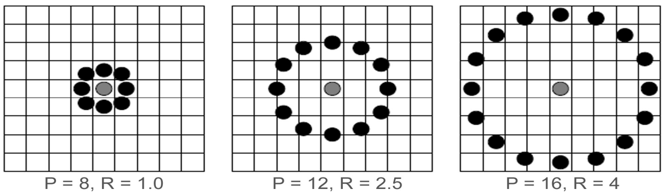

Fig. 2. The neighbouring pixels for different LBP operators.

$$LBP_{P,R}(f_c)=\sum_{p=0}^{P-1}S(f_n-f_c)\,2^n \quad \text{where,}$$

$$S(x)=\begin{cases}1 & if\ x\geq 0\\ 0 & otherwise\end{cases} \tag{3}$$

and (P, R) are P neighboring pixels on a circle of radius R. The center pixel is assigned a new gray-level as found during the operation. After applying this process on the entire image the output image, called as the LBP image or LBP face as shown in the Fig. 4(d), is generated. The LBP operator produces 2^P different output values, corresponding to the 2^P different binary patterns that can be formed by the P neighborhood pixels. This LBP operator can be of different sizes as shown in Fig. 2. For the increasing R, if the neighborhood pixels or the sampling points are not on the co-ordinates of the pixel then the value of the sampling points can be considered by the bilinear interpolation. In [22], authors have shown that the operator (P=8, R=2) gives better result on most of the cases. Hence, in this paper, we have also carried out our experiments on this operator (P=8, R=2) along with the original (P=8, R=1).

C. Proposed Illumination Compensation Method

If the features of the original image without enhancement are directly used for classification, then the recognition rate of the system will be degraded. Thus, it requires some pre-processing task before the feature extraction for better recognition. To overcome this problem, we proposed an efficient illumination compensation method which will yield more informative image in this section.

After taking Fourier transform of the degraded image the phase components (ϕ_f) are preserved which give the shape information and are important for face classification. It is seen that, only the phase part is not sufficient for extracting suitable features for classification [20]. The phase spectrums of different persons are different. But the magnitude components are similar even for different persons. Because, the faces of all people consist of common facial features like eyes, nose, mouth, eye brows and others which have similar frequency information and of course similar magnitude spectrum [12]. The illumination variations are compensated by compensating the magnitude spectrum 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 [20]. This image is converted into the LBP image(f_{LBP}), called as LBP face as described in the above section, for using as the compensate magnitude $\left|F_{I_{LBP}}(c,d)\right|$ which contains the multi-resolution properties as well as some invariant information of the face image. The reasons behind the using of local binary pattern are that: 1) the restored images might be composed of micro patterns which will be useful for better classification [22] because of invariant properties, and 2) the shape along with the structure gives the complete information about the image. This information gives us an innovative idea to prevent the uneven illumination from the images having lighting variations. The LBP image as well as the original degraded image is transformed to the frequency domain by 2D-DFT. The magnitude of the original image $\left|F_f(c,d)\right|$ is then substituted with the magnitude of a linear representation model as:

$$\left|F_p(c,d)\right|=\alpha\,(|\,F_f(c,d)\,|)+\beta\,(|\,\mathrm{F}_{I_{LBP}}(c,d)\,|) \tag{4}$$

where $(\alpha+\beta)=1$.

The values of parameters α and β are chosen as 0.5 as [25]. Finally, the proposed resulting image f_P is obtained by applying the inverse 2D-DFT as per given below:

$$f_P(a,b)=\frac{1}{mn}\sum_{u=0}^{m-1}\sum_{v=0}^{n-1}F_p(c,d)e^{j2\pi\phi_f(ca/\mathrm{m}+db/\mathrm{n})} \tag{5}$$

The architecture of our presented normalization process is illustrated in Fig. 3. In this figure the details process of getting the restored image is shown.

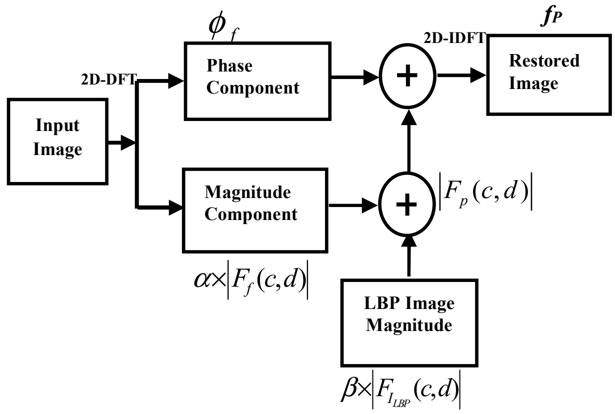

Fig.3. Proposed architecture for the restoration process.

(a) (b) (c) (d)

Fig. 4. Illumination compensated images. (a) original images (b) compensated by HE (c) compensated by [20] and (d) compensated by the proposed method.

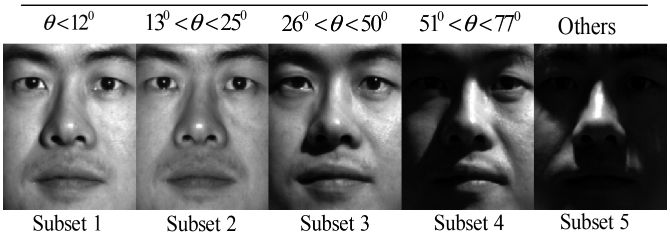

Fig.5. Example of different subset images of [23].

The good frontal images and their restored images by the different methods are shown in Fig. 4 which are used during the simulation process.

I. Evaluation of The Proposed Method

In this section, the details about the face database, feature extraction methods, and classification are briefly explained.

A. Extended Yale-B Face Database

The bench mark database named as Extended Yale-B face database [23] which is mainly designed to test system under extremely illumination variation conditions. This database has 2432 face images of 38 persons; each person is acquisitioned under 64 illumination conditions for a single pose. These 64 illumination variations images of the frontal pose (Pose00) are considered. All the images are subdivided into five subgroups according to the azimuth and elevation of face and the light source direction. For the Subset 1 $\theta\ is < 12^0$, for Subset 2 $13^0 < \theta < 25^0$, for Subset 3 $26^0 < \theta < 50^0$, for Subset 4 $51^0 < \theta < 77^0$ and for Subset 5 rest of the images which are shown in Fig.5. 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 pixels. The subset 1 is considered as a training set and rest are used for the classification.

B. Feature Extraction Method

The feature extraction step is to select the most relevant features for better representation of the face image after dimensionality reduction of the high dimensional image data through the deterministic or statistical transformation. It is seen that the selection of features is not so easy to decide which features are most suitable and/or what optimal dimension should be used for recognition. To examine the efficacy of the presented method the state-of-the-art technique named as LDA is used for feature extraction. Along with LDA, a spatial domain method called as Gabor wavelet based is also used for testing. For the detailed mathematical evaluation the original papers [7] and [26] may be referred.

C. Classification

The classifier used for classification should be fast and should need less memory; hence, it is required to decrease the computational complexity. Thogh many classifier have been proposed but it is observed that the nearest neighbor classifier is the most suitable for this purpose. It is very easy, fast and efficient algorithm where there is nothing to train and the matching process is done during the testing. Among the different distance matrices we have used Euclidian distance to measure the nearest distance. The distances are measured to each training image stored in the database from the test image. The nearest distance image is identified as the test image. If the identified class and the test class is same then the test is considered as the correct recognition otherwise it is treated as false recognition. Similar test has been done thousand times and the recognition rate is found as:

$$RR(\%) = \left(\frac{No\ of\ Correct\ Recognition}{Total\ no\ of\ Test\ Images} \right) \times 100 \qquad (6)$$

II. Experimental Results

After illumination normalization in the pre-processing step the feature extraction is performed using LDA and Gabor wavelet function for classification. The recognition rates based on the original images ($I_{original}$), restored images using HE ($I_{histogram}$), Fourier transform ($I_{Fourier}$) [25], and the restored images using the proposed method ($I_{proposed}$) are measured.

The results in percentage are mentioned in Table I and shown in Fig. 6. It is observed from the table that the recognition rates yielded by our presented method are the highest among all the normalization methods as well as in all the feature extraction methods. Using the proposed method, 100%, 100%, 95.86%, and 94.70% of recognition rate are achieved for Subset 2, 3, 4 and Subset 5, respectively considering α and β values equal to 0.5. Compared to all these methods, the proposed method improves the identification rate about 8-25% for all images taken into account.

Table II shows the results for different combination LBP operators i.e. (P=8; R=1) and (P=8; R=2). For the LBP operator (P=8; R=2), the recognition rate further increases up to 98.24%, 54.14% and 49.30% for Subset 3, 4 and 5, respectively for the LDA based method against 96.70%, 49.62%, and 46.53% as recorded in Table I. Similarly, the recognition rate increases up to **96.56%** and **95.75%** for Subset 4 and 5, respectively for the Gabor based method

TABLE I. ACCURACY IN PERCENTAGE USING THE DATABASE EXTENDED YALE-B APPLYING DIFFERENT METHODS AND DIFFERENT NORMALIZED IMAGES

Method	**R.Image**	**Subset2**	**Subset3**	**Subset4**	**Subset5**	**All**
LDA	$I_{original}$	**100**	86.93	28.94	16.23	58.02
	$I_{histogram}$	**100**	90.25	42.12	32.96	66.31
	$I_{Fourier}$	**100**	94.12	46.38	37.44	69.48
	$I_{proposed}$	**100**	96.70	49.62	46.53	73.20
Gabor	$I_{original}$	**100**	100	71.43	28.60	75.01
	$I_{histogram}$	**100**	100	86.56	81.48	92.01
	$I_{Fourier}$	**100**	100	93.42	92.94	96.59
	$I_{proposed}$	**100**	**100**	**95.86**	**94.70**	**97.64**

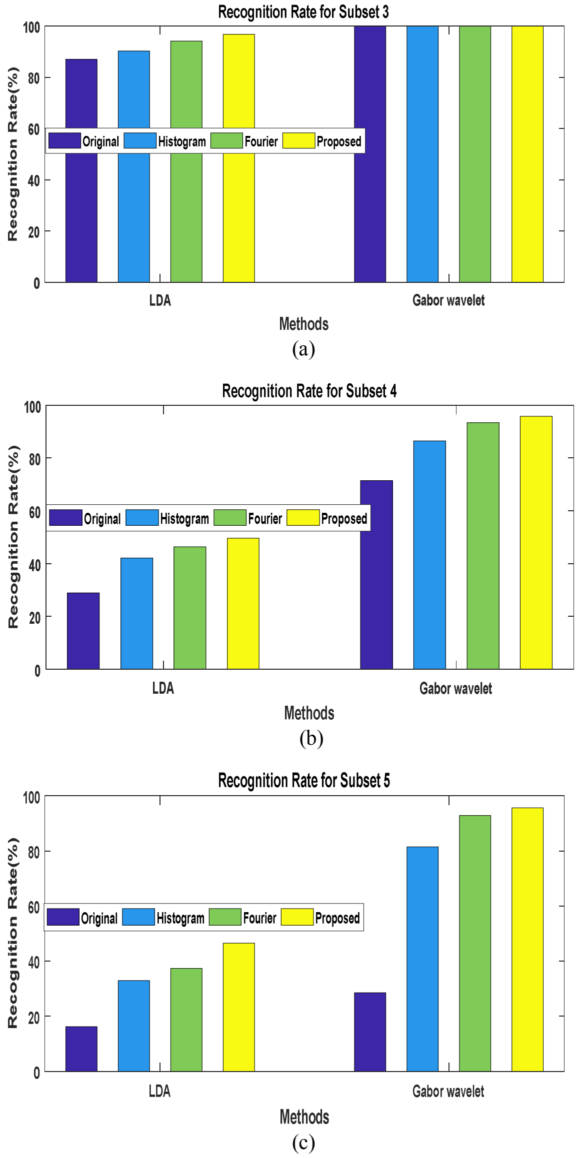

Fig.6. The recognition rate of different illumination normalization techniques using LDA and Gabor wavelet methods on (a) Subset-3 (b) Subset-4 and (c) Subset-5 images.

TABLE II. RECOGNITION RATES (%) FOR LDA AND GABOR WAVELET BASED FEATURE EXTRACTION METHODS WITH TWO DIFFERENT LBP OPERATOR.

Method/ LBP Operator	**LDA**			**Gabor**		
	Subset3	**Subset4**	**Subset5**	**Subset3**	**Subset4**	**Subset5**
P=8, R=1	96.70	49.62	46.53	100	95.86	94.70
P=8, R=2	98.24	54.14	49.30	**100**	**96.56**	**95.75**

against 95.86% and 94.70% whereas for Subset 3 it is already reached to 100%.

It is observed that the change in recognition rate is **~200%** for very poorly illuminated image and **~10%** for slightly illumination variation image. Typically, for a moderately illuminated image, the change is **~180%**. Hence, it is confirmed that the proposed method performs better for extremely poor illuminated images. Further, we are working on the detailed analysis about the variations of α and β. And also during our study we have found that varying the α and β values the results can be improved.

III. CONCLUSION

An efficient illumination compensation method based on DFT and LBP is presented. Illumination compensation is done in the frequency domain by keeping the shape information intact and modifying only the magnitude information. The magnitude components of the distorted image are modified by adding the magnitude components of LBP image of any frontal well-lit image taken from the training database in the frequency domain. The resulting image, which is used for face recognition is found by taking the inverse 2D-DFT.The simulation results yield using the Extended Yale B database proves the effective of the proposed method. The recognition rate for different subsets is achieved as **100%** for Subset 2 and 3**,** and **96.56% and 95.75%** for the Subset 4 and Subset 5, respectively. The change in recognition rate is **~200%** for the very poorly illuminated image to **~10%** for the well illuminated image. Typically, for a moderately illuminated image, the change is **~180%**. It is concluded that the method presented in this paper works better for extremely poor illuminated images. In this proposed method, the highest recognition rate can be achieved using Gabor wavelet method. In future work, we will try to implement our proposed method with other latest recognition methods with different illumination variation based face databases.

REFERENCES

[1] R. Chellappa, C. L. Wilson, and S. Sirohey, “Human and machine recognition of faces: a survey,” Proceedings of IEEE, vol. 83, no. 5, pp. 705-740, 1995.

[2] W. Zhao, R. Chellappa, P.J. Phillips and A. Rosenfeld, “Face recognition: a literature survey,” ACM Computing Surveys, vol. 35, no. 4, pp. 399–458, 2003.

[3] Y. Adini, Y. Moses, and S. Ullman, “Face recognition: The problem of compensating for changes in illumination direction,”

IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp.721-732, 1997.

[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] C. C. Liu and D. Q. Dai, “Face recognition using dual-tree complex wavelet features,” IEEE Transactions on Image Processing, vol. 18, no. 11, pp. 2593-2599 Nov (2009)

[6] M. Turk and A. Pentland, "Eigenfaces for face recognition," Journal of Cognitive Neuroscience, vol. 3, pp.71-86, 1991.

[7] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, “Eigenfaces vs. fisherfaces: recognition using class specific linear projection,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19, pp. 711–720, 1997.

[8] T. Ahonen, A. Hadid, and M. Pietikainen, “Face description with local binary patterns: Application to face recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 12, pp. 2037–2041, 2006.

[9] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, “Robust face recognition via sparse representation,” IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 31, no. 2, pp. 210-227, 2009.

[10] Georghiades, A. S., Belhumeur, P. N. and Kriegman, D. J, “From few to many: Illumination cone models for face recognition under variable lighting and pose,” IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 23, no. 2, pp. 643–660, 2001.

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

[12] R M. Savvides, B. V. K. Vijay Kumar, and P. K. Khosla, “Eigenphases vs. eigenfaces,” in Proceedings of International Conference on. Pattern Recognition, pp. 810–813, 2004.

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

[14] A. Shashua and T. Riklin-Raviv, “The Quotient image: Class-based re-rendering and recognition with varying illuminations,” IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 23, no. 2, pp. 129–139, 2001.

[15] 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.

[16] T. Chen, W. Yin, X. S. Zhou, D. Comaniciu and T. S. Huang, “Total variation models for variable lighting face recognition”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.28, no. 9, pp. 1519–1524, 2006.

[17] 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.

[18] D. Shan and R. Ward, "Wavelet-based illumination normalization for face recognition," IEEE International Conference on Image Processing (ICIP), pp.954-957. 2005.

[19] S. K. Dandpat and S. Meher, “Quality based illumination compensation for face recognition,” IEEE International Conference on Image Information Processing (ICIIP), 2011.

[20] 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.

[21] 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.

[22] T. Ojala, M. Pietikainen, and T. Maenpaa, “Multi resolution gray-scale and rotation invariant texture classification with local binary patterns”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, pp. 971–987, 2002.

[23] Online Available: (Exteneded Yale B Face Database) http://vision.ucsd.edu/~iskwak/ExtYaleDatabase/ExtYaleB.html.