Illumination Compensation and Enhancement for Face Recognition

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***Abstract*— Face images of the same person under different illuminations represent a challenge for face recognition. Traditional methods based on the Lambertian model construct a face image invariant to illuminations by combining a number of the images of different illuminations linearly. A drawback with the Lambertian model is that a single-point light source placed at infinity is assumed. This paper proposes an efficient scheme for illumination compensation and enhancement of face images. Our illumination model is universal without requiring the assumption of a single-point light source, so it circumvents and overcomes the limitations of the Lambertian model. In practice, it is reasonable to assume that the variations in intensity and illumination directions cause the face images of the same person different. The proposed approach can learn the average representations of face images under changing illuminations so as to compensate or enhance the face images and to eliminate the effect of different and uneven illuminations while keeping the intrinsic properties of the face surface. Our experiments have provided promising results, demonstrating that the proposed methods are effective.**

I. INTRODUCTION

Face recognition can achieve a highly accurate performance under controlled conditions, such as unchanged light sources, frontal-view images, no occlusion, neutral facial expression, etc. Human faces share a similar shape and structure, but illumination variations and different lighting directions always make images of the same person look dissimilar. As shown in Figure 1, the different face images of the same person with variations in illuminations are not discernible as the same man.

Face recognition with different illuminations is a difficult problem, in particular in outdoor circumstances. Illumination variations remain an unsolved problem in face recognition, despite a lot of research having been devoted to solving it [1]. In the past decade, the illumination problem has received considerable attention in both the face-recognition-related industries and academic circles. However, it is still one of the prominent issues for appearance- or image-based face recognition approaches. The development of illumination-compensation techniques for face recognition is important, and modeling face variations in realistic settings is still a heuristic issue, especially in uncontrolled environments such as outdoor and natural settings. Without solving this problem, accurate and robust face recognition cannot be achieved [1, 2].

II. RELATED WORKS

The illumination problem in face recognition has drawn many researchers' attention in the past decades. In [2], Adini et al. presented an empirical and systematic study, and evaluated the sensitivity of some representations to changes in illumination. Three different categories of approaches were discussed. The first method used gray-level information to extract the three-dimensional shape of an object, using the shape-from-shading approach [3]. This is an ill-posed problem, and the assumptions used make it difficult to apply to general object recognition. Therefore, this approach is not effective for face recognition. The second approach used image representations that are relatively insensitive to illumination changes, such as the edge maps of images [4, 5, 6] and a basic image-representation model for face recognition [7, 8]. The third approach to solve the illumination-variation problem was to model several images of the same face taken under different illumination conditions [9, 10]. More recently, a 3D morphable face model was employed to produce synthetic images under varying poses and illuminations. Frontal, semi-profile, and profile face images of the same person are used to generate 3D face models in [11]. Zhao and Chellappa [12] proposed a method using symmetric shape-from-shading for Illumination-insensitive face recognition. A method based on quotient images [13] was introduced, which assumes – based on the Lambertian model – that faces of the same class have the same shape but different textures. In [14], Zhao et al. used illumination ratio images to produce new training images for face recognition with a single frontal-view image. Xie and Lam [15] proposed a 2D face-shape model to eliminate the effect of difference in the face shape of different individuals for face recognition. Later, in [16], they also proposed an efficient illumination-normalization method using an illumination model with a Lambertian surface for face recognition. Recently, photometric stereo has been used to obtain a fast and non-contact surface reconstruction of Lambertian surfaces in [17], while in [18], the 3D face-reconstruction methods assume that human faces can be modeled as Lambertian, and show that human skin exhibits nearly-Lambertian reflectance properties. However, these methods share the same drawbacks; a single-point light source placed at infinity is assumed, based on the Lambertian model.

Most existing approaches to the illumination problem rely primarily on universal representations, which are in general insufficient to model the variations caused by illumination changes [2]. It has been shown theoretically that an image representation or a function used for recognition which is invariant to illumination changes does not exist [2, 19]. Solving image variations caused by change in illumination direction can be achieved by utilizing more domain-specific knowledge of face images.

Instead of deriving universal representations, those traditional methods based on the Lambertian model usually assume a single illuminant placed at infinity, and use a number of faces to construct a 3D face model for achieving illumination invariance. Illumination compensation and enhancement utilizing specific individual information can possibly provide an effective and useful way to achieve a better face-recognition rate. In this paper, we focus on illumination compensation and enhancement for face images. We use an illumination model [32], which is universal and does not require the assumption of a single-point light source, thereby overcoming the limitation of the Lambertian model. Our proposed approach captures the mean representations of face images under different illuminations so as to compensate or enhance face images, and consequently, to achieve robust face recognition.

The rest of the paper is organized as follows: In Section III, we describe our proposed methods for illumination compensation and enhancement. Section IV presents the experimental results, and a conclusion and discussion are given in Section V.

Figure 1. Five face images of the same person from the YaleB face database under different illumination conditions.

III. THE PROPOSED METHODS

A. Illumination Model

Some works have proposed methods to handle variable illuminations based on the Lambertian model, with the assumption that a single illuminant is placed at infinity, and utilizing a number of face images to construct 3D models that are invariant to illumination. In real situations, face recognition is usually carried out in outdoor, uncontrolled environments, with various illumination sources from different directions. To overcome these limitations of the Lambertian model, the illumination model used is more universal, not requiring the assumption of a single-point light source.

According to the Retinex theory [32], the intensities of an image $I(x,y)$ can be represented as the product of illumination s and surface reflectance $R(x,y)$. Based on this theory, an automatic image-processing algorithm for compensating illumination-induced variations was proposed in [33], which estimates the illumination field and then compensates for it. However, this method is subject to artifacts. Du and Ward [34] proposed a wavelet-based normalization method, which enhances the contrast as well as the edges of face images for illumination normalization in order to facilitate face-recognition tasks. In [35], a facial-image illumination-invariant algorithm, based on the fusion of wavelet analysis and the local binary pattern, was introduced. In the same year, a simple algorithm which can alleviate illumination effects by setting the coefficients in the wavelet approximation sub-band to zero was proposed in [36].

In contrast to the previous work, an effective scheme is proposed in this paper for illumination compensation and enhancement which is efficient and easy to implement. The intensity of a face image $I(x,y)$ is expressed as follows:

$$I(x,y) = R(x,y)L(x,y), \tag{1}$$

where $R(x,y)$ is the face's surface reflectance representation matrix and $L(x,y)$ is the illumination-effect matrix.

B. Wavelet Transform

The wavelet transform is a multi-resolution analysis that represents image variations at different scales [22, 23]. Psycho-physical investigation has shown that the Human Visual System (HVS) does a frequency analysis when we see images [20, 21]. Therefore, the wavelet transform has often been used for the analysis of spatial-frequency content, and shows tremendous advantages over the Fourier transform. The computation of the wavelet transform of a 2D image involves recursive filtering and sub-sampling. The fast discrete multilevel 2D wavelet transform is called the Mallet algorithm [23].

C. Illumination Compensation for Face Images

What make the face images of one person look dissimilar, as shown in Figure 1? In general, people have a similar facial shape and structure, so it is reasonable to approximate the face surface-reflectance representation matrix $R(x,y)$ as a constant matrix, which reflects the intrinsic property of a face surface. Consequently, the dissimilarity between images of the same person under different illumination conditions is mainly caused by the differences in the illumination-effect matrix $L(x,y)$.

Humans have similar face structures and shapes, but the face images of the same person do not look similar under different lighting conditions. Thus, it is reasonable to infer that the reflectance-representation matrix $R(x,y)$ of faces with a similar shape and structure has a slight difference, while the illuminations-effect matrix $L(x,y)$ can vary significantly, depending on the illumination conditions.

In our algorithm, wavelet analysis is applied to the illumination-effect matrix $L(x,y)$, which changes according to illumination conditions. As the reflectance-representation matrix $R(x,y)$ is similar for different people, we can infer $L(x,y)$ from the corresponding face image $I(x,y)$ by using (1). The corresponding illumination condition is embedded in the various wavelet subbands obtained by wavelet decomposition.

The 2-D discrete wavelet transform (DWT) of signal $f(x,y)$ with size $M \times N$ is defined as[23]:

$$W_{\varphi}(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f\varphi_{j_0,m,n} \quad \text{and}$$

$$W_{\psi}{}^{i}(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f\psi^{i}_{j_0,m,n}, \tag{2}$$

where $\varphi(x)$ and $\psi(x)$ are the scaling function and the wavelet function, respectively, j_0 is an arbitrary initial scale, and i={H, V, D}, H is the horizontal detail coefficients, V the vertical detail coefficients, and D the diagonal detail coefficients. The decomposition also produces one approximation image, denoted as A. The wavelet transform can recursively decompose the A bands into sub-bands.

After applying the 2D discrete wavelet decomposition (DWT) to a face image $I(x,y)$ into S levels, a decomposition vector is formed as follows:

$$\begin{aligned}&\mathrm{DWT}(I(x,y))\\&=\left[W_{\varphi}(S,m,n)\ \ W_{\psi}{}^{i}(S,m,n)\ \ W_{\psi}{}^{i}(S\text{-}1,m,n)\ \ \ldots\ldots\ \ W_{\psi}{}^{i}(1,m,n)\right]^{T}\\&=C\end{aligned} \tag{3}$$

where T denotes the transpose operation, i={H, V, D}, $W_{\varphi}(S,m,n)$ and $W_{\psi}{}^{i}(S,m,n)$ represent the lexicographically ordered vectors containing the scaling coefficients and wavelet coefficients, respectively, at scale S, and C is a column vector containing the coefficients at different scales.

The illumination-effect matrix $L(x,y)$ changes dramatically. The information about these variations, which represents the illumination conditions of the faces, is divided into and resides in the different wavelet frequency sub-bands. Figure 2 shows examples of two face images of the same person under different illuminations, decomposed using the wavelet transform. One level of wavelet decomposition yields 3 detailed images and an approximation image. As can be seen from Figure 2, the 3 corresponding frequency sub-bands of the same person (Figures 2(c), (d) and (e)) are different from each other due the changes in the illumination-effect matrix $L(x,y)$.

The illumination model in (1) is nonlinear. Hence, before wavelet analysis, the logarithmic transformation is applied so as to convert (1) into a linear model, as follows:

$$I_l(x,y)=\log(I(x,y)+\beta), \tag{4}$$

where β is a small positive integer. Assume that there are Q face images of the same person in the training set. We can learn the mean illumination-effect matrix $\overline{L}(x,y)$ so as to compensate the face images for uneven lighting and shadows. Let $K(x,y)$ be a face image of a class in the face image database, under even and frontal illumination. Decompose $K(x,y)$ using the discrete 2D wavelets transform as follows:

$$\mathrm{C}_K=\mathrm{DWT}(\log(K(x,y)+\beta)). \tag{5}$$

The Q face images under different illuminations of the same person in the training set are transformed in the same way:

$$\mathrm{C}_j=\mathrm{DWT}(\log(I_j(x,y)+\beta)),\ \text{where } 1 \le j \le Q. \tag{6}$$

The average of the different illumination-effect matrices $L(x,y)$ is computed for the different frequency sub-bands:

$$\overline{C}=\frac{1}{Q}\sum_{j=1}^{Q}(C_K-C_j). \tag{7}$$

When an image is under an uneven illumination condition, shadows may appear, and the image may look different in those regions with insufficient illumination. Therefore, the formulation of $\overline{C}$ in (7) takes the value of the summation of the differences in the wavelet coefficients. This can make images lighter and shadowless.

Suppose $Z(x,y)$ is a face image under uneven lighting and with shadows. $\overline{C}$ can then be used for illumination compensation as follows:

$$C_z^{'}=\overline{C}+C_z. \tag{8}$$

The compensated face image $Z_c(x,y)$ can be obtained using the inverse discrete 2D wavelet transform:

$$Z_c(x,y)=\mathrm{IDWT}(C_x^{'}). \tag{9}$$

The mean illumination-effect matrix $\overline{L}(x,y)$ can also be calculated as follows:

$$\overline{L}(x,y)=\mathrm{IDWT}(\overline{C}). \tag{10}$$

D. Illumination Enhancement for Face Images

Inspired by the shadowless lamp used in surgical operations to compensate illumination and remove shadows, we propose an efficient method for face image illumination enhancement. We call it the illumination-enhancement algorithm (IEA).

The mean information about the changed illuminations $\overline{C}$ can be utilized for face image illumination enhancement, not only to compensate for uneven lighting but also to enhance the image by removing any shadows in the image $Z(x,y)$, as follows:

$$C_z^{'} = \alpha\overline{C} + C_z, \tag{11}$$

where $\alpha \geq 1$, and is called the "illumination-enhancement factor". When $\alpha = 1$, the illumination-enhancement algorithm will become the illumination-compensation algorithm described in Section III. *C*.

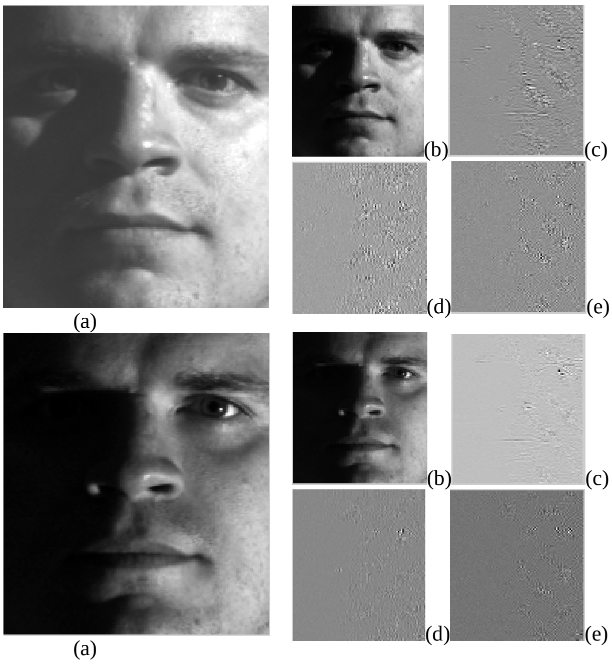

Figure 2. Wavelet transformation of two face images of the same person from the YaleFace Database,, under different illumination conditions.
(a) Original face images of the same person.
(b) Approximation image, denoted by *A*, contains the low-frequency information.
(c) *H* Subband contains the horizontal information at high frequency.
(d) *V* Subband contains the vertical information at high frequency.
(e) *D* Subband contains the diagonal information at high frequency.

IV. EXPERIMENTAL RESULTS

In this section, we will evaluate our proposed illumination-compensation and -enhancement algorithms. We will first show the visual quality of the face images processed by our algorithms. Then, our algorithms will also be evaluated using face recognition.

A. Face Databases

To evaluate the performances of our proposed algorithms, we employ the Yale Face Database B [37] and the extended Yale Face Database B [38], which are commonly used to evaluate the performance of illumination-invariant face recognition methods. The Yale Face Database B consists of 10 classes, named from yaleB01 to yaleB10. The extended Yale Face Database B contains 28 human subjects, named from yaleB11 to yaleB13, and from yaleB15 to yaleB39. Each subject in these two databases is under 9 poses and 64 illumination conditions. The total number of distinct subjects in the two databases is 38.

B. Performances in Terms of Visual Quality

To compare our algorithms with others, the logarithmic transformation in [24] was used for the correction of face images. Physiological evidence shows that the response of cells in the retina can be approximated as a log function of the intensity [25]. In our experiment, the "db4" wavelet was used with 1-level decomposition applied to the cropped face images, which are of size 168×196. Figure 3 shows some experimental results which illustrate the superior performance of our algorithms in terms of illumination compensation and illumination enhancement. Fig. 3(c) shows the results based on the histogram-equalization method in [34], which enhances the contrast of the approximation coefficients and multiplies each element in the detail coefficient matrix by a scaling factor (>1). In our experiments, we set the scaling factor at 2. This method can enhance the fine details, such as the beard and wrinkles, but cannot eliminate the illumination effects efficiently. Fig. 3(d) illustrates the results based on [36], which alleviates the illumination influence by setting the coefficients in the wavelet approximation sub-band to zero. However, this scheme discards the detail information, which is important for recognition. Figs 3(f) and 3(g) exhibit a better visual quality than Figs 3(c) and 3(d). Furthermore, it can be observed that, after illumination compensation, the face images shown in Fig. 3(f) are much better and more even in terms of visual quality than those compensated by Log Transformation, as shown in Fig. 3(b), in particular when the original face images are under uneven illumination. Figure 3(f) shows face images after illumination enhancement with the illumination-enhancement factor α =3, where uneven lighting is compensated and the shadows are smoothed. The effect of the illumination enhancement is that a smooth and even frontal light source is projected on to the face images, so that shadows can be greatly reduced. Figure 4 illustrates some face images of the same class processed using our illumination-compensation algorithm and our illumination-enhancement algorithm. Experimental results show that our simple, non-iterative algorithm can achieve a good performance for illumination compensation and illumination enhancement for face images, while the symmetrical structure of the face images is retained.

C. Performances in Terms of Face Recognition

In this section, we will evaluate the effectiveness of the proposed approaches for face recognition. In this paper, we focus on the issue of illumination compensation and illumination enhancement for face images, rather than face recognition algorithms. Nevertheless, a good illumination-compensation and -enhancement method should help to improve the face recognition rate.

The PCA-based algorithm [26] (also known as eigenfaces) is a benchmark of appearance- and image-based face recognition approaches [1]. Therefore, it is used in these experiments to illustrate the effectiveness of our algorithm for face recognition. Pentland et al. [27] have shown that the first three eigenvectors represent illuminations on face images, and have also empirically shown that a superior face recognition performance can be achieved if the first three eigenvectors are excluded. Elimination of more than three eigenvectors will worsen the recognition results [28], [29]. Therefore, we will evaluate the following illumination-compensation and -enhancement algorithms and PCA-based algorithms:

1. PCA-based algorithm [26];
2. PCA-based algorithm with the first three eigenvectors removed [27];
3. Log Transformations and PCA-based algorithm;
4. Illuminations normalization [34] and PCA-based algorithm;
5. Illuminations invariant [36] and PCA-based algorithm;
6. Illumination compensation and PCA-based algorithm; and
7. Illumination enhancement and PCA-based algorithm.

These seven PCA-based algorithms are denoted as Algorithm1, Algorithm2, Algorithm3, Algorithm4, Algorithm5, Algorithm6, and Algorithm7, respectively. In the experiments, all the 38 distinct subjects from the Yale Face Database B were used. The face for each subject which is under front lighting is used as a training sample, while the rest are used for testing. As in [30, 31], the L_1 norm distance metric is used, which is a more suitable distance measure than the Euclidean distance metric (L_2) for PCA-based algorithms.

Figure 5 shows the recognition rates for each of the 38 subjects, based on the five PCA-based algorithms. Table I tabulates the average recognition rates of the five PCA-based algorithms. It is obvious that Algorithm 6 and Algorithm7 can achieve significantly better performances than the other three methods. The average recognition rates are 67.56% and 88.77% for the illumination-compensation algorithm and the illumination-enhancement algorithm, respectively. It should be noted that the illumination-enhancement scheme significantly outperforms the illumination-compensation scheme in terms of its recognition rate. This is because, after illumination enhancement, the face images of the same subject will resemble each other more than they will use the illumination-compensation scheme, as is shown in Figure 4. If no compensation/normalization scheme is employed, the average recognition rate is 26.58% only. The average recognition rate increases to 31.97% if the first three eigenvectors are not used. The performance of the algorithm with Log Transformations can further improve the rate slightly, to 34.83%. The experimental results are consistent with those in [27, 28, 29], and prove that this simple scheme is effective. Moreover, our proposed Algorithm6 and Algorithm7 perform better than Algorithm4 and Algorithm5. This is because Algorithm4 enhances fine-detail information by multiplying the detail coefficient matrix by a scaling factor, although this cannot completely eliminate the illumination effects. Algorithm5 attempts to smooth out the illumination influence by setting the wavelet approximation coefficients to zero; this may lead to some detail information, which is important for recognition, being missed. The advantage of our proposed approaches is that they can change the detail information on face images, such that illumination compensation and enhancement take place simultaneously. The experiment results show that our proposed methods are effective and have great potential.

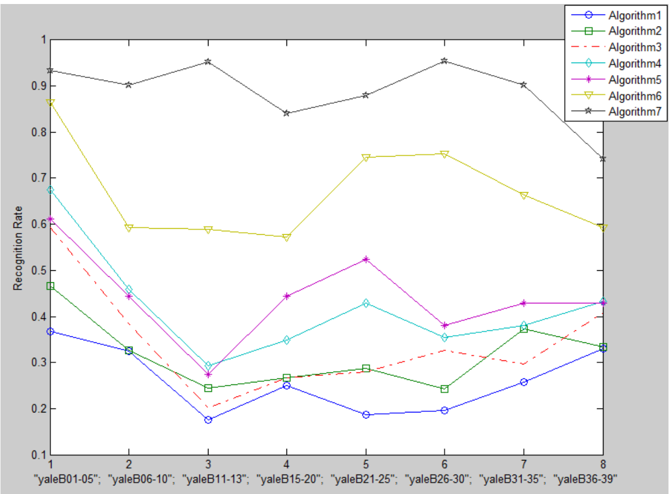

Figure 5. Face recognition rates for the 38 distinct subjects in the Yale Face Database B and the extended Yale Face Database B.

TABLE I
THE AVERAGE RECOGNITION RATES OF THE SEVEN FACE RECOGNITION SCHEMES FOR THE YALE FACE DATABASE B AND THE EXTENDED YALE FACE DATABASE B.

	Average Recognition Rate
Algorithm1	**0.2658**
Algorithm2	**0.3197**
Algorithm3	**0.3483**
Algorithm4	**0.4215**
Algorithm5	**0.4422**
Algorithm6	**0.6756**
Algorithm7	**0.8877**

In addition, the face recognition experiments also indicate that the illumination problem is important and prominent for face recognition. Using the illumination-compensation and -enhancement methods, the recognition rate can be improved, and this demonstrates that the proposed schemes are an important pre-processing step for practical face recognition.

V. CONCLUSION AND DISCUSSION

In this paper, we have employed a simple illumination model for illumination compensation and enhancement of face images. In contrast, the traditional Lambertian model requires a number of face images to reconstruct 3D models for illumination invariance, with the assumption of the existence of a single-point light source. The proposed approach can overcome these limitations of the Lambertian model, and is suitable for outdoor environments without any postulation of light sources. Experiments show the superior performances of our proposed methods in terms of both visual quality and face recognition rate.

REFERENCES

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

[2] Yael Adini, Yael Moses, Shimon Ullman, “Face Recognition: The Problem of Compensating for Changes in Illumination Direction”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 721-732, July 1997.

[3] B.K.P. Horn and M. Brooks, Seeing Shape from Shading. Cambridge,Mass.: MIT Press, 1989.

[4] J.F. Canny, “A Computational Approach to Edge Detection,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 8, pp. 679-698, 1986.

[5] R.M. Haralick, “Digital Step Edges from Zero Crossing of Second Directional Derivatives,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 6, pp. 58-68, 1984.

[6] V. Torre and T. Poggio, “On Edge Detection,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 8, pp. 147-163, 1986.

[7] K. Wong, H. Law, and P. Tsang, “A System for Recognizing Human Faces,” Proc. ICASSP, pp. 1,638-1,642, 1989.

[8] V. Govindaraju, D.B. Sher, R. Srihari, and S.N. Srihari, “Locating Human Faces in Newspaper Photographs,” Proc. CVPR 89, pp. 549-554, 1989.

[9] S. Edelman, D. Reisfeld, and Y. Yeshurun, “A System for Face Recognition that Learns from Examples,” Proc. European Conf. Computer Vision, S. Sandini, ed., pp. 787-791. Springer-Verlag, 1992.

[10] P. Hallinan, “A Low-Dimensional Representation of Human Faces for Arbitrary Lighting Conditions,” Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 995-999, 1994.

[11] V. BLANZ AND T. VETTER, 1999. “A Morphable model for the synthesis of 3D faces”. In Proceedings,SIGGRAPH’99, 187–194.

[12]W. Zhao, R. Chellappa, 2000. “Illumination-insensitive face recognition using symmetric shape-from-shading”. In: Proc. IEEE Conf. CVPR, Hilton Head.

[13] A. Shashua, T. Riklin-Raviv, 2001. “The quotient image: Class based rerendering and recognition with varying illuminations”. IEEE Trans. Pattern Anal. Machine Intell. 23 (2), 129–139.

[14] J. Zhao, Y. Su, D. Wang, S. Luo, 2003. “Illumination ratio image: Synthesizing and recognition with varying illuminations”. Pattern Recognition Lett. 24 (15), 2703–2710.

[15] Xie, X., Lam, K.M., “Face recognition under varying illumination based on a 2D face shape model”. Pattern Recognition, 38(2), 221–230, 2005.

[16] Xie, X., Lam, K.M., “An efficient illumination normalization method for face recognition”. Pattern Recognition Letters 27(6): 609-617, 2006.

[17]Toni Kuparinen and Ville Kyrki, “Optimal Reconstruction of Approximate Planar Surfaces Using Photometric Stereo,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, no. 12, pp. 2282–2289, 2009.

[18]I. Kemelmacher-Shlizerman, R. Basri, “3D Face Reconstruction from a Single Image Using a Single Reference Face Shap”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Volume: 33 Issue:2 On page(s): 394 – 405, Feb. 2011.

[19] Y. Moses and S. Ullman, “Limitation of Non-Model-Based Recognition Schemes,” Proc. ECCV-92, Springer-Verlag, pp. 820-828, 1992.

[20] Devalois, R.L., D.G. Albrecht, and L.G. Thorell, “Spatial - frequency selectivity of cells in acquire visual cortex,” Vision Research, 22, pp. 545-559, 1982.

[21] Caelli, T., Visual Perception, Pergamon Press, 1981.

[22]I. Daubechies, "The wavelet transform, time-frequency localization and signal analysis," IEEE Trans. on Information Theory, Vol.36, pp.961-1005, 1990

[23] S. G. Mallet, "A theory for multiresolution signal decomposition: the wavelet representation," IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 11, pp. 674-693, July 1989.

[24] D. Reisfeld and Y. Yeshurun, “Robust Detection of Facial Features by Generalized Symmetry,” ICPR A, pp. 117-120, 1992.

[25] F. Werblin, “Control of Retinal Sensitivity,” J. General Physiology, vol. 63, pp. 62-87, 1974.

[26] Turk, M., Pentland, A., 1991. “Eigenfaces for recognition”. J. Cognitive Neurosci. 3, 71–86.

[27] A. Pentland, T. Starner, N. Etcoff, N. Masoiu, O. Oliyide, and M. Turk, “Experiments with Eigenfaces,” Proc. Looking at People Workshop Int'l Joint Conf. Artifical Intelligence, Aug. 1993.

[28] H. Moon and P.J. Phillips, “Analysis of PCA-based Face Recognition Algorithms,” Empirical Evaluation Techniques in Computer Vision, K.J. Bowyer and P.J. Phillips, eds., IEEE CS, 1998.

[29] Martinez, A.M.; Kak, A.C. “PCA versus LDA”, IEEE Transactions on Pattern Analysis and Machine Intelligence, pp 228 – 233, Volume: 23 Issue:2 , Feb 2001

[30] Draper, B.A., Baek, K., Bartlett, M.S., Beveridge, J.R., 2003. “Recognizing faces with PCA and ICA”. Computer Vision and Image Understanding, 91 (1–2), 115–137.

[31] H. Moon, P.J. Phillips, “Computational and Performance aspects of PCA-based Face Recognition Algorithms”, Perception, Vol. 30, pp. 303-321, 2001.

[32] B. K. P. Horn, "Determining lightness from an image," Comput. Graphics Image Process. 3, 277-299 (1974).

[33] R. Gross and V. Brajovic, "An Image Preprocessing Algorithms for Illumination Invariant Face Recognition", Audio- and Video-Based Biometric Person Authentication, pp.10 - 18.2003

[34]D. Shan and R. Ward. “Wavelet-based Illumination Normalization for Face Recognition. Image Processing”, ICIP 2005. IEEE International Conference on, 2005, 2, pp. 954-947

[35]A.B.J. Teoh, Y.Z. Goh, M.K.O. Goh, ”Illuminated Face Normalization Technique by Using Wavelet Fusion and Local Binary Patterns”. 10th Intl. Conf. on Control, Automation, Robotics and Vision Hanoi, Vietnam, 17–20 December 2008. Pp. 422-427.

[36] Y.Z. Goh, A.B.J. Teoh, M.K.O. Goh,” Wavelet based illumination invariant preprocessing in face recognition”, in: Proceedings of the Congress on Image and Signal Processing, vol.3, 2008, pp.421–425.

[37] K.C. Lee and J. Ho and D. Kriegman, "Acquiring Linear Subspaces for Face Recognition under Variable Lighting ", IEEE Trans. Pattern Anal. Mach. Intelligence, 2005, vol. 27, no. 5, pages 684-698.

[38] A.S. Georghiades, P.N. Belhumeur, and D.J. Kriegman, “From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose”, IEEE Trans. Pattern Anal. Mach. Intelligence, 2001, vol. 23, no. 6, pages 643-660.

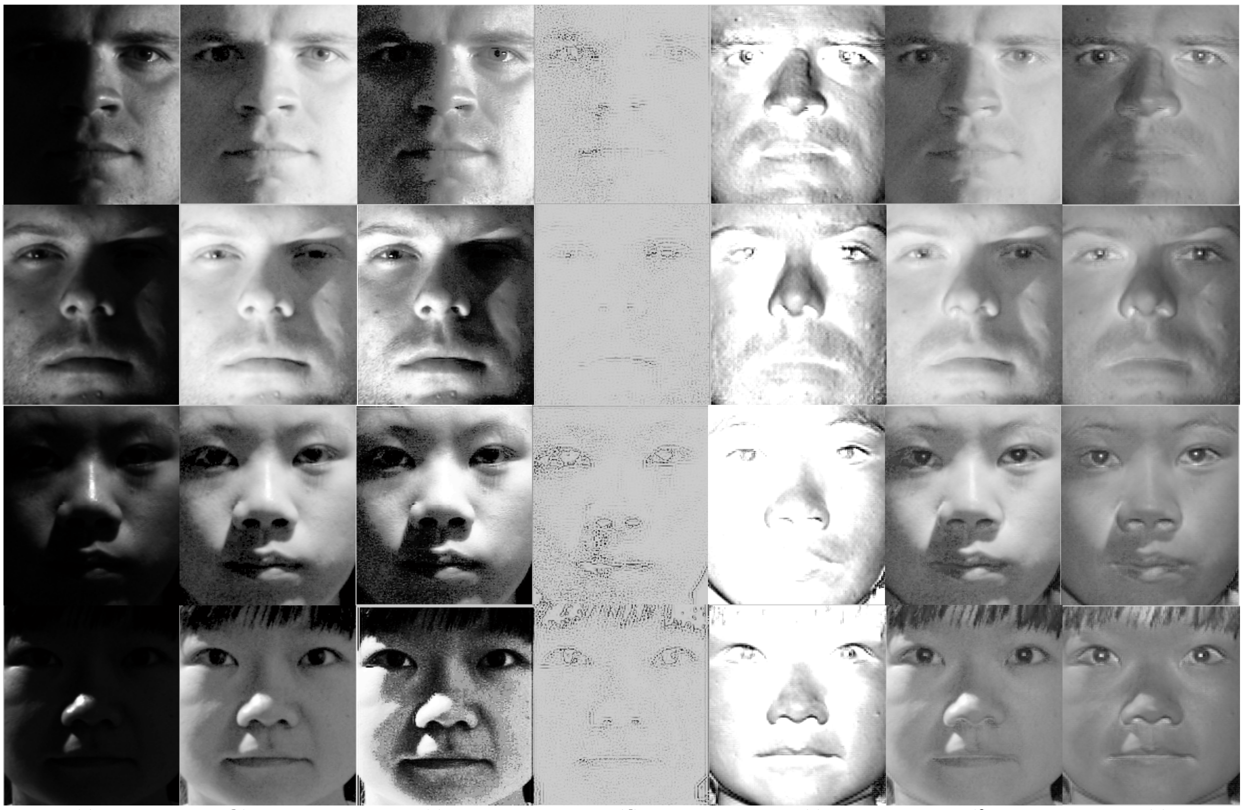

Figure 3. Face images using different illumination-compensation and illumination-enhancement methods:
(a) original face images from the Yale Face Database B,
(b) Log Transformations,
(c) the method in [34],
(d) the method in [36],
(e) the mean illumination-effect matrix $\bar{L}(x,y)$,
(f) our illumination-compensation method, and
(g) our illumination-enhancement method.


(a)

(b)

(c)

Figure 4. Face images from one representative classes processed using our illumination-compensation and illumination-enhancement algorithms:

(a) original face images from the class “yaleB06”,

(b) results with illumination compensation, and

(c) results with illumination enhancement.