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Quality Based Illumination Compensation for Face Recognition

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***Abstract*— Design of a robust face recognition system is greatly affected due to varying lighting conditions, poses and expressions. The accuracy of the system can be increased by normalizing and compensating the illumination variations in the pre-processing step. This paper presents a wavelet based illumination compensation method after verifying the quality of the face images. Here the image quality is measured in terms of luminance with reference to the well-lit face images. We measure the quality of the image globally as well as locally before normalization and compensation. Experimental results on the Extended Yale-B face database show that the proposed method improves the face recognition performance for the face images with large illumination variations. It is simple and can be efficiently implemented in face recognition system when the face images are badly affected by varying illumination conditions.**

***Keywords*— Face recognition, Illumination normalization, Wavelet transform, Extended Yale-B face database.**

I. INTRODUCTION

Now a days the attention towards face recognition is increased owing to its wide range of applications in information security, access control, law enforcement, passport and surveillance etc. Face recognition is a leading biometric method among other biometric methods such as finger prints, voice and iris recognition when the identifiers are uncooperative as well as in uncontrolled environments. Recently researchers focus on robust face recognition systems which are invariant to illumination variations, poses and expressions. Illumination variation is still a challenging problem for face recognition as face appearance can change dramatically due to illumination changes. The variations between the images of the same face due to illumination are almost always larger than the image variations due to change in face identity [1]. To normalize and compensate the illumination affect many methods have been proposed [1]-[14].

Basically all these approaches can be classified into two categories. They are pre-processing based and model based. In model based [2]-[4] approaches attempts are made to model the variations caused by varying lighting conditions. Theoretically model based approaches are ideal but to get template which is encompass all the possible changes is very difficult. And also applying model based approaches into real application need some additional constraints or assumptions and large number of training data [2]. In other cases illumination affect is compensated in pixel wise transformations like histogram equalization (HE), Gamma correction and by homomorphic filtering [5]. Though non uniform illumination variations are improved by region based HE [6], block-based HE [7], still their performances are not satisfactory. In literature there are other approaches like retinex model [8], Active Shape Models (ASM) [9], Active Appearance Models (AAM) [10], quotient image [11] are used for illumination normalization. In [12] Chen et al proposed that illumination variation can be reduced by truncating the low frequencies dct coefficients in the logarithmic domain. In discrete wavelet domain the 2D image signal is decomposed into different levels and by rectifying the low and high frequency components, illumination variations of the images can be compensated [13]-[14].

In this paper we propose a quality based illumination normalization and compensation technique used in [15] on wavelet domain as [16]. Here our main objective is to measure the illumination quality of a given face image and is to decide whether the image should be preprocessed to normalize its illumination variations or not. We decompose the image into the different levels adaptively according to the quality of the image to get its low frequency and high frequency components. Then different band coefficients are manipulated separately. Finally, after reconstructed the image by applying the inverse discrete wavelet transform to the rectified subband coefficients, we apply the Principal component analysis (PCA) [17] for recognition task.

The rest of this paper is organized as follows. The image quality measurement used in this proposed method and Discrete Wavelet Transform (DWT) is briefly described in Section II. In section III, details of evaluation method for the proposed technique on Ex. Yale-B face database is explained. Experimental results are presented and discussed in section IV and we concluded our paper in Section V.

II. IMAGE QUALITY MEASUREMENT AND WAVELET TRANSFORM

The gray level of an image $X(i, j)$ can be expressed as the product of reflectance $R(i, j)$ and luminance $L(i, j)$ i.e.

$$X(i, j) = R(i, j) \cdot L(i, j) \qquad (1)$$

We know the illumination variations lie in the low frequency band and the reflectance components which represent the structures or edges of the image lie in the high frequency band. Our aim is to recover reflectance components of the image which focus under varying illumination conditions. Thus taking logarithm of (1) we get the sum of low-pass and high-pass components. The illumination-reflectance equation will be

$$\text{Log}\, X(i, j) = \text{Log}\, R(i, j) + \text{Log}\, L(i, j) \qquad (2)$$

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Then multi-level DWT is applied to separate the low and high frequency components by using suitable wavelet filters. The level of decomposition will be determined after measuring the luminance quality of image globally.

A. *Image Quality Measure*

The degradation of an image can be measured by the image metrics like PSNR, RSME, method noise and Universal Quality Index (UQI) etc. The mathematically defined quality measure UQI [15] is a combination of three factors: 1) loss of correlation; 2) luminance distortion; and 3) contrast level distortion. If x and y are reference and test image respectively then UQI is defined *as:*

$$UQI = \frac{4\sigma_{xy}\mu_x\mu_y}{(\sigma_x^2+\sigma_y^2)[\mu_x^2+\mu_y^2]} \tag{3}$$

This can be further written as a product of above said three factors as:

$$UQI = \frac{\sigma_{xy}}{\sigma_x\sigma_y} * \frac{2\mu_x\mu_y}{\mu_x^2+\mu_y^2} * \frac{2\sigma_x\sigma_y}{\sigma_x^2+\sigma_y^2} \tag{4}$$

where,

$$\mu_x = \frac{1}{mxn}\sum_{i=1}^{m}\sum_{j=1}^{n} x(i,j)\ , \quad \mu_y = \frac{1}{mxn}\sum_{i=1}^{m}\sum_{i=1}^{n} y(i,j)\ ,$$

$$\sigma_x{}^2 = \frac{1}{mxn-1}\sum_{i=1}^{m}\sum_{i=1}^{n}(x(i,j)-\mu_x)^2\ ,$$

$$\sigma_y{}^2 = \frac{1}{mxn-1}\sum_{i=1}^{m}\sum_{j=1}^{n}(y(i,j)-\mu_y)^2\ ,$$

$$\sigma_{xy} = \frac{1}{mxn-1}\sum_{i=1}^{m}\sum_{j=1}^{n}(x(i,j)-\mu_x)(y(i,j)-\mu_y)$$

The UQI defined in (4) provides luminance quality (LQ) as

$$LQ = \frac{2\mu_x\mu_y}{\mu_x^2+\mu_y^2} \tag{5}$$

With a range of [0, 1], measures the closeness between the average luminance of *x* and *y*. It reaches the maximum value of 1 if and only if $\mu_x = \mu_y$. The total quality of an image is measured by measuring the local quality index LQ_k by sliding a window of size 8x8 from top-left corner to the bottom-right corner of the image in total *K* steps as [15] and is given by

$$GLQ = \frac{1}{K}\sum_{k=1}^{K} LQ_k \tag{6}$$

B. *Discrete Wavelet Transform*

Wavelet transform due to its localization property has become an indispensable signal and image processing tool for a variety of applications. A wavelet transform is the representation of a function by wavelets. There are several ways of implementation of DWT to decompose a signal into low and high frequency sub-bands at different levels. In 2D DWT, the 2D image signal is passed through a 2D filter banks consisting of low-pass and high-pass filters and decomposes into four sub-bands after sub-sampling by two. After one level of decomposition, the image is decomposed into approximation coefficients, LL1 (low-low) and detailed coefficients; LH1 (low-high), HL1 (high-low) and HH1 (high-high). The HH subband gives the details of the image; the HL subband gives the horizontal features while the LH subband represents the vertical structures. The LL subband is low resolution residuals consisting of low frequency components and can be further split into higher levels of decomposition. It is convenient to level the subbands of transform as shown in Fig.1 (a). In Fig.1 (b) an example of second level of decomposition of Lena image using Daubechies' tap-8 (Db-8) wavelet is shown. In this paper we use wavelet transform to decompose the images into multiresolution subbands.

III. EVALUATION OF THE PROPOSED METHOD

A. *Extended Yale-B Face Database*

Since this paper mainly deals with illumination problem, we used Extended Yale-B face database. Extended Yale-B contains 2414 images of 38 individuals; each photographed under 64 illumination conditions. These images are divided 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 (others) as shown in Fig.2. The images are resampled to a fixed size of 128 x 128 for the purpose.

B. *ORL Face Database*

In order to test the algorithm mentioned in Section-II we used ORL (Olivetti Research Laboratory) face database. This database contains 400 images that belong to 40 people, each person in 10 different poses. The images are in greyscale, with dimension of 92x112 pixels and are resampled to 128 x 128 to avoid dimension mismatch as shown in Fig.3. This database is used to show that the reference image used to calculate the luminance quality index of an image can be taken independently.

C. *Reference Image*

To calculate the image quality for a given image we require a reference image. In this work we took the mean face of all

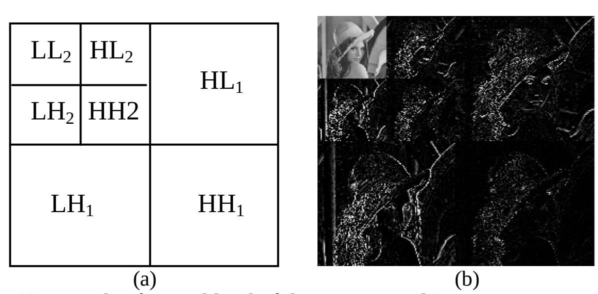

Figure 1. (a) Example of second level of decomposition (b) Lena image using (Db-8) wavelet.

Subset 1 Subset 2 Subset 3 Subset 4 Subset 5

$\theta < 12^o$ $13^o < \theta < 25^o$ $26^o < \theta < 50^o$ $51^o < \theta < 77^o$ (others)

Fig. 2- Example image of each subset of Extended Yale-B Face Database.

Fig.3- Example images of ORL Face Database (only 5 poses out of 10).

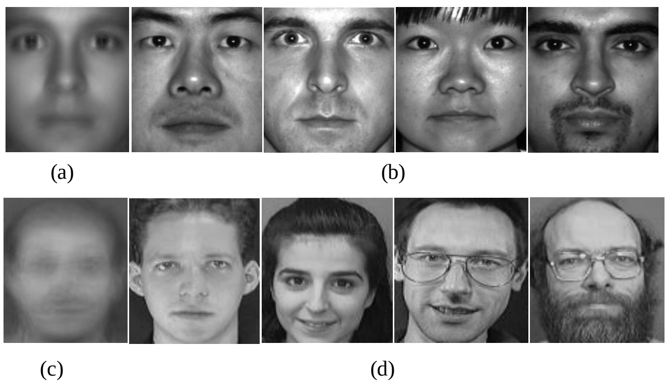

Fig. 4- (a) Average image and (b) Examples of gallery images of Extended Yale-B database (c) Average image and (d) Examples of gallery images of ORL face database.

the faces captured in frontal pose and under direct illumination (i.e. *POOA+000E+00* image of each individual) of the 38 individuals of the Extended Yale-B as reference image. The average image and samples of Extended Yale-B database are shown in Fig.4 (a) and (b). For ORL database we took all the first pose of every individual. The average image and examples of face images are shown in Fig.4(c) and (d).

D. Classification

The test face is projected to the face space got after PCA and then comparison is done using a similarity measure that resembles the test face with other training faces in the database. The simplest way to determine which face provides the best resemblance is the Euclidean distance. Euclidean distance is defined as the straight-line distance between the two points. The distance between a test face T and the training vectors V is, $d = \sqrt{\|V - T\|^2}$. In this approach, distances from the feature space of the query image to every feature in the database are calculated. The index of the image which has the smallest distance with the image under test is considered to be the required index. We consider the k-nearest distances to avoid the outlier.

IV. Experiment and Results

The lighting condition of each image of each subject of Yale-B database is well defined. But to know the quality of the image in respect to luminance, we calculate the global luminance quality as explained in section II for different subsets. We take the reference image as shown in fig.4. The distributions of luminance quality index of the images of different subsets are shown in Fig.5 and 6. From the figures we came to know that the poor illumination quality images are in subset 4 and 5 due to extreme change in illumination conditions. In [15] authors proved that poor luminance quality index of the image reflects the poor illumination condition and hence it requires illumination normalization. In this proposed method we have first measured the luminance quality and accordingly normalization process is applied. Less quality image goes less number of levels of decomposition. We modify the coefficients as described in [16]. High quality index images are bypassed in the pre-processing step or just go through histogram equalization process. A normalized face image is reconstructed from the modified coefficients by inverse DWT as shown in Fig. 7. Finally, we apply PCA directly to further reduce the dimensionality. Here we consider Subset 1, 7 images for each subject in total 266 images, as the training images and stored as gallery. The face image from remaining 4 Subsets is taken randomly as test image and matched with the images in the gallery so as to find a best match. The recognition rates using the Euclidean distance classifier are measured. The detail results are shown in Table 1 and in Fig. 8. It is shown from Table 1 and Fig. 8 that our proposed method outperforms when the image is more degraded due to illumination variations.

V. Conclusions

In this paper quality based adaptive illumination elimination algorithm is presented. By rectifying the coefficients of wavelet subbands we remove the illumination components satisfactorily. This method is simple and also able to remove the illumination effect from the facial images effectively. The performance of the method has been evaluated and compared with existing illumination invariant preprocessing algorithm on Extended Yale-B face database. The results obtained from the experiments show that the proposed method significantly improves the recognition rate for more degraded facial images. This method can be implemented as a preprocessing stage for face recognition algorithms. We also plan to conduct further experiments on different databases with more subjects.

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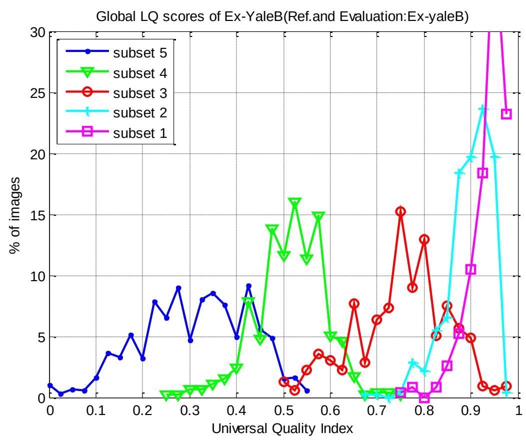

Figure 5. Distribution of global luminance quality for images in Ex.Yale-B face database, reference image average image of Ex.Yale-B database.

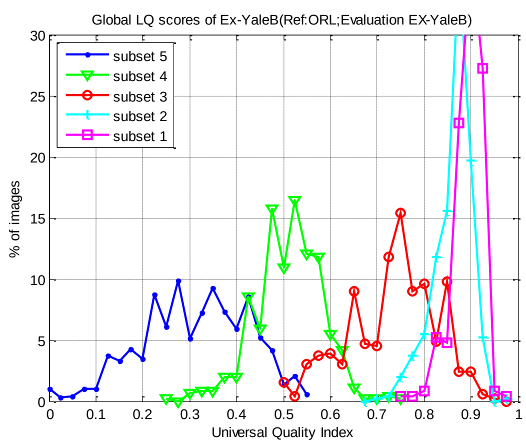

Figure 6. Distribution of global luminance quality for images in Ex.Yale-B face database, reference image average image of ORL database.

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

Fig. 7- Normalised Images . Top Line is for Subset 4, Bottom is for subset 5. (a) Original images; (b) histogram equalized images; (c) Wavele based normalzation images; (d) normalized images using proposed method.

TABLE 1: Recognition rate compare to other method

Methods	Subset 2	Subset 3	Subset 4	Subset 5	Average
Row Image	95	79	51	32	66
HEQ	100	97.5	78	62	84.5
Wavelet Based [16]	100	100	94.7	90.8	95.6
Proposed method	**100**	**100**	**96**	**93.5**	**97**

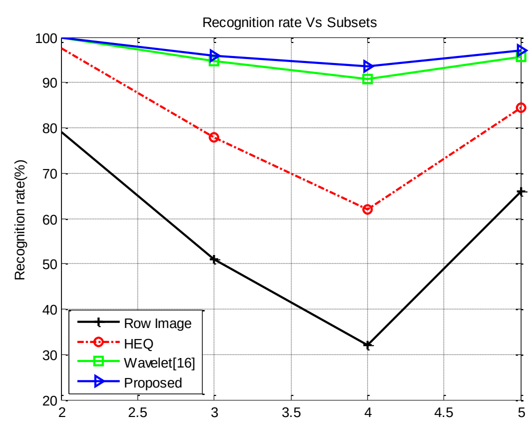

Figure 8. Recognition rate comparison with other methods on Ex.Yale-B face database.