# WAVELET-BASED ILLUMINATION NORMALIZATION FOR FACE RECOGNITION

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## ABSTRACT

The appearance of a face image is severely affected by illumination conditions that hinder the automatic face recognition process. To recognize faces under varying illuminations, we propose a wavelet-based normalization method so as to normalize illuminations. This method enhances the contrast as well as the edges of face images simultaneously, in the frequency domain using the wavelet transform, to facilitate face recognition tasks. It outperforms the conventional illumination normalization method - the histogram equalization that only enhances image pixel gray-level contrast in the spatial domain. With this method, our face recognition system works effectively under a wide range of illumination conditions. The experimental results obtained by testing on the Yale Face Database B demonstrate the effectiveness of our method with 15.65% improvement, on average, in the face recognition system.

## 1. INTRODUCTION

A practical face recognition system needs to work under different imaging conditions, such as different face poses, and different illumination conditions. In this paper, we focus on face recognition under different illumination conditions. Face appearance can change dramatically due to illumination changes, and "the variations between the images of the same face due to illumination are almost always larger than image variations due to change in face identity" [1]. A common approach to overcoming image variations is to use image representations that are insensitive to these variations. However, the empirical study in [1] indicates that none of these invariant representations can overcome image variations.

To deal with the illumination variation problem, much work has been proposed, such as the Illumination Cone method proposed by Georghiades *et al*. [2] and the Quotient Image method proposed by Shashua *et al*. [3]. These methods need to assume that faces are already aligned, which means, the training images have the same poses but of various illuminations. There exists however little work on how to perform the alignment automatically under variable illuminations. A shape-from-shading (SFS) approach [4] uses the gray-level information to extract the three-dimensional shape of the object. This method needs to make assumption of either the object shape and reflectance properties or the illumination conditions. In the face eigen-subspace domain, Belhumeur *et al.* suggested discarding a few leading principal components [5]. This method must assume that the leading principal components capture only variations due to lighting.

Illumination conditions also have a substantial effect on the robustness of face alignment algorithms. Current alignment methods such as Active Shape Models (ASM) [6] and Active Appearance Models (AAM) [7] attempt to model the appearance of important facial features, but feature search based on these models can become unstable when there exist significant shading and shadowing which can effectively mask subtle features and introduce misleading features as well.

One of our research interests is the problem of coexistence of pose and illumination variations. That means we cannot assume pose alignment as the Illumination Cone method does [2]. Contrast enhancement can be used when pose and illumination variations coexist. Contrast enhancement, in general, is achieved by utilizing the entire brightness range in a given image. The histogram of an image is usually used to determine which particular gray scale transformation is required to enhance the image contrast. Histogram equalization (HEQ) is one of the most useful contrast enhancement schemes. When an image's histogram is equalized, image pixel values are mapped to uniformly distributed pixel values, as much as possible. However, the HEQ technique only enhances the contrast of the global image in the spatial domain, it does not particularly considers the details involved in face images that are very important in face recognition tasks.

This paper proposes a new scheme to normalize face image illumination in the wavelet domain. We decompose an image into its low frequency and high frequency components. Then different band coefficients are manipulated separately. We apply histogram equalization to the approximation (low frequency) coefficients and at

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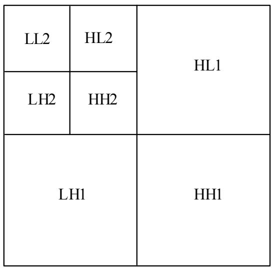



Figure 1. Multi-resolution structure of wavelet decomposition of an image

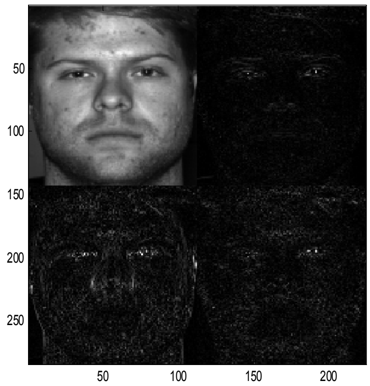



Figure 2. Wavelet decomposition of a face image

the same time accentuate the detail (high frequency) coefficients by multiplying by a scalar so as to enhance edges. A normalized image is obtained from the modified coefficients by inverse wavelet transform. The resultant image has not only enhanced contrast but also enhanced edges and details that will facilitate the further face recognition task.

The remainder of this paper is organized as follows: Section 2 briefly describes the wavelet transform. In section 3, we introduce the proposed approach in detail. Sections 4 and 5 show the experimental results, and our conclusions.

## 2. WAVELET ANALYSIS

Wavelet transform is a representation of a signal in terms of a set of basis functions, which is obtained by dilation and translation of a basis wavelet. Since wavelets are short-time oscillatory functions having finite support length (limited duration both in time and frequency), they are localized in both time (spacial) and frequency domains. The joint spatial-frequency resolution obtained by wavelet transform makes it a good candidate for the extraction of details as well as approximations of images.

In the two-band multi-resolution wavelet transform, signal can be expressed by wavelet and scaling basis functions at different scale, in a hierarchical manner.

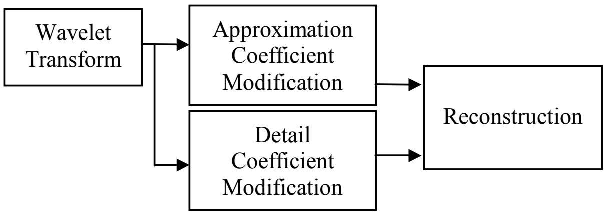



Figure 3. Block diagram of the proposed illumination normalization method

$$f(x) = \sum_k a_{0,k} \phi_{0,k}(x) + \sum_j \sum_k d_{j,k} \psi_{j,k}(x) \qquad (1)$$

$\phi_{j,k}$ are scaling functions at scale $j$ and $\psi_{j,k}$ are wavelet functions at scale $j$. $a_{j,k}$, $d_{j,k}$ are scaling coefficients and wavelet coefficients.

For 2D discrete wavelet transform (DWT), an image is represented in terms of translations and dilations of a scaling function and a wavelet functions. The scaling and wavelet coefficients can be easily computed using a 2D filter bank consisting of low-pass and high-pass filters. After one level of 2D decomposition, an image is divided into four sub-bands: LL (Low-Low), which is generated by the approximation coefficients; LH (Low-High), HL (High-Low), and HH (High-High), which are generated by the detail coefficients, as shown in Figure 1 and Figure 2.

After applying wavelet transform, the given image is decomposed into several frequency components in multi-resolution. Using different wavelet filter sets and/or different number of transform-levels will result in different decomposition results. Since selecting wavelets is not our focus in this paper, we randomly choose 1-level db10 wavelets in our experiments. However, any wavelet-filters can be used in our proposed method.

## 3. ALGORITHM DISCRIPTION

Wavelet-based image analysis decomposes an image into approximate coefficients and detail coefficients. Contrast enhancement can be done by histogram equalization of the approximation coefficients and meanwhile edge enhancement can be achieved by multiplying the detail coefficients with a scalar (>1). A normalized image is obtained from the modified coefficients by inverse wavelet transform. The block diagram of the proposed scheme is shown in Figure 3.

### 3.1. Histogram Equalization of the Approximation Coefficients

If the original image does not use most of the available dynamic range, the transformed coefficients will not use most of the dynamic range either. Therefore the coefficients value range over which the histogram equalization is performed in the wavelet domain can be expanded to achieve a better contrast enhancement result.

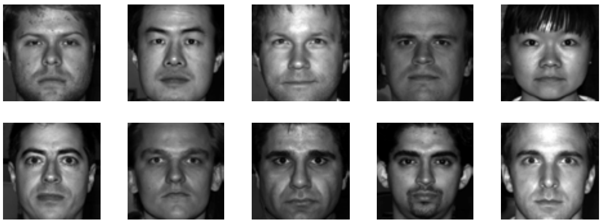


Figure 4. 10 subjects of the Yale Face Database B

Contrast enhancement is usually achieved by equalizing the histogram of the image pixel gray-levels in the spatial domain so as to redistribute them uniformly. Histogram equalization arranges the gray-levels of the image by using the histogram form information. Then, a mapping function is applied to the original gray-level values.

The accumulated density function of the histogram for the processed image histogram would approximate a straight line. This redistribution of pixel brightness to approximate the uniform distribution improves the contrast of the image.

We here use histogram equalization to enhance the contrast of the approximation coefficients. Therefore, the illumination of the approximation image (the LL sub-band in Figure 2) is also normalized.

### 3.2. Enlargement of the Detailed Coefficients

Edge enhancement is to emphasize the fine details in the original image. The perceptibility of edges and small features can be improved by enlarging the amplitude of the high frequency components in the image. To accentuate details, we multiply each element in the detail coefficient matrix (the LH, HL, and HH sub-bands in Figure 2) with a scale factor (>1).

### 3.3. Image Reconstruction

The enhanced image is reconstructed from the histogram equalized approximation coefficients and the enlarged detail coefficients in all three directions using inverse wavelet transform.

## 4. EXPERIMENTS

### 4.1. Yale Face Database B

To evaluate the performance of the proposed illumination normalization method, we test it on the Yale Face Database B [2], which was built by the Center for Computational Vision and Control at Yale University. This database contains 5760 single light source images of 10 subjects (persons). Each subject has 9 poses and each pose has 64 different illumination conditions. The size of each image is 640(w) x 480 (h). Figure 4 shows the 10 subjects from the Yale Face Database B.

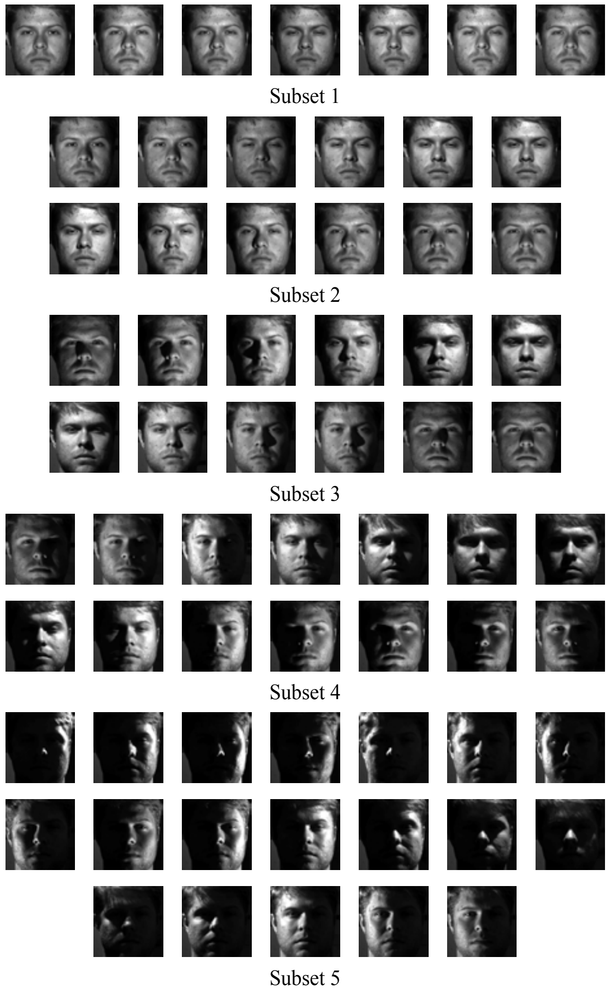
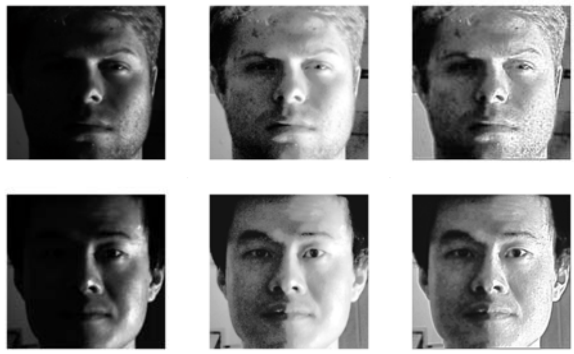



Figure 5. 64 illumination conditions of one person's images in frontal pose in the Yale Face Database B

Since this paper mainly deals with the illumination problem, we only choose the 64 frontal pose images captured under 64 different lighting conditions for each of the ten persons. Example images of one person in frontal pose are shown in Figure 5. The images are divided into five subsets according to the light-source directions (azimuth and elevation): Subset 1 (angle < 12 degrees from optical axis), Subset 2 (20 < angle < 25 degrees), Subset 3 (35 < angle < 50 degrees), Subset 4 (60 < angle < 77 degrees), and Subset 5 (others).

### 4.2. Experimental Results on Yale Face Database B

The results of applying the proposed normalization method on two different images of two different persons are shown in Figure 6. Histogram equalized images are somehow blurred. The enhanced images using the proposed method are sharper and have more details. Intuitively, the new method enhanced images are more suitable for face recognition.



(a) (b) (c)

Figure 6. (a) Original image; (b) Histogram equalized image; and (c) Enhanced image using proposed method

In our experiments, Subset 1 (7 images for each person) is chosen as the gallery and each of the images in the remaining 4 subsets is matched to the images in the gallery so as to find a best match. The recognition rates using the Euclidean distance nearest-neighbor classifier are illustrated in Table 1 and Figure 2. It is shown from Table 1 that our proposed method outperforms the histogram equalization method in every single subset. On average, the recognition rate is improved to 95.65% from 80% (for the HEQ method), which is 15.65% improvement in face recognition.

## 5. CONCLUSIONS

This paper presents a wavelet-based normalization method. This method is especially suitable for normalizing illumination variations of face images prior to the automatic face recognition. This method uses wavelet decomposition to get different band information of face images. Then the different band coefficients are manipulated separately. Compared with the popular histogram equalization method, it has the advantage of taking into account both contrast and edge enhancements simultaneously. Thus, it facilitates face recognition tasks. With this method, our face recognition systems work effectively under a wide range of illumination conditions. The experimental results demonstrate the effectiveness of our method with 15.65% improvement, on average, in face recognition.

The proposed method also has added benefit. Many current face recognition algorithms are based on wavelet-related methods. Our wavelet-based illumination pre-processing method facilitates the further feature extraction and recognition steps since the wavelet coefficients are already obtained after this processing.

## 6. ACKNOWLEDGEMENT

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Table 1. Recognition rate comparisons of different methods on Yale Face Database B

| Methods | Subset 2 | Subset 3 | Subset 4 | Subset 5 | Average |
|---|---|---|---|---|---|
| Raw image | 95.83 | 76.67 | 46.67 | 25.24 | 56.2 |
| HEQ | 100 | 97.5 | 75 | 60 | 80 |
| Our method | 100 | 100 | 94.76 | 90.83 | 95.65 |

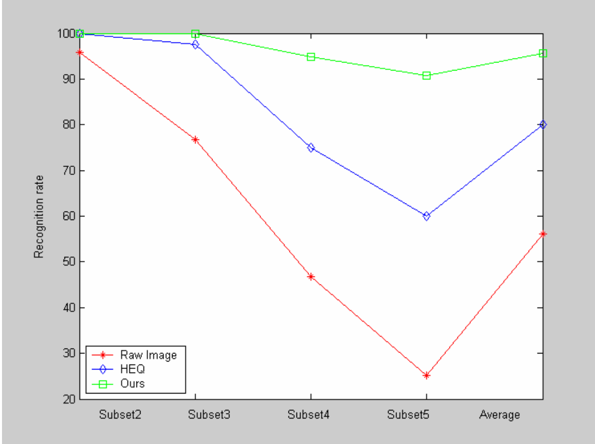


Figure 7. Recognition rate comparisons of different methods on Yale Face Database B

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