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A SURVEY ON HUMAN FACE RECOGNITION INVARIANT TO ILLUMINATION

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ABSTRACT

Human face recognition is one of the research areas in the current era of the research. It is one the widely used biometric technique for identification and verification of the human face. There are many challenges to face recognition which degrade the performance of the algorithm. The illumination variation problem is one of the well-known problems in face recognition in uncontrolled environment. In this paper an extensive and up-to-date survey of the existing techniques to address this problem is presented. Different authors have given so many techniques for illumination reduction from the face image but still some combined survey is missing so we have tried to fill that gaps in this paper. We have collected various preprocessing techniques suggested by different authors and shown their results in a tabular form. After preprocessing we can use any of the recognition method for face recognition. There are so many online face databases available so we can use any of them.

Keywords: PCA (Principle component Analysis), HE (Histogram Equalization), AHE (Adaptive Histogram Equalization), BHE (Block-based Histogram Equalization), DWT (Discrete Wavelet Transform), DCT (Discrete Cosine Transform), LBP (Local Binary Pattern), DMQI (Dynamic Morphological Quotient Image), LTP (Local Ternary Pattern), DSFQI (Different Smoothing filters Quotient Image).

I. INTRODUCTION

Face recognition has been an active research area over the last 30 years. It has been studied by scientists from different areas of psychophysical sciences and those from different areas of computer sciences. Psychologists and neuroscientists mainly deal with the human perception part of the topic, whereas engineers studying on machine recognition of human faces deal with the computational aspects of face recognition.

Face recognition has applications mainly in the fields of biometrics, access control, law enforcement, and security and surveillance systems. Biometrics are methods to automatically verify or identify individuals using their physiological or behavioral characteristics [1].

The necessity for personal identification in the fields of private and secure systems made face recognition one of the main fields among other biometric technologies. The importance of face recognition rises from the fact that a face recognition system does not require the cooperation of the individual while the other systems need such cooperation. Figure 1.shows the sketch for any pattern recognition technique.

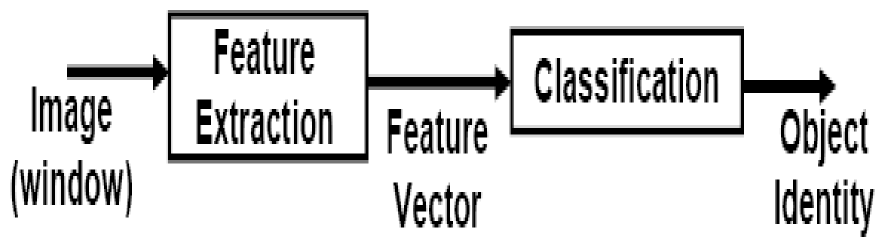

Figure 1 Sketch of pattern recognition architecture

The topic seems to be easy for a human, where limited memory can be a main problem; whereas the problems in machine recognition are manifold. Some of possible problems for a machine face recognition system are mainly;
1) Facial expression change
2) Illumination change
3) Aging
4) Rotation:
5) Size of the image
6) Frontal vs. Profile

II. ILLUMINATION PROCESSIONG

Illumination variation is one the main challenging problem in any face recognition system. There are two main approaches for illumination processing: Active approach and Passive approach [2].**Active approaches** apply active sensing techniques to capture face images which are invariant to environment illumination. **Passive approach** attempt to overcome illumination variation in face images due to environment illumination change and we will focus on this approach. Figure 2 is the framework of any face recognition methods invariant to illumination.

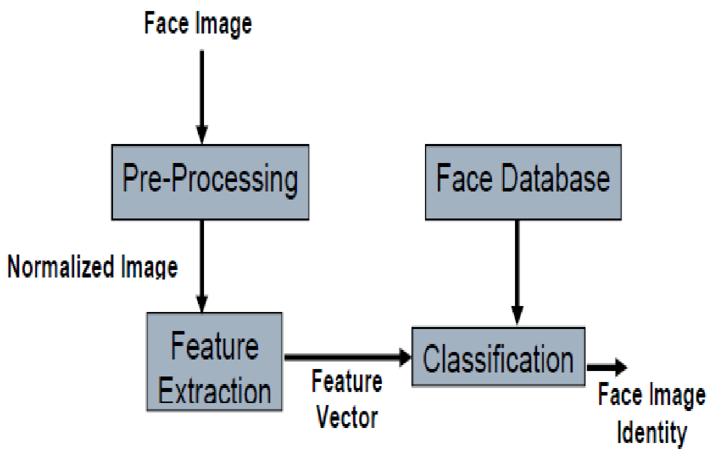

Figure 2. Framework of face recognition methods

III. PRE-PROCESSING

Often images are not in the correct form to be plugged straight into a recognition algorithm. The image may contain more information than one single face, and the lighting conditions in the test image may not be the same as in the sample data for training the algorithm. This can greatly affect the effectiveness or the recognition rate of the algorithm. Therefore, to obtain the best possible results, it is necessary to pre-process an image to normalize lighting and remove noise before inserting it into a recognition algorithm. Many researchers have used so many techniques some of which are explained in following section.

1) Histogram Equalization (HE)

Histogram equalization (HE) is a classic method. It is commonly used to make an image with a uniform histogram, which is considered to produce an optimal global contrast in the image. However, HE may make an image under uneven illumination turn to be more uneven [3].

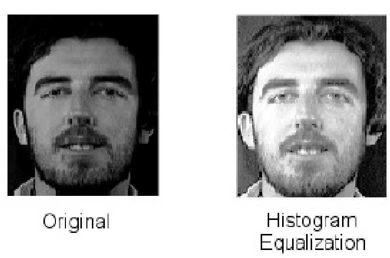

Figure 3. Histogram equalization of an image

2) Adaptive Histogram Equalization (AHE)

It computes the histogram of a local image region centered at a given pixel to determine the mapped value for that pixel; this can achieve a local contrast enhancement. However, the enhancement often leads to noise amplification in “flat” regions, and “ring” artifacts at strong edges. In addition, this technique is computationally intensive [4].

3) Block-based Histogram Equalization (BHE)

This method is also called local histogram equalization or region based histogram equalization. The face image can be divided into several small blocks according to the positions of eyebrows, eyes, nose and mouth. Each block is processed by HE. In order to avoid the discontinuity between adjacent blocks, they are overlapped by half with each other. BHE is simple so that the computation required of BHE is much lower than that of AHE. The noise produced by BHE is also very little.

4) LogAbout Method

The LogAbout method which is an improved logarithmic transformations as the following equation:

$$g(x,y) = a + \frac{\ln(f(x,y)+1)}{b \ln c} \tag{1}$$

Where g(x, y) is the output image; f(x, y) is the input image; a, b and c are parameters which control the location and shape of the logarithmic distribution. Logarithmic transformations enhance low gray levels and compress the high ones. They are useful for non-uniform illumination distribution and shadowed images. However, they are not effective for high bright images [6]. An example of what the LogAbout algorithm does can be seen in below figure 4.

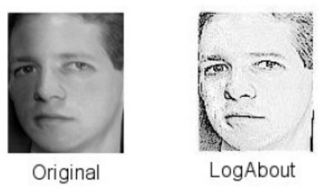

Figure 4. LogAbout Illumination Normalization

5) **Sub-Image Homomorphic Filtering**

In Sub-Image Homomorphic filtering method, the original image is split vertically in two halves, generating two sub-images from the original one (see the upper part of below figure 5). Afterwards, a Homomorphic Filtering is applied in each sub-image and the resultant sub-images are combined to form the whole image. The filtering is subject to the illumination reflectance model as follows:

$$I(x, y) = R(x, y) L(x, y) \tag{2}$$

Where I(x, y) is the intensity of the image; R(x, y) is the reflectance function, which is the intrinsic property of the face; L(x, y) is the luminance function. Based on the assumption that the illumination varies slowly across different locations of the image and the local reflectance changes quickly across different locations, a high-pass filtering can be performed on the logarithm of the image I(x, y) to reduce the luminance part, which is the low frequency component of the image, and amplify the reflectance part, which corresponds to the high frequency component [7].

Similarly, the original image can also be divided horizontally (see the lower part of below figure 5) and the same procedure is applied. But the high pass filter can be different. At last, the two resultant images are grouped together in order to obtain the output image.

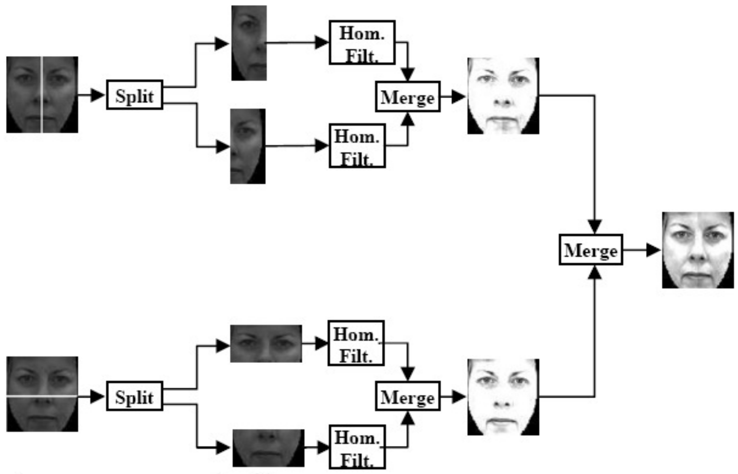

Figure 5. Sub-Image Homomorphic Filtering

6) **Discrete Cosine Transform (DCT)**

In a face image, illumination usually changes slowly compared with the reflectance except some casting shadows and secularities on the face. As a result, illumination variations mainly lie in the low-frequency band. Therefore, we can remove the low frequency part to reduce illumination variation. The low frequency DCT coefficients are set to zero to eliminate illumination variations. Figure 6 shows the images with various illumination conditions and normalized images using DCT components [8].

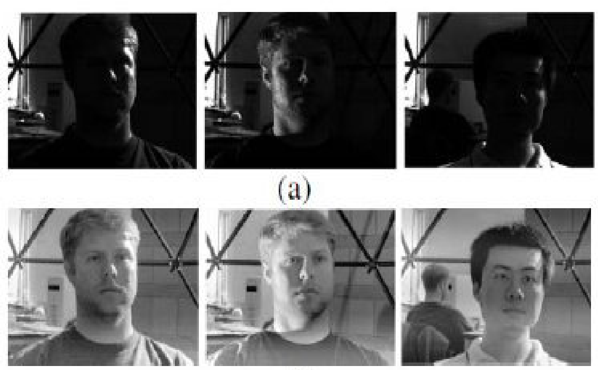

Figure 6. Original and DCT applied images

7) **Discrete Wavelet Transform (DWT)**

Besides the DCT, discrete wavelet transform (DWT) is another common method in face recognition. There are several similarities between the DCT and the DWT: 1) They both transform the data into frequency domain; 2) As data dimension reduction methods, they are both independent of training data compared to the PCA. Because of these similarities, there are also several studies on illumination invariant recognition based on the DWT. Similar to the idea in (Chen et al., 2006), a method on discarding low frequency coefficients of the DWT instead of the DCT was proposed (Nie et al., 2008). Face images are transformed from spatial domain to logarithm domain and 2-dimension wavelet transform is calculated by the algorithm. Then coefficients of low-low sub band image in *n*-th wavelet decomposition are discarded for face illumination compensation in logarithm domain. The experimental results prove that the proposed method outperforms the DCT and the quotient images. The kind of wavelet function and how many levels of the DWT need to carry out are the key factors for the performance of the method. Different from the method in (Nie et al., 2008), Han et al. (2008) proposed that the coefficients in low-high, high-low and high-high sub band images were also contributed to the effect of illumination variation besides the low-low sub band images in *n*-th level. Based on the assumption, a homomorphic filtering is applied to separate the illumination component from the low-high, high-low, and high-high sub band images in all scale levels. A high-pass Butterworth filter is used as the homomorphic filter. Figure 7 shows the wavelet decomposition of an image.

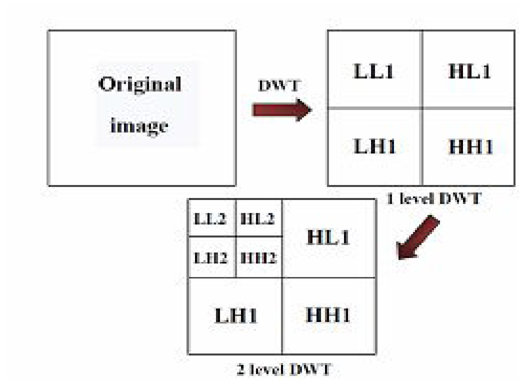

Figure 7. Wavelet decomposition of an image.

The novelty of the DWT method is that the light variation in an image can be modeled as multiplicative noise and additive noise, instead of only the multiplicative term in which may be instructive in modeling the face under illumination variations in future.
However, by comparing the results of the DWT method and the DCT, we find the result of the DWT method is worse than that of the DCT. Hence, the DWT method is not as effective as the DCT for illumination invariant recognition.

8) Dynamic Morphological Quotient Image (DMQI) method

In the framework of Lambertian model, the intensity of point (x, y) in an image *I* is modeled as shown in equation (1), where R and L are components of reflectance and illumination respectively. Estimating R and L only from the input image I is a well-known ill-posed problem. Therefore there are two assumptions: (1) the illumination L is smooth and (2) the reflectance R can be varied randomly [9].
According to the Lambertian reflectance theory, *R* depends on the albedo and surface normal and hence is the intrinsic representation of an object. It is *R* that represents the identity of a face. *L* is the illumination and is the extrinsic factor.
Dynamic Morphological Quotient Image (DMQI) method in which mathematical morphology operation is employed to smooth the original image to obtain a better luminance estimate. However, in DMQI, there is some pepper noise in dark area.

9) Different Smoothing filters Quotient Image (DSFQI)

Different Smoothing filters Quotient Image (DSFQI) give a new demonstration in which it is proved that the same smoothing functions with different scales also contribute to extract the illumination invariant features. Figure 8 denotes this merit. It tends to retain the remarkable face features such as edges and verges, and gains the intrinsic representation of an object [10].

Figure 8. Original, DMQI and DSFQI images

10) Local Binary Pattern (LBP)

Local Binary Pattern (LBP) (Ojala et al., 2002) is a local feature which characterizes the intensity relationship between a pixel and its neighbors. The face image can be divided into some small facets from which LBP features can be extracted. These features are concatenated into a single feature histogram efficiently representing the face image. LBP is unaffected by any monotonic grayscale transformation in that the pixel intensity order is not changed after such a transformation [11].

11) Improved Local Binary Pattern (ILBP)

In order to utilize the excellent discriminative power and computational simplicity of the LBP descriptor, while abating the performance degradation due to varying illumination conditions for face recognition. We have shown an enhanced LBP-based face recognition algorithm that fuses illumination invariant DMQI with discriminative LBP descriptors. In our DMQI-LBP algorithm, illumination variations in face images are first normalized with the DMQI, then the DMQI is segmented into 7×7 sub-blocks, and uniform patterns are extracted in these sub-blocks to form the LBP feature histograms. Finally, LBP histograms from all sub-blocks are concatenated into face feature vectors, and a weighted chi-square distance metric which considers the different roles of each sub-block for face recognition, is evaluated to measure the similarity between a probe face feature and the stored subject face features [11].

12) Local Ternary Pattern (LTP)

A local ternary pattern (LTP), another important extension of original LBP is proposed. The most important difference between the LTP and LBP is that the LTP use 3-valued codes instead 2-valued codes in the LBP. Because of the extension, the LTP is more discriminant and less sensitive to noise. To apply the uniform pattern in the LTP, a coding scheme that split each ternary pattern into its positive and negative halves is also proposed in (Tan & Triggs, 2010). The resulted halves can be treated as two separated LBPs and used for further recognition task. The local directional pattern is more robust against noise and non-monotonic illumination changes [11].

IV. COMPARISON OF DIFFERENT PRE-PROCESSING METHODS

Here in this section we are comparing the performance results given by various authors in their research paper. To evaluate the performances of different methods under varying lighting conditions without other variances, there are four popular face databases, the Yale B, Extended Yale B, CMU PIE and FERET database. In the Yale Face database B, there are 64 different illumination conditions for nine poses per person. To study the performances of methods under different light directions, the images are divided into 5 subsets based on the angle between the lighting direction and the camera axis. The Extended Yale B database consist 16128 images of 28 subjects with the same condition as the Original Yale B. In the CMU PIE, there are altogether 68 subjects with pose, illumination and expression variations.
The performances of several pre-processing techniques are shown in table 1.This table shows the error rate calculated by different methods by varying images in the subset from different databases. The dotted lines in the table in one row indicate the result obtained by extended Yale B database. In table 'n/a' indicate that author has not used that database for performance measure. In method column in table '+'is used for combining preprocessing methods.

Methods	Error Rate (%)				
	Yale B / Yale B + Extended Yale B			CMU PIE	FERET
	Sub set3	Sub set4	Sub set5		
Non	10.8	51.4	77.4	43.0	n/a
RHE	17.8	71.1	79.4	14.6	n/a
LogAbout	14.4	42	30.7	43.0	n/a
LOG+DCT	n/a	n/a	n/a	0	n/a
	12.9	12.4	15.2		
HE	9.2	54.2	41.1	47.8	n/a
	62.3	78.7	89.9		
DCT	0	0.18	1.71	0.36	n/a
	16.4	14.5	16.2		
DCT+LBP	10.12	15.33	17.29	n/a	n/a
DWT	0	0.19	0.53	n/a	n/a
LTV	n/a	n/a	n/a	0	n/a
	20.6	23.9	21.7		
DCT+PCA	n/a				5.84
DMQI	2.98	3.98	4.93	n/a	n/a
DSFQI	1.22	1.62	1.76	n/a	n/a

Table 1 Performance Comparisons of Different Methods

V. CONCLUSION

The modeling approach is the fundamental way to handle illumination variations, but it always takes heavy computational burden and high requirement for the number of training samples. The LBP is an attractive area which can tackle illumination variation coupled with other variations such as pose and expression. For normalization methods, the methods on discarding low-frequency coefficients are simple but effective way to solve the illumination variation problem. However, a more accurate model needs to be studied instead of simply discarding low-frequency coefficients. However, each technique still has its own drawbacks.

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