J. Vis. Commun. Image R. 25 (2014) 970–977

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

# Face recognition under large illumination variations using homomorphic filtering in spatial domain

Hossein Shahamat *, Ali A. Pouyan [1]

*Department of Computer Engineering and Information Technology, Shahrood University of Technology, No. 316, Daneshgah Ave., Shahrood 3619995161, Semnan, Iran*

ARTICLE INFO

*Article history:*
Received 19 June 2013
Accepted 17 February 2014
Available online 4 March 2014

*Keywords:*
Frequency domain filtering
Butterworth high-pass filter
Illumination normalization
Face image preprocessing
Face representation
Homomorphic parameters
Kernel function
Reflectance component

ABSTRACT

This paper proposes a homomorphic filtering in spatial domain for reducing of illumination effects in face recognition systems. Also, in this research a simple kernel of homomorphic filter is proposed. Application of this method causes considerable reduction in computational time in the preprocessing step. When a new face image with an arbitrary illumination is given, the homomorphic filter is applied and its reflectance component is extracted. Then the reflectance component is divided into several local regions and histograms of each local region are extracted using multi-resolution uniform local Gabor binary patterns (MULGBP). These histograms are combined for obtaining the overall histogram of the images. Finally, for face recognition, a simple histogram matching process is performed between new face image histogram and the gallery images histogram. The results show that the proposed method is robust for large illumination variation with a reasonable computational complexity.



## 1. Introduction

Face recognition is increasingly investigated for personal security and access control applications. A challenge in face recognition is finding efficient and discriminative facial appearance descriptors that can counteract large variations in illumination, pose, facial expression, aging, partial occlusions and other changes [1]. In contrast with other biometric analysis, face is generally regarded as the most accepted component for users, since it provides a friendly and convenient method of identification. Many researchers have investigated face recognition and several algorithms have been proposed in the last two decades. While majority of them work well under controlled environments they exhibit poor performance when face images are captured under uncontrolled conditions.

Several face image preprocessing methods have been proposed to cope with illumination changes. Histogram equalization (HEQ) [2] is one of the most useful contrast enhancement schemes. However, since HEQ technique only enhances the contrast of global image in spatial domain, it does not particularly consider the details involved in face images. Wang et al. [3] proposed the self-quotient image (SQI), which is defined as the ratio of the input image and its smooth versions. It is based on the Quotient Image method [4] to achieve lighting invariant. The wavelet-based illumination normalization method [5] applies histogram equalization to the low frequency and accentuate the high frequency coefficients. Jobson et al. [6] proposed the multi scale retinex (MSR) method. It cancels much of low frequency information through dividing the image by a smoothed version of itself. Xie et al. [7] decomposed a face image into large- and small-scale features, normalized illumination separately on both features, and finally recovered a normal illumination image through combining both features together. Tan and Triggs [8] proposed an integrative framework that combines the strengths of robust illumination normalization, local texture based face representations, distance transform based matching, kernel-based feature extraction and multiple feature fusion. Using Weber's Law, Wang in [9] considers the ratio between local difference and the center degree as a kind of illumination invariant component. These methods are quite effective but their ability to handle extreme uneven illumination variations remains limited. A novel preprocessing method based on statistical bilinear model [10] is proposed by Jun et al. [11]. This method transforms input face image into sixteen face images exhibiting different illuminations. It yields high recognition rates but its computational complexity is not reasonable.

In this paper, illumination effects are reduced using homomorphic filter in spatial domain, instead transforming an image into sixteen images using bilinear model. It reduces total face recognition time. Furthermore, the proposed method is applied on two

* Corresponding author. Fax: +98 273 3391600.
*E-mail addresses:* Shahamat@shahroodut.ac.ir, Hossein_Shahamat@yahoo.com (H. Shahamat), apouyan@shahroodut.ac.ir (A.A. Pouyan).
[1] Fax: +98 273 3391600.

http://dx.doi.org/10.1016/j.jvcir.2014.02.007

different face databases. The experimental results are reasonably good and it shows to be robust to great illumination variation.

In recent years, many representation methods have been proposed. They include subspace discriminant analysis [12], SVM [13], principal component analysis (PCA) [14] and independent component analysis (ICA) [15]. These methods are statistical and suffer the generalization problem due to unpredictable distribution of the face images in a real environment. Non-statistical face representation methods such as local binary patterns (LBP) [16] and local Gabor binary patterns (LGBP) [17] have been proposed to solve this problem. Multi-resolution uniform local Gabor binary pattern (MULGBP) method for face representation is proposed by Jun et al. [11]. The MULGBP method is obtained by applying multiple ULBPs (uniform LBP) to Gabor magnitude maps. Finally, a histogram matching-based classifier determines identity of the input face image. In this paper, when the proposed method is used for preprocessing, and the MULGBP technique is used for face representation, a very high recognition rate is obtained.

The rest of the paper is organized as follows: Section 2 presents details of illumination effects reduction using the proposed method. It describes the homomorphic filtering in frequency domain. Then, our homomorphic filtering in spatial domain is explained. Section 3 briefly describes face representation using MULGBP, and face recognition using histogram matching. Section 4 introduces two different face databases which are used in this paper. Sections 5 and 6 show the experimental results and conclusion.

## 2. Illumination effects reduction

### 2.1. Frequency domain filtering

Filtering in the frequency domain consists of modifying Fourier transform of an image and then computing the inverse transform to obtain the processed result [2]. Thus, given a digital image $f(x,y)$, the basic filtering equation has the form:

$$g(x,y) = \Im^{-1}[H(u,v)F(u,v)], \tag{1}$$

where $\Im^{-1}$ is the inverse Fourier transform, $F(u,v)$ is the Fourier transform of the input image $f(x,y)$, $H(u,v)$ is a filter function and $g(x,y)$ is the filtered image. The product $H(u,v)F(u,v)$ is formed using array multiplication.

### 2.2. Homomorphic filtering

The illumination-reflectance model introduced in [18] can be used to develop a frequency domain procedure for improving the appearance of an image by simultaneous intensity range compression and contrast enhancement [2]. According to this model, each pixel value $f(x,y)$ can be expressed as the product of an illumination component $i(x,y)$ and a reflectance component $r(x,y)$:

$$f(x,y) = i(x,y)r(x,y). \tag{2}$$

In order to separate these two independent components and to facilitate their separate processing, logarithm transform on Eq. (2) has been taken, thus

$$z(x,y) = \ln\ f(x,y) = \ln\ i(x,y) + \ln\ r(x,y). \tag{3}$$

Then, the Fourier transform of Eq. (3) is calculated:

$$\Im\{z(x,y)\} = \Im\{\ln\ f(x,y)\} = \Im\{\ln\ i(x,y)\} + \Im\{\ln\ r(x,y)\} \tag{4}$$

Or:

$$Z(u,v) = F_i(u,v) + F_r(u,v), \tag{5}$$

where $F_i(u,v)$ and $F_r(u,v)$ are the Fourier transform of $ln\ i(x,y)$ and $ln\ r(x,y)$, respectively. If we process $Z(u,v)$ using a filter function $H(u,v)$, then:

$$S(u,v) = H(u,v)Z(u,v) = H(u,v)F_i(u,v) + H(u,v)F_r(u,v). \tag{6}$$

The filtered image is obtained by taking the inverse Fourier transform of Eq. (6):

$$\begin{aligned} s(x,y) &= \Im^{-1}\{S(u,v)\} \\ &= \Im^{-1}\{H(u,v)F_i(u,v)\} + \Im^{-1}\{H(u,v)F_r(u,v)\}. \end{aligned} \tag{7}$$

By defining:

$$i'(x,y) = \Im^{-1}\{H(u,v)F_i(u,v)\} \tag{8}$$

And:

$$r'(x,y) = \Im^{-1}\{H(u,v)F_r(u,v)\} \tag{9}$$

Eq. (7) can be expressed as follows:

$$s(x,y) = i'(x,y) + r'(x,y). \tag{10}$$

As $z(x,y)$ is the logarithm of original image $f(x,y)$, the exponential (inverse of logarithm) operation yields desired enhanced image $g(x,y)$, as follows:

$$g(x,y) = e^{s(x,y)} = e^{i'(x,y)}.e^{r'(x,y)} = i_0(x,y)r_0(x,y) \tag{11}$$

where, $i_0(x,y)$ and $r_0(x,y)$ are illumination and reflectance component of the output image, respectively. The images enhancement procedure using homomorphic filtering is summarized in Fig. 1.

The illumination component of an image is generally characterized by slow spatial variations, while the reflectance component tends to vary abruptly, particularly at the junctions of dissimilar objects. These characteristics lead to associating low frequencies of logarithm of an image with illumination and the high frequencies with reflectance. Although these associations are rough approximations, they have advantage in illumination normalization of face images. Suppressing the low frequencies potentially reduces the illumination effect in face images without destroying too much of details. A good deal of control can be gained over the illumination and reflectance components with a homomorphic filter. This control requires specification of a filter function $H(u,v)$, that affects the low and high frequency components of the Fourier transform in different ways. In this paper, reflectance component of images are considered for further processes. Therefore, homomorphic filtering with a Butterworth high pass kernel is a convenient way to achieve this component [2]. It is defined as follows:

$$H(u,v) = (\gamma_H - \gamma_L)\left(\frac{1}{1 + (D_0/D(u,v))^{2n}}\right) + \gamma_L. \tag{12}$$

Where, $D(u,v)$ is distance from the origin of the centered Fourier transform, $D_0$ is the cutoff distance measured from the origin, and $n$ is the order of the Butterworth filter.

### 2.3. Homomorphic filtering in spatial domain

All frequency filters can also be implemented in the spatial domain. If there exists a simple kernel for the desired filter effect, it is

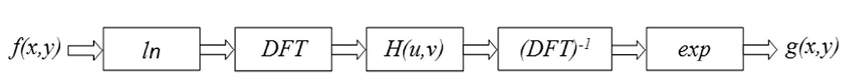


**Fig. 1.** Overall procedure of homomorphic filtering.