Sub-Image Homomorphic Filtering Technique for Improving Facial Identification under Difficult Illumination Conditions

K. Delac, M. Grgic, T. Kos
University of Zagreb, Faculty of Electrical Engineering and Computing
Department of Wireless Communications
Unska 3 / XII, HR-10000 Zagreb, Croatia
Phone: + 385 1 6129 851, Fax: + 385 1 6129 568, E-mail: kdelac@ieee.org

Keywords: Outdoor Face Recognition, Homomorphic Filtering, Illumination Compensation

Abstract – In this paper we will propose a simple modification of standard homomorphic filtering technique and thus significantly improve face recognition performance on images with difficult illumination conditions. We will also give a detailed theoretical description of a homomorphic filter and compare our proposed method to common illumination compensation techniques used in face recognition literature. The comparisons will be performed on standard grayscale FERET database and this will, in addition, be the first evaluation of homomorphic filter on this database. Results will show that our method yields significantly better identification results than standard illumination compensation methods currently used in face recognition.

1. INTRODUCTION

It is well known that the appearance of an object can be severely affected by illumination. Naturally, automatic face recognition performance is also affected [1], [2]. The problem is that the variation between images of different faces can be smaller than the variations between images of the same face under different illumination. It can even be shown that illumination causes larger variation in face images than pose [3]. Reports from independent evaluations consistently confirm that state-of-the-art face recognition systems cannot cope with large differences in illumination between gallery and probe images [4], [5], further emphasizing the indoor-outdoor images matching problem as a direct implication.

At the very beginning of modern machine face recognition [6], it became quite obvious that different illumination in various images will be a problem. Simple histogram equalization immediately emerged as an *ad hoc* solution, with its two main advantages being its computational simplicity and relatively good overall performance. Recent 3D model-based approaches for solving this issue do tend to give better results but are computationally very expensive, and therefore still somewhat unattractive. Consequently, 2D techniques (like histogram equalization) are still worth exploring. This is best supported by the fact that simple histogram equalization is still a *de facto* standard in preprocessing face images prior to recognition.

A very promising and moderately computationally complex 2D method for compensating illumination changes is *homomorphic filtering*, based on illumination-reflectance model [7], [8]. The procedure is well known in image analysis and processing but was rarely addressed and used in face recognition. Some comparisons to other illumination compensation methods can be found in [9], but with scarce theoretical or implementation details.

This paper gives a detailed theoretical background on homomorphic filtering, along with some proposed modifications, specifically designed to address face recognition. We will show that by dividing the face image into sub-images, and performing homomorphic filtering on each sub-image individually, the performance can be significantly improved. Actually, we will show that by combining two filtered sub-image representations we can improve overall performance even further. To support our assumptions we will compare our proposed technique to current standard practice on a very difficult "different illumination" sub-section of grayscale FERET database [2], following a standard verification procedure.

The rest of this paper is organized as follows: in Section 2 we shall give a detailed theoretical background of homomorphic filtering, followed by the description of our proposed modifications; in Section 3 we shall present our experimental setup and show results of some standard procedures compared to our proposed method; Section 4 concludes the paper and lists possible improvements and further work.

2. HOMOMORPHIC FILTERING

2.1. Illumination-Reflectance Model

In general, an image can be regarded as a two-dimensional function of the form $I(x,y)$, whose value at spatial coordinates (x,y) is a positive scalar quantity whose physical meaning is determined by the source of the image [7]. Assuming that we are dealing with grayscale images, we can say that when an image is generated from a physical process, its values are proportional to energy radiated by a physical source. In other words, an image is an array of measured light intensities and is a function of the amount of light reflected of the objects in the scene. The intensity is a product of *illumination* (the amount of source illumination incident on the scene being viewed) and *reflectance* (the amount of illumination reflected by the objects in the scene). If we denote illumination as $L(x,y)$ and reflectance as $R(x,y)$, then an image $I(x,y)$ can be expressed as:

$$I(x,y) = R(x,y) \cdot L(x,y) \qquad (1)$$

The model of image formation just described is well known as the *illumination-reflectance model* and can be used to address the problem of improving the quality of an image that has been acquired under poor illumination conditions.

2.2. Basic Homomorphic Filtering

As already hinted in the previous section, illumination results from the lighting conditions present when the image is captured, and can change when lighting conditions change. Reflectance results from the way the objects in the image reflect light, and is determined by the intrinsic properties of the object itself, which (we can safely assume in this theoretical analysis) does not change. We can further argue that illumination varies slowly in space (slow spatial changes ↔ low spatial frequency) while reflectance can change abruptly (high spatial frequencies). For our given problem of eliminating apparent changes in facial appearance with the change in lighting conditions, we would like to enhance the reflectance while reducing the contribution of illumination, hence, we need to somehow separate the two components from (1) and then high pass the resulting image in frequency domain. *Homomorphic filtering* [7], [8] is a frequency domain filtering process that does just that. If we could somehow transform the expression in (1) from multiplication to addition, the problem of high pass filtering would become trivial as we could use the multiplication or convolution property of the Fourier transform $\Im$. An obvious way to solve this problem is to take a natural logarithm (base *e*) of both sides of (1):

$$\begin{aligned} Z(x,y) = \ln[I(x,y)] = \ln[R(x,y)\cdot L(x,y)] = \\ \ln[R(x,y)] + \ln[L(x,y)] \end{aligned} \tag{2}$$

and use the Fourier transform:

$$\Im\{Z(x,y)\} = \Im\{\ln[R(x,y)]\} + \Im\{\ln[L(x,y)]\} \tag{3}$$

or:

$$Z(u,v) = F_R(u,v) + F_L(u,v) \tag{4}$$

where $F_R(u,v)$ and $F_L(u,v)$ are the Fourier transforms of $\ln[R(x,y)]$ and $\ln[L(x,y)]$, respectively. Now we can high pass the $Z(u,v)$ by means of a filter function $H(u,v)$ in frequency domain and obtain a filtered version $S(u,v)$:

$$\begin{aligned} S(u,v) = H(u,v)\cdot Z(u,v) = \\ H(u,v)\cdot F_R(u,v) + H(u,v)\cdot F_L(u,v) \end{aligned} \tag{5}$$

Taking an inverse Fourier transform of (5) provides:

$$\begin{aligned} s(x,y) = \Im^{-1}\{S(u,v)\} = \\ \Im^{-1}\{H(u,v)\cdot F_R(u,v)\} + \Im^{-1}\{H(u,v)\cdot F_L(u,v)\} \end{aligned} \tag{6}$$

and finally, the desired filtered (enhanced) image $I'(x,y)$ can be obtained by the exponential operation:

$$I'(x,y) = e^{s(x,y)} \tag{7}$$

The high pass filter normally used in this procedure is the Butterworth filter [7] defined as:

$$H(u,v) = \frac{1}{1 + \left[\dfrac{D_0}{D(u,v)}\right]^{2n}} \tag{8}$$

where n defines the order of the filter. D_0 is the cutoff distance from the center and $D(u,v)$ is given by:

$$D(u,v) = \left[(u - M/2)^2 + (v - N/2)^2\right]^{1/2} \tag{9}$$

where M and N are the number of rows and columns of the original image, respectively (for any further details an interested reader is referred to [7], [8]). The whole process is summarized in Fig. 1.

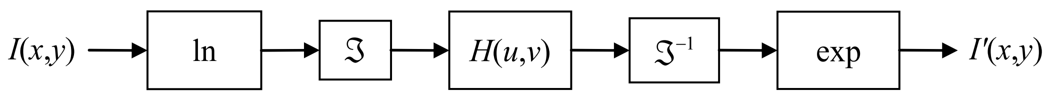

Fig. 1. Homomorphic filtering procedure

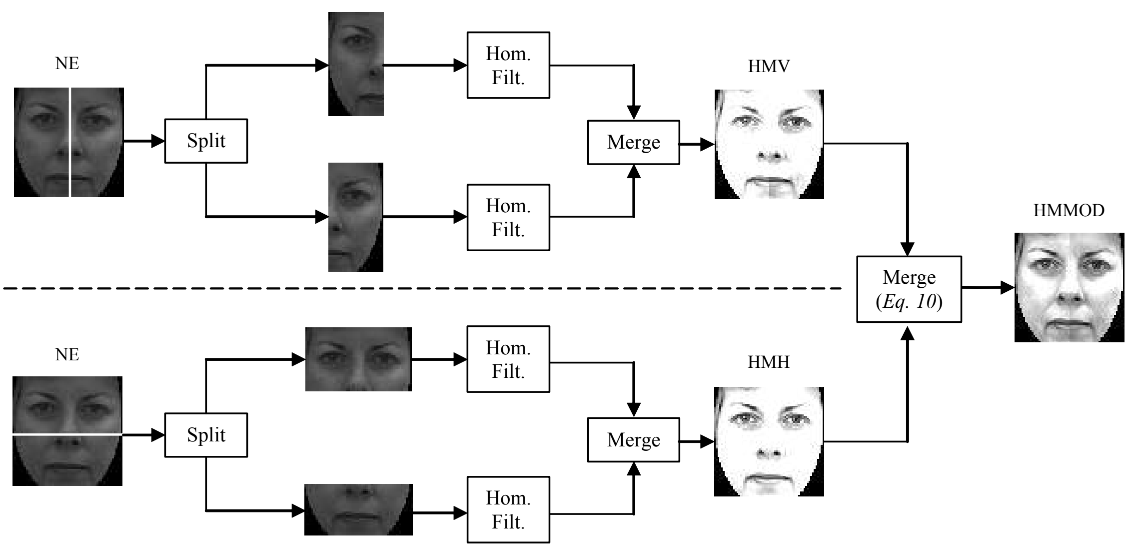

Fig. 2. Sub-image homomorphic filtering

(a) (b) (c) (d) (e) (f) (g)

Fig. 3. Image examples: (a) Geometrically normalized and masked image with no enhancements (NE), (b) histogram equalized (HE), (c) homomorphically filtered image (HM), (d) homomorphically filtered and contrast adjusted image (HMADJ), (e) two vertical sub-images filtered separately (HMV), (f) two horizontal sub-images filtered separately (HMH), (g) proposed combination (HMMOD)

2.3. Proposed Modification

While the results of a standard homomorphic filtering over the whole image just described give promising results (reported in [9] on a smaller database and confirmed in our experiments in Section 3), we wanted to see if the results could be further improved. Many well-known enhancement algorithms such as histogram equalization and homomorphic filtering are global in nature and are intended to enhance an image and deal with it as a whole. We tried to split the original image in sub-images and filter each sub-image individually. First we decided to try and split the image into two halves vertically (thus obtaining two *sub-images* of the original image) and then apply the filter to each half individually. Second idea was to split the image horizontally and again apply the filter to each half individually.

Encouraged by the good results obtained with both these methods (see Section 3 for details) we further tried to combine the filtering results into a joint representation. Let $I_{HMV}(x,y)$ be the image split vertically and each half filtered with homomorphic filter individually, let $I_{HMH}(x,y)$ be the same for horizontally split images and let $I_{HMMOD}(x,y)$ be our proposed modification:

$$I_{HMMOD}(x,y) = \frac{1}{2} \cdot [I_{HMV}(x,y) + 0.75 \cdot I_{HMH}(x,y)] \qquad (10)$$

Since I_{HMV} scored higher results than I_{HMH} in our tests we decided to keep the whole I_{HMV} and multiply I_{HMH} with a constant of 0.75 (chosen based on experimental results), to lower its influence on the final representation. This combination produced highest results in our experiments and was kept as a final representation. The whole procedure is summarized in Fig. 2, and examples of the filtered image can be seen in Fig. 3. We will show in the following section that our method yields superior results, and therefore justifies further research of the homomorphic filtering variations as a means of simple yet efficient image preprocessing.

3. EXPERIMENTS

To test our proposed method we decided to use the grayscale FERET database [2]. We were mainly motivated by the fact that FERET was never used to test the preprocessing by homomorphic filter. We used standard FERET identification protocol (gallery and probe sets) and focused here on the *fc* probe set (different illumination test). Other papers normally report their results for similar techniques that deal with different illumination conditions on smaller databases with low number of subjects. The results are thus often nonrealistic as the methods can be biased to a certain database. The *fc* probe set from FERET seems to be one of the most difficult ones with its 194 images (one image per subject) taken under very difficult illumination conditions and that is why we decided to use it in our comparisons.

To compare our proposed method to histogram equalization and standard homomorphic filtering, we used standard Principal Component Analysis (PCA) as an identification algorithm [6]. Nearest neighbor matching was combined with L1 norm (the city block distance). For PCA training, we used 500 randomly drawn images from the entire database and chose them so that they do not overlap with the gallery or *fc* probe set. All images were geometrically normalized prior to performing the experiments and cropped to 64x64 pixels. Eyes are all in the same positions and all the images are masked with an elliptical mask as shown in Fig. 3a. Recognition was done in 200 dimensional subspace.

The filtering for all the addressed methods was done after the geometrical normalization but prior to masking in order to avoid the influence of zeros of the mask to histogram equalization and image adjustment results. In all tests, enhancement and/or filtering were done on *all* images used (training, gallery and probe set).

3.1. Methods Tested

No enhancement (NE). For this test we only geometrically normalized the images (actually, images were geometrically normalized in all subsequent tests as well). No filtering or histogram equalization is used (Fig. 3a).

Standard histogram equalization (HE). Images were geometrically normalized and a standard histogram equalization (HE) technique was employed. HE enhances the contrast of images by transforming the values in an intensity image, so that the histogram of the output image is approximately uniformly distributed on pixel intensities of 0 to 255 (Fig. 3b).

Homomorphic filter (HM). Standard homomorphic filtering of geometrically normalized images using Butterwort high pass filter with D_0=0.25 and n=1 (Fig. 3c).

HM with contrast adjustment (HMADJ). Homomorphic filtering (with the same D_0 and n values as before; these Butterworth filter parameters are the same throughout all the experiments) followed by a modified version of HE. After homomorphic filtering the pixel values are mapped to new values such that 1% of data in the final image is saturated at low and high intensities of the filtered image. This increases the contrast of the output image (Fig. 3d).

HM vertical (HMV). Homomorphic filtering of two sub-images obtained by vertically dividing the input image into two halves prior to filtering and then filtering each of them. The resulting image is obtained by concatenating the two filtered halves (Fig. 3e).

HM horizontal (HMH). The same procedure as in HMV with the exception of an image being horizontally divided (Fig. 3f).

HM modified (HMMOD). Method proposed in Section 2.3, consisting in combining results from HMV and HMH (Fig. 3g).

Table 1. Results of applying all the techniques on FERET database images and standard FERET protocol tests with *fc* probe set. The numbers in the table represent rank 1 recognition rate (RR) in percentages of correctly recognized images over the whole probe set.

Method	NE	HE	HM	HMADJ	HMV	HMH	HMMOD
RR (%)	4.12	46.90	52.06	56.70	57.21	52.57	**60.30**

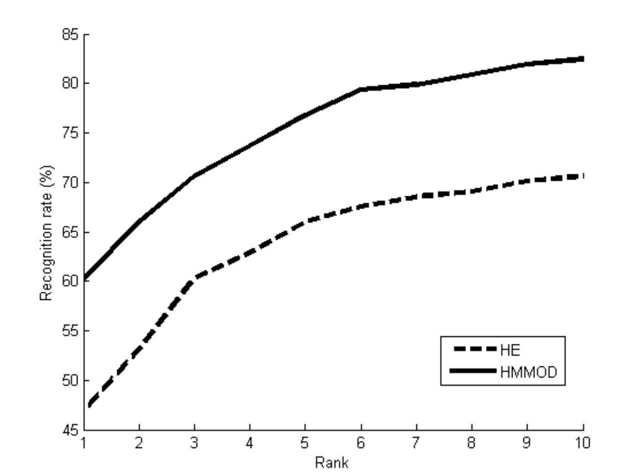

Fig. 4. Cumulative Match Score (CMS) curves for HE and our proposed HMMOD; FERET *fc* probe set

3.2. Results

The rank 1 recognition performance results of testing all the methods presented in Section 3.1 using the grayscale FERET database with standard *fc* (different illumination test) probe set can be seen in Table 1. We can get a feel on how difficult this test set really is by looking at the extremely low recognition rate on NE images (4.12%). Standard preprocessing practice often reported in papers is the HE, which yielded 46.90% in our experiment. We can see a significant improvement by using HM and HMADJ with 52.06% and 56.70%, respectively. Our vertically and horizontally split sub-images scored 57.21% and 52.57%, respectively, and this is still significantly better that the HE method. In the last column of Table 1, we can see that our proposed combination HMMOD is clearly superior to all other methods and yields 60.30% recognition rate which is 13.40% higher than the standard HE. The superiority of HMMOD is further confirmed in Fig. 4, where you can see the cumulative match score curves for HE and HMMOD.

4. CONCLUSIONS

In this paper we give detailed description of illumination-reflectance model and standard homomorphic filtering, along with our modifications. We tested all the described techniques on a FERET grayscale dataset and showed that our modified sub-image homomorphic filtering gives significantly better results for the FERET *fc* probe set.

Homomorphic filtering in general was rarely addressed in face recognition literature and, to the best of our knowledge, was never tested on the FERET database before. Our preliminary results, both on standard homomorphic filtering and on our modified versions, show promising results and justify further research of the homomorphic filtering for the illumination changes task.

ACKNOWLEDGMENTS

Portions of the research in this paper use the FERET database of facial images collected under the FERET program. The authors would like to thank the FERET Technical Agent, the U.S. National Institute of Standards and Technology (NIST) for providing the FERET database.

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