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Automatic Image Shadow Identification using LPF in Homomorphic Processing System

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Abstract. In this paper, we have used homomorphic system and HSV color space for shadow detection. Here, we have defined a LPF to detect the shadow over a dark object on the background. In this case, we omit the phase information in order not to emphasize the reflection component. Furthermore, the presented experimental results which are obtained for shadow identification, show the efficiency of the proposed method.
Keywords: Shadow identification, Homomorphic system, HSV color space, LPF.

1 Introduction

Shadow occurs when an object totally or partially occludes directly from the light source. Generally, shadow is divided in two parts: 1- Self shadow which is a part of shadow on the main object where is not illuminated by light. 2- Cast shadow, which is the object's shadow on background. Basically, cast shadow itself is divided in to umbra and penumbra. The umbra corresponds to the area where the light is totally absorbed by object whereas the penumbra is an area of shadow where light is partially blocked. Different parts of shadow are illustrated in Fig. 1. Several approaches based on model [4] or shadow properties [1],[3] have been proposed for shadow identification and classification, especially for detecting self and cast shadow. The value component of HSV (Hue, Saturation,Value)color space converted from RGB which determines the darkness/lightness of a color, has been used for shadow identification. A better results have been obtained in any images because intensity value in the shadow area will be slightly lower than non-shadow area [5],[6]. The method is applied under the following assumption:

- The texture of image background is flat or near to flat.
- Both object and its shadow are within the image.
- Images are simple (with low activity).

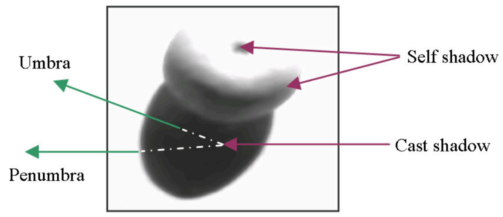

Fig. 1. Types of shadow

As an application for shadow identification we can mention for instance cloud shadow identification and data visibility in cloud shadow covered area in remote sensing images or shadow detection using in Mobile Robotic Vision to identify the object from its shadow. Shadow detection also can be used in moving object to identify the real object from its shadow especially in control traffic system. The body of this paper sketches out a system to recognize shadow by utilizing of the homomorphic processing in order to operate on luminance and reflectance of an image separately [8]. The procedure of proposed method for identifying shadow has the following steps: the first step is the homomorphic filtering process, the second step is the background detection using median filter for calculating the appropriate gain [2] in the case of HPF (this step is omitted for LPF) and the third step is shadow identification. This paper is organized as follows. The concept of the homomorphic system is described in section 2. The proposed method to identify shadow area is introduced in the section 3. Experimental results based on the proposed method and discussions about the results are presented in section 4 and section 5 concludes the paper.

2 Homomorphic system

When an image generated via physical process, its gray-level values are proportional to energy radiated by a physical source. Consequently, gray-level values of image pixels, *f(x,y)*, must be nonzero and finite. Also *f(x,y)* has two multiplicand components: 1- illumination, *i(x,y)*, which is determined by the illumination source 2- reflection, *r(x,y)*, which is determined by material and color of objects in the image [7].

$$f(x, y) = i(x, y).r(x, y) \tag{1}$$

Where the nature of *i(x,y)* component is nonzero and finite, and *r(x,y)* component is between zero (total absorption) and one (total reflection). In theory, shadow is the area of an image with the lower illumination value than other parts of the image but its reflection component is the same as other parts of the object which shadow occurred on it [7]. So, for shadow detection, we propose a new method to distinguish the illumination changes. To this end, we need to separate two components of each gray-level value, *f(x,y)*, [8]. Equation (1) can not be used directly to operate separately on illumination and reflection components in the frequency domain, that is:

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

In the first process, the homomorphic filter will separate the image illumination and reflection components, by taking logarithm operation of every pixel and converting the gray-level components multiplication to addition, for further process in result, as shown in Fig. 2

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

$$FFT\{\ ln[f(x,y)]\} = FFT\{\ ln[i(x,y)]\} + FFT\{\ ln[r(x,y)]\} \tag{4}$$

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

Whereas, $F_i(u,v)$ and $F_r(u,v)$ are the Fourier transform of illumination $ln[i(x,y)]$ and reflection $ln[r(x,y)]$, respectively. Furthermore, we process $F_f(u,v)$ by means of a linear filter function $H(u,v)$. Therefore, the key to the approach is the separation of the illumination and reflection components achieved in the form given in Equation (5) and to performance a linear filtering as in the following Equation:

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

Where $Z(u,v)$ is the Fourier transform of the result.

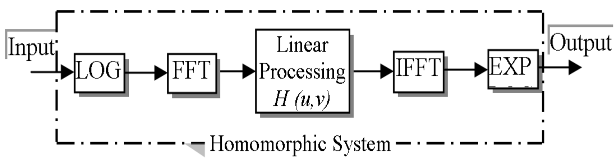

Fig. 2. Block diagram of the homomorphic system

3 Shadow identification

The illumination component of an image generally is characterized by slow spatial variation, while the reflection component tends to vary abruptly, particularly at the junctions of dissimilar objects. These characteristics lead to associate the low frequency components of the Fourier transform of an image with the illumination and the high frequencies with the reflection. Although these associations are rough approximation, they can be used for some advantages.

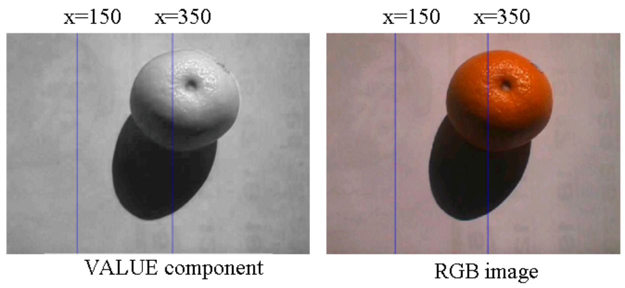

Fig. 3. Real images in value component and RGB color space with two scanned lines

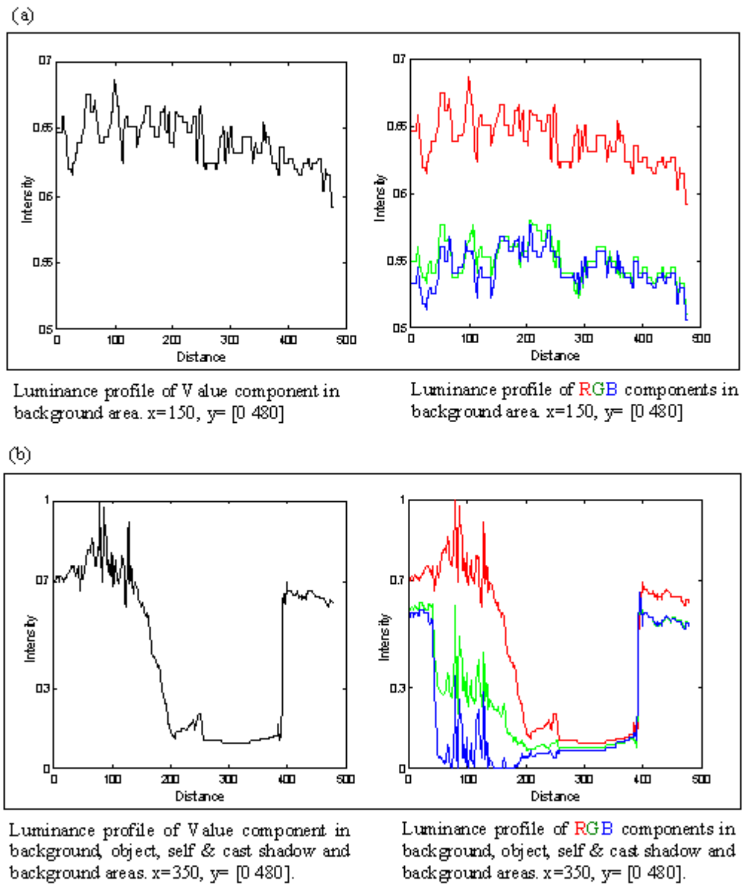

Fig. 4. Luminance changes profile in shadow and non-shadow area

Since luminance is a color feature that is sensitive to shadow as pointed out earlier, we convert the RGB color space components to HSV (Hue, Saturation, Value) color space components. As HSV color space corresponds closely to the human perception of color [6] and it has been proven that it is more accurate in distinguishing shadow area than the RGB color space and also gray-scale space. The relation between the RGB components with GSI and V components are as follow:

$$GSI = 0.299R + 0.587G + 0.114B \tag{7}$$

$$V = max(R, G, B) \tag{8}$$

Where, GSI is the Gray Scale Intensity and V is the Value component of the HSV color space. Now, V component will be used for shadow detection.

For study of shadow performance, luminance profile of two different scanned line *x=x0* in the Y direction of the V component and RGB components are shown in Fig. 4. Fig. 3 , shows a real image with 480 by 640 pixels. Its intensities on the two scanned lines in the Y direction at x equal to 150 and 350 are shown in Fig. 4. Any pixel on a scanned line with the intensity approximately equal to minimum pixel intensity is labelled as shadow. As can be seen from Fig. 4(a), there is no shadow on the scanned line x=150 in Value and RGB components. In Fig. 4(b) the valleys with lower intensity, show the shadow area. Also as shown in Fig. 4(a) and (b) the profile of Value component of HSV color space image has the similar behavior as red component of RGB color space image which is the dominant color in this image.

3.1 High pass filter

Edges and sharp transitions in gray-values in an image contribute significantly to high-frequency content of its Fourier transform. In this part, first of all we are trying to extract the reflection components of image gray-levels in homomorphic system by using high pass filter (HPF) as reflection component has more contribution in high frequency. At this stage, a good deal of control can be gained over the reflection component with an appropriate homomorphic filter. In order to emphasize more on reflection coefficients, HPF is used as linear processing. The following HPF is a candidate to detect the reflection component:

$$H(u, v) = (\gamma_H - \gamma_L)[1 - \exp^{-c(D^2(u,v)/(D_0)^2)}] + \gamma_L \tag{9}$$

$$(\gamma_L < 1, \gamma_H > 1)$$

Where D_0 is the cutoff frequency and constant c has been introduced to control the sharpness of the slope of the filter function in transition between γ_L and γ_H . $D(u, v)$ is the distance from the origin of the centered transform in frequency plane. In the next process, the background of the original image and the high pass filtered image which contains the reflection component and a very small portion of illumination component, $\varepsilon i(x, y) + r(x, y)$, are detected by using an order filtering such as median filter [2]. Since we want to detect the value of background, the window size for the median filter is the size of whole image that is 480 by 640 for our test images. Then, we calculate the appropriate gain from these two median values for automatic background equalization. Fig. 5 illustrates the block diagram of gain calculating and background equalization. The median process is as follow:

$$O_m = median\{f(x, y)\} \tag{10}$$

$$F_m = median\{f_h(x, y)\} \tag{11}$$

$$G = \frac{F_m}{O_m} \tag{12}$$

Where, O_m and F_m, are the median gray-level of the original image (f) and the median of the homomorphic filtered image (f_h) for the background detection. Here, we assume that the median gray-level is laid on the background. Furthermore, G is the calculated gain for the background equalization. In the third process, by using the calculated gain in the second step, the backgrounds of the original image and the filtered-image will be equalized. It is clear that most of the pixels within image belong to the background (in low activity image) then after the background equalization, we subtract filtered and equalized original images in order to identify the shadow. Fig. 5 illustrates the block diagram of the proposed system.

$$eq(x, y) = G.f(x, y) \tag{13}$$

$$s(x, y) = f_h(x, y) - eq(x, y) \tag{14}$$

Where, *eq(x,y)* is an equalized image which will be subtracted from filtered image in order to identify shadow part, *s(x,y)*. Moreover, we suppose that the reflection component will be more emphasized through high pass filtering. Since original image is subtracting from the filtered image, then, the reflection part is eliminated in order to get the illumination part to identify as shadow candidate area [8].

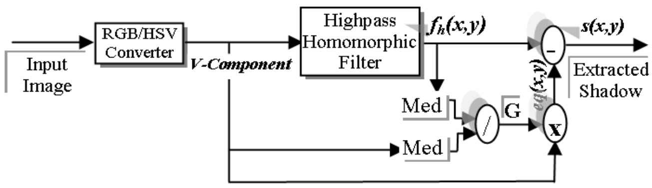

Fig. 5. Block diagram of the proposed system using HPF

3.2 Low pass filter

Conventional low-pass filters (LPF) used for smoothing can be applied by selecting a circular aperture in frequency space and keeping the low frequency data inside the circle. Here, low pass filter is used as the homomorphic processing filter. As we pointed out earlier we suppose that the LPF has more emphasize on illumination and the shadow area in an image is the illumination changes. Since the shadow area directly affected by shortage of intensity, it means that the shadow area has the lower illumination. We are trying to find the illumination changes by LPF in order to detect the shadow area. Choosing the LPF as the base linear filter for homomorphic system enables us to reach to our goal -extracting shadow area- by less computational load compared with using HPF as the base linear filter for the system. We use homomorphic system to be able to operate on illumination and reflection components of an image gray-level separately. As the LPF will emphasize more on illumination we will apply the LPF instead of HPF in filtering the Value component of HSV color space image. Generally, we are expecting a kind of smooth image as an output when we use the LPF in the homomorphic system. In this stage we have illumination changes or shadow area and of course a very small portion of reflection component, $i(x, y) + \varepsilon r(x, y)$, as LPF can not remove totally the effect of reflection. If we remove the phase information from the output of inverse Fourier transform to have real and positive values for real image pixels we will reach to a better visibility for the shadow area. This illumination changes as an output of LPF in homomorphic system will be labelled as shadow area. For more flexibility in the LPF, we choose the following algorithm for LPF transfer function, H(u,v):

$$H(u, v) = 1 - [(\gamma_H - \gamma_L)[1 - \exp^{-c(D^2(u,v)/(D_0)^2)}] + \gamma_L] \tag{15}$$

$$(\gamma_L < 1, \gamma_H > 1)$$

Where D_0 is the cutoff frequency and constant c has been introduced to control the sharpness of the slope of the filter function in transition between γ_L and γ_H. $D(u, v)$ is the distance from the origin of the transform in the frequency plane. By choosing an appropriate cutoff frequency from the power spectrum of image in homomorphic system, while the image is filtered in the homomorphic system, the LPF will emphasize more on illumination changes.

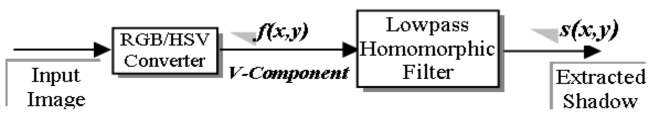

Fig. 6. Block diagram of the proposed system using LPF

3.3 Comparison between LPF and HPF

Fig. 7 illustrates the block diagram of the LPF and HPF as a linear processing in the homomorphic system. Obviously using the LPF approach has been greatly improved the detection of shadow areas as compared to the HPF approach.

– The computational load in the LPF approach is enormously lower than the one to detect the shadow area in the HPF approach.
– LPF approach is significantly powerful to detect the shadow over the dark objects (Fig. 8(k)).

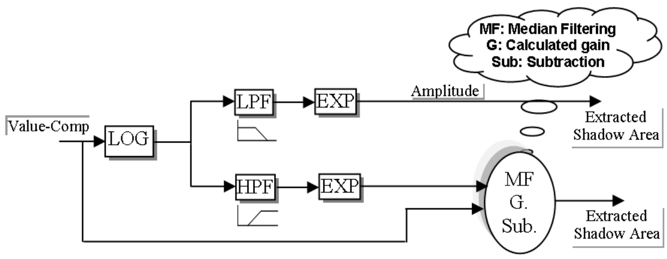

Fig. 7. Comparison between two implemented system (LPF,HPF)

4 Experimental Results

The proposed shadow identification method was tested in variety of color images under the assumption in section 1 and we setup the filter by $\gamma_L = 0.2$, $\gamma_H = 3$, $c = 1$ and $D_0 = 150$. The results are presented in this section. We used many images having different color contents. As an example, the results for the *Orange* image are shown in Fig. 8. RGB color space and Value component of HSV color space of the original image are shown in Fig. 8 (a) and (b) respectively. Fig. 8 (c) and (d) depicted the result of proposed method using gray-scale image instead of Value component with LPF and HPF respectively. The results of processing using the dominant component of RGB color space image (RED component) by LPF and HPF are illustrated in Fig. 8 (e) and (F). Fig. 8 (g) and (h) show the results of the proposed method using LPF and HPF as a homomorphic filter and the Value component of HSV color space image as their input. Another test image in RGB color space and value component of HSV color space have shown in Fig. 8 (i) and (j). This image illustrates the shadow of one object (Orange) over another dark object (book). Fig. 8 (k) and (l) show the result of the proposed method respectively using LPF and HPF. As we can see from the result the dark object is detected as shadow area by using HPF which means this filter is not suitable in the cases which the object's shadow occurred on another dark object but by using LPF, it is clearly obvious that just the shadow area are detected. These examples allow us to recognize the powerful behavior of the homomorphic system and HSV color space using LPF in shadow identification. It is the robustness of this method which automatically extract the only shadow parts.

5 Conclusion

In this paper, we presented a shadow identification method based on the homomorphic system using Value component of HSV color space. We applied and compared the result of LPF and HPF as the homomorphic filters in the Fourier transform domain. Results show that the Value component of HSV color space works better than the gray-scale images and even better than the Red component in RGB color space which is the dominant component of object (*Orange test image*). Moreover, the robustness of the LPF shows its significant characteristic to detecting the shadow area even over the dark objects(Fig. 8 (k)).Further work will focus on defining a strategy to classify self and cast shadow points in shadow candidate area separately. Also,a new technique to improve the quality of the method on extracting the shadow will be investigated.

References

1. C.Jing and M. O. Ward, "Shadow Segmentation and Classification in a constrained Environment," CVGIP: Image Understanding, 59 (2): 213-225, 1994.
2. P.L. Rosin and T. Ellis, "Image Difference Threshold Strategies and Shadow Detection,"
3. G. F. Lea and R. Bajcsy, "Combining Color and Geometry for the Active, Visual Recognition Shadows,"ICCV: 1995, IEEE
4. E. Salvador, Andrea Cavallaro and T. Ebrahimi, "ShadowIdentification and Classification Using Invariant Color Model," ICASSP 2001. May 7-11, 2001.
5. B. Ran and H. X. Liu, "Development of A Vision-Based Real Time Lane Detection and Tracking System forIntelligent Vehicles," 1415 Engineering Drive, Madison, WI, 53706, USA, 1999.
6. N. Herdotou, K.N. Plataniotis, and A.N. Venetsanpoulos,"A color segmentation scheme for object-based video coding," in Proceeding of the IEEE Symposium on Advances in Digital Filtering and Signal Processing, 1998, pp. 25-29.
7. Rafael C. Gonzales, Richard E. Woods, "Digital Image Processing".
8. M.R. Asharif, H. Etemadnia, "Homomorphic Processing Approach for Image Shadow Identification",International Symposuim on Telecommunications, IST 2003, Isfehan, Iran, Aug.16-18, 2003.

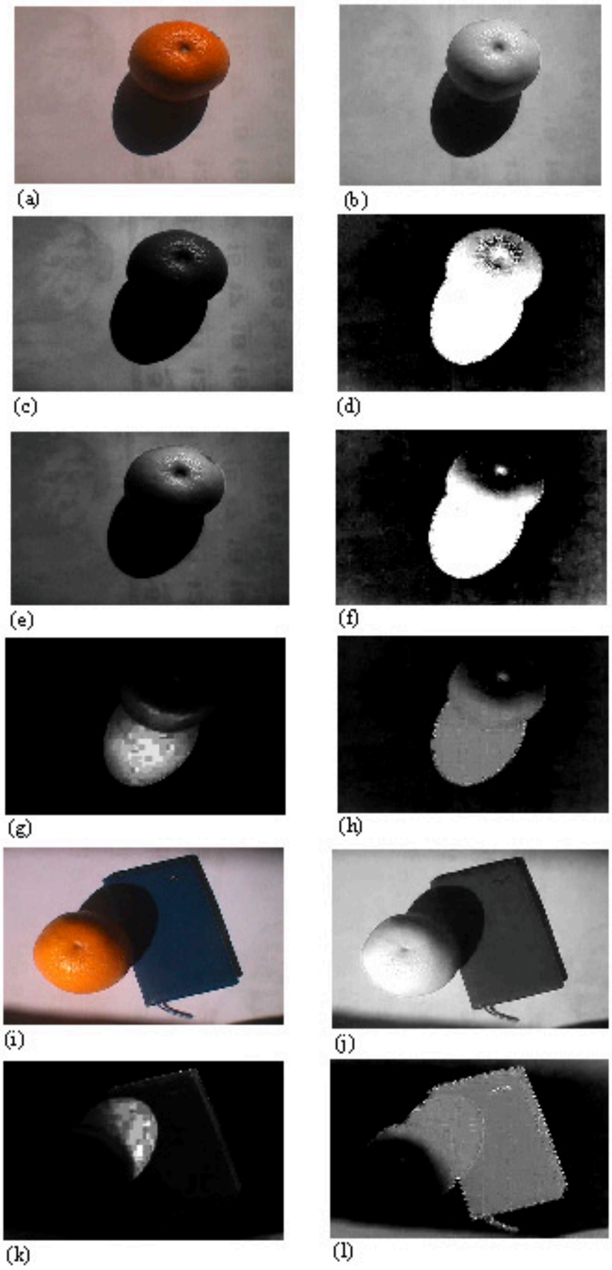

Fig. 8. (a): RGB color space image; (b): Value comonet of HSV color space image; (c): Result of LPF using gray-scale image; (d)Result of HPF using gray-scle image; (e): Result of LPF using Red component of RGB image as dominant color; (f): Result of HPF using Red as dominant color; (g): Result of proposed method using LPF; (h): Result of proposed method using HPF; (i): RGB color space image; (j): Value component of HSV color space image; (k): Result of proposed method using LPF; (l): Result of proposed method using HPF.