Shading Attenuation in Human Skin Color Images

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Abstract. This paper presents a new automatic method to significantly attenuate the color degradation due to shading in color images of the human skin. Shading is caused by illumination variation across the scene due to changes in local surface orientation, lighting conditions, and other factors. Our approach is to estimate the illumination variation by modeling it with a quadric function, and then relight the skin pixels with a simple operation. Therefore, the subsequent color skin image processing and analysis is simplified in several applications. We illustrate our approach in two typical color imaging problems involving human skin, namely: (a) pigmented skin lesion segmentation, and (b) face detection. Our preliminary experimental results show that our shading attenuation approach helps reducing the complexity of the color image analysis problem in these applications.

1 Introduction

Interpret the shading of objects is a important task in computer vision. This is specially true when dealing with human skin images, because the color of structures can be significantly distorted by shading effects. The occurrence of shading depends mainly on the color of the object and the light illuminating them. However, roughness of the surface, the angles between the surface and both the light sources and the camera, and the distance of the surface from both the light sources and the camera, can also significantly influence the way the scene is processed [1]. Specifically, human skin images are impacted by these factors and the analysis of these images can become difficult if the uneven illumination is not correctly understood and corrected.

In teledermatology, for example, often a standard camera color image containing a skin lesion is transmitted to a specialist, or analyzed by a pre-diagnosis system, without special attention to the illumination conditions [2][3]. However, these conditions can affect the quality of the visualization, and impact on the physician diagnosis, or limit the efficiency of the pre-screening system. Pigmented skin lesions typically have low diagnosis accuracy if the illumination condition is insufficient. These lesions usually are darker than healthy skin, and automatic approaches to segment such lesions tend to confuse shading areas with lesion areas. As a consequence, the early detection of malignant cases is more difficult

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without removing shading effects from the images. Considering that melanoma is the most dangerous type of pigmented skin lesion, and that this disease results in about 10000 deaths in 40000 to 50000 diagnosed cases per year (only considering the United States of America [4]), any contribution to improve the quality of these images can be an important step to increase the efficiency of pre-diagnosis systems, and to help to detect cases in their early-stages.

Another important human skin color imaging application that is severely affected by shading effects is face detection. In this case, color images containing human skin are used in head pose estimation or in face recognition systems, and shading effects may occlude some important features of the face (e.g., eyes, nose, head geometry). Usually, it is not feasible to control the illumination condition during image acquisition, and an automatic preprocessing step to mitigate these effects is an important contribution to these systems efficiency, as will be illustrated later.

In this paper, we propose an new automatic approach to attenuate the shading effects in human skin images. In Section 2, we describe the algorithm that executes this operation. In Section 3, some preliminary experimental results of our method are shown, focusing on the benefits of this operation for the color image analysis of pigmented skin lesions and face images. Finally, in Section 4 we present our conclusions.

2 Our Proposed Shading Attenuation Method

Our method for shading effect attenuation improves on the approach proposed by Soille [5]. He proposed to correct the uneven illumination in monochromatic images with a simple operation:

$$R(x, y) = I(x, y) \ / \ M(x, y), \tag{1}$$

where, R is the resultant image, I is the original image, $M = I \bullet s$ is the morphological closing of I by the structuring element s, and (x, y) represents a pixel in these images. The main idea behind Soille method is to use the closing operator to estimate the local illumination, and then correct the illumination variation by normalizing the original image I by the local illumination estimate M. The division in Eq. 1 relights unevenly illuminated areas, without affecting the original image characteristics. Unfortunately, it is often difficult to determine an efficient structuring element for a given image, specially for human skin images that have so many distinct features, such as hair, freckles, face structures, etc. In this way, the results tends to be unsatisfactory for this type of images, as can be seen in Figs. 1(b)-(c).

Our method modifies the Soille approach by providing a better local illumination estimate M. In order to provide this local illumination estimate, we start by converting the input image from the original RGB color space to the HSV color space, and retain the Value channel V. This channel presents a higher visibility of the shading effects, as proposed originally by Soille.

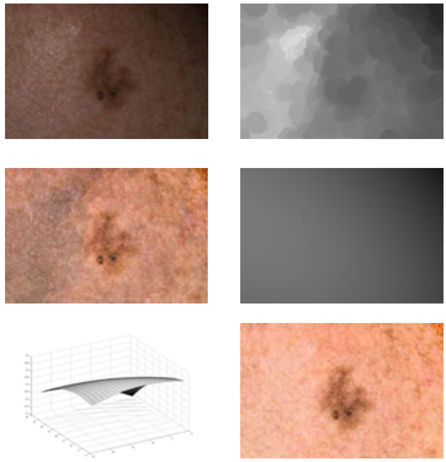

Fig. 1. Shading attenuation in a pigmented skin lesion image : (a) Input image; (b) Morphological closing of Value channel by a disk (radius = 30 pixels); (c) Unsatisfactory shading attenuation after replacing the Value channel by $R(x, y)$, as suggested by Soille [5]; (d) Local illumination based on the obtained quadric function; (e) 3D plot of the obtained quadric function; (f) Shading attenuation by using our approach.

We propose an approach inspired on the computation of shape from shading [1]. The human body is assumed to be constituted by curved surfaces (e.g. arms, back, faces, etc.) and, in the same way humans see, digital images present a smoothly darkening surface as one that is turning away from the view direction. However, instead of using this illumination variation to model the surface shape, we use this information to relight the image itself.

Let S be a set of known skin pixels (more details in Section 3). We use this pixel set to adjust the following quadric function $z(x, y)$:

$$z(x, y) = P_1x^2 + P_2y^2 + P_3xy + P_4x + P_5y + P_6, \tag{2}$$

where the six quadric function parameters P_i $(i = 1, ..., 6)$ are chosen to minimize the error ϵ:

$$\epsilon = \sum_{j=1}^{N} \left[V(S_{j,x}, S_{j,y}) - z(S_{j,x}, S_{j,y})\right]^2 , \tag{3}$$

where, N is the number of pixels in the set S, and $S_{j,x}$ and $S_{j,y}$ are the x and y coordinates of the jth element of the set S, respectively.

Calculating the quadric function $z(x, y)$ for each image spatial location (x, y), we have an estimate z of the local illumination intensity in the image V. Replacing $M(x, y)$ by $z(x, y)$, and $I(x, y)$ by $V(x, y)$ in Eq. 1, we obtain the image $R(x, y)$ normalized with respect to the local illumination estimate $z(x, y)$. The final step is to replace the original Value channel by this new Value channel, and convert the image from the HSV color space to the original RGB color space.

As a consequence of this image relighting, the shading effects are significantly attenuated in the color image. Figs. 1(d)-(e) illustrate the results obtained with our shading attenuation method.

3 Experimental Results and Discussion

As mentioned before, our method is initialized by a set of pixels S known to be associated with skin areas. In this section, we discuss how to select this set of pixels S in two typical applications of human skin color image analysis, namely, the segmentation of pigmented skin lesions and of faces in color images. Our goal is to show that our shading attenuation approach helps in the analysis of these images, making the processing steps simpler.

3.1 Pigmented Skin Lesion Segmentation in Color Images

In this application, the focus is in the image skin area that contains the lesion. As consequence, during image acquisition, the lesion is captured in the central portion of the image, and is surrounded by healthy skin. Therefore, we assume the four image corners to contain healthy skin. This assumption is common in dermatological imaging, and also has been made by other researchers in this field [6] [7]. Therefore, we use 20×20 pixel sets around each image corner, and determine S as the union of these 1600 pixels (i.e. the four pixel sets).

Many methods have been proposed for analyzing pigmented skin lesions in dermoscopic images [8]. However, dermoscopes are tools used by experts, and there are practical situations where a non-specialist wishes to have a qualified opinion about a suspect pigmented skin lesion, but only standard camera imaging is available on site (i.e., telemedicine applications). In the following discussion we focus in this situation that justifies the use of telemedicine and standard camera imaging. To illustrate the effectiveness of our method, we compare the segmentation results in pigmented skin lesions with and without the application of our method. Usually, pigmented skin lesions correspond to local darker skin discolorations. The segmentation method used is a well known thresholding procedure based on Otsu's method [9]. This algorithm assumes two pixel classes, usually background and foreground pixels (specifically in our case, healthy and unhealthy skin pixels), and searches exhaustively for the threshold th that maximizes the inter-class variance $\sigma_b^2(th)$:

$$\sigma_b^2(th) = \omega_1(th)\omega_2(th)\left[\mu_1(th) - \mu_2(th)\right]^2 , \tag{4}$$

where, ω_i are the a priori probabilities of the two classes separated by the threshold th, and μ_i are the class means. To segment the input color images, we determine a threshold th for each one of the RGB channels, and establish a pixel as lesion if at least two of its RGB values are lower than the computed thresholds. At the end, we eliminate possible small segmented regions filtering the thresholding result with a 15×15 median filter.

In Fig. 2, we present some pigmented skin image segmentation examples. These pigmented skin lesions images are publicly available in the Dermnet dataset [10]. Although our segmentation method is very simple, the application of the shading attenuation method increases its efficacy. In this way, the feature extraction and the classification procedure (typically the next steps in pre-diagnosis systems) have higher probability to produce accurate results.

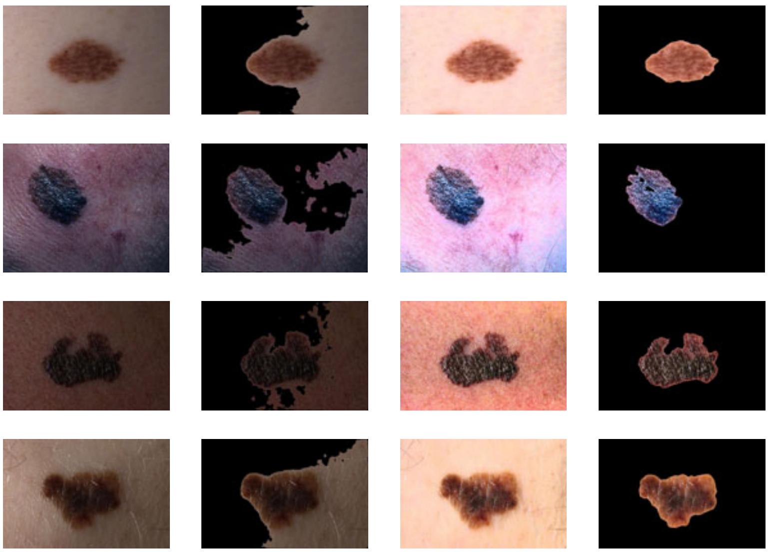

Fig. 2. Examples of pigmented skin lesion segmentation. In the first and second columns, the original images and their respective segmentation results. The third and fourth columns show the resulting images after the application of our shading attenuation method, and the respective segmentation results.

Our method may fail in some situations, as illustrated in Fig. 3. The situations illustrated in Fig. 3 are: (a) our method is adequate to model and attenuate the global illumination variation (which changes slowly), but tends to have limited effect on local cast shadows; and (b) our approach tends to fail on surface shapes that are not locally smooth, since the quadric function is not able to capture the local illumination variation in this case. In such cases, the segmentation method may confuse healthy and unhealthy skin areas. Possibly, better results could be achieved in such cases by acquiring the images in a way that surface shapes are smoother and illumination varies slowly across the scene.

3.2 Face Segmentation in Color Images

A face can be found in virtually any image location. In this case, the selection of the initialization pixel set S it is not as trivial as in the pigmented skin lesion

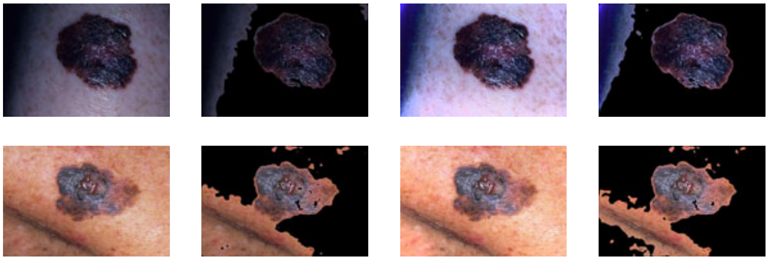

Fig. 3. Illustrations of cases where our shading attenuation method tends to fail, such as cast shadows (first line) and surface shapes not well modeled by quadric functions (second line). The first and second columns show the original images and their respective segmentation results. The third and fourth columns show the resulting images after the application of our shading attenuation method, and the respective segmentation results.

(a) (b) (c)

Fig. 4. Illustration of skin pixels localization using Eq. 5 : (a) Input image; (b) Binary mask; and (c) adjacent pixels identified as human skin.

segmentation problem. Therefore, we obtain the initialization pixel set S based on previously known color information [11]. A pixel is considered to be associated to a skin region in an RGB face image if :

$$\begin{gathered} R > 95 \;\;\wedge\;\; G > 40 \;\;\wedge\;\; B > 20 \;\;\wedge \\ \max(R,G,B) - \min(R,G,B) > 15 \;\;\wedge \\ |R - G| > 15 \;\;\wedge\;\; R > G \;\;\wedge\;\; R > B, \end{gathered} \tag{5}$$

where, $\wedge$ denotes the logical operator *and*.

In Fig. 4, we present an example of the initialization skin pixels set S obtained with Eq. 5. Although this criterion to determine pixels associated to skin color is used often [11], it can be very imprecise in practical situations, specially when there is image shading. However, its use here is justifiable since all we need is a set of adjacent image pixels with skin color (i.e. likely to be located in skin regions) to initialize our error minimization operation (see Eqs. 2 and 3), and erroneous pixels should not influence significantly the final result.

Once S has been determined, the shading effects in the face image can be attenuated. To demonstrate the efficacy of our method in this application, we show the face segmentations with, and without, shading attenuation using a known Bayes Classifier for the pixels based on their corrected colors [11]. A pixel is considered skin if:

$$\frac{P(c|skin)}{P(c|\neg skin)} > \theta, \tag{6}$$

$$where \ \ \theta = \kappa \times \frac{1 - P(skin)}{P(skin)}. \tag{7}$$

In Eq. 6, the a priori probability $P(skin)$ is set to 0.5, since we use the same number of samples for each class (i.e. 12800 skin pixels and 12800 non-skin pixels). The constant κ also is set to 0.5, increasing the chance of a pixel be classified as skin, and $P(c|skin)$ and $P(c|\neg skin)$ are modeled by Gaussian joint probability density functions, defined as:

$$P = \frac{1}{2\pi |\sum|^{1/2}} \times e^{-\frac{1}{2}(c-\mu)^T \sum^{-1}(c-\mu)}, \tag{8}$$

where, c is the color vector of the tested pixel, and μ and $\sum$ are the distribution parameters (i.e., the mean vector and covariance matrix, respectively) estimated based on the training set of each class (skin and non-skin).

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$$P = \frac{1}{2\pi |\sum|^{1/2}} \times e^{-\frac{1}{2}(c-\mu)^T \sum^{-1}(c-\mu)}, \tag{9}$$

where, c is the color vector of the tested pixel, and μ and $\sum$ are the distribution parameters (i.e., the mean vector and covariance matrix, respectively) estimated based on the training set of each class (skin and non-skin).

Figs. 5 and 6 illustrate some face segmentation examples. These face images are publicly available in the Pointing'04 dataset [12]. The images in Fig. 5 show four different persons, with different physical characteristics and different poses (i.e. angles between their view direction and the light source), resulting in different shading effects. Clearly, the skin pixels, and consequently the face, is better segmented after we apply our shading attenuation method in all these different situations. In Fig. 6, we present four examples of the same person, just varying her head pose (the angle between her view direction and the light source). It shall be observed that even when the face is evenly illuminated, the face is better segmented after using our shading attenuation method. However, inaccuracies may occur near facial features partially occluded by cast shadows (e.g. near the nose and the chin). Based on these results, it should be expected that algorithms that extract facial features (e.g., eyes, mouth and nose) would perform their tasks more effectively, which helps in typical color image analysis problems such as head pose estimation or face recognition.

Fig. 5. Face segmentation examples. In the first and second columns are shown the original images, and their respective segmentation results. In the third and fourth columns, are shown images after the application of our shading attenuation method, and their respective segmentation results.

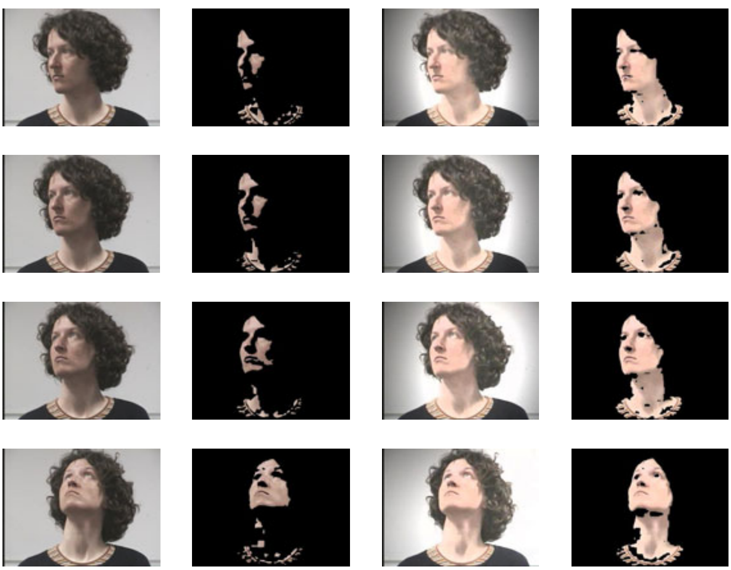

Fig. 6. Face segmentation examples for the same person varying its head pose. In the first and second columns are shown the original images, and their respective segmentation results. In the third and fourth columns, are shown images after the application of our shading attenuation method, and their respective segmentation results.

4 Conclusions

This paper presented a method for attenuating the shading effects in human skin images. Our preliminary experimental results indicate that the proposed method is applicable in at least two typical color image analysis problems where human skin imaging is of central importance. In the case of pigmented skin lesion segmentation, our shading attenuation method helps improving the lesion detection, and, hopefully, contributes for the early identification of skin cancer cases. We also studied the application of our shading attenuation method as a tool to increase the robustness of face segmentation, and our experiments suggest that potentially it can contribute to improve the efficiency of head pose estimation and facial recognition systems. We plan to further develop our approach using more complex quadric functions, and do a more extensive testing of our shading attenuation method in typical color imaging applications.

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References

1. Shapiro, L., Stockman, G.: Computer Vision. Prentice Hall, Englewood Cliffs (2001)
2. Whited, J.D.: Teledermatology research review. Int. J. Dermatol. 45, 220–229 (2006)
3. Massone, C., Wurm, E.M.T., Hofmann-Wellenhof, R., Soyer, H.P.: Teledermatology: an update. Semin. Cutan. Med. Surg. 27, 101–105 (2008)
4. Melanoma Research Project, `http://www.melresproj.com`
5. Soille, P.: Morphological operators. In: Jähne, B., Haußecker, H., Geißler, P. (eds.) Handbook of Computer Vision and Applications, vol. 2, pp. 627–682. Academic Press, San Diego (1999)
6. Celebi, M.E., Kingravi, H.A., Iyatomi, H., Aslandogan, Y.A., Stoecker, W.V., Moss, R.H., Malters, J.M., Grichnik, J.M., Marghoob, A.A., Rabinovitz, H.S., Menzies, S.W.: Border detection in dermoscopy images using statistical region merging. Skin Res. Technol. 14, 347–353 (2008)
7. Melli, R., Grana, C., Cucchiara, R.: Comparison of color clustering algorithms for segmentation of dermatological images. In: Reinhardt, J.M., Pluim, J.P.W. (eds.) Medical Imaging 2006: Image Processing, SPIE, vol. 6144, p. 61443S (2006)
8. Maglogiannis, I., Doukas, C.: Overview of advanced computer vision systems for skin lesions characterization. IEEE Transactions on Information Technology in Biomedicine 13, 721–733 (2009)
9. Otsu, N.: A threshold selection method from gray-level histograms. IEEE Transactions on Systems, Man and Cybernetics 9, 62–66 (1979)
10. Dermnet Skin Disease Image Atlas, `http://www.dermnet.com`
11. Vassili, V.V., Sazonov, V., Andreeva, A.: A survey on pixel-based skin color detection techniques. In: Proc. Graphicon 2003, pp. 85–92 (2003)
12. Gourier, N., Hall, D., Crowley, J.L.: Estimating face orientation from robust detection of salient facial features. In: Proceedings of Pointing 2004, ICPR, International Workshop on Visual Observation of Deictic Gestures, Cambridge, UK (2004)