Asymmetric Facial Shape Based on Symmetry Assumption

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Abstract. It has been known that it is hard to capture the high-frequency components (shadows and specularities) during the modeling of illumination effects. In this paper, we propose a reflectance model to simulate the interaction of light and the facial surface under the assumption that face is strictly axial symmetry. This model works well not only in fitting the intensities of pixel but also in processing the DC component contained in the image. To compute a facial 3D shape, we first augment the input images to get a symmetric facial normal field, then propose a method to obtain a more accurate normal field, and finally compute an integrable shape using the field. Experimental results for face relighting, facial shape recovery demonstrate the effectiveness of our method.

Keywords: shape recovery, face relighting, Non-Lambertian model, symmetry.

1 Introduction

For computing a facial 3D shape, it is useful to make an assumption about the interaction of light and the facial surface i.e. the reflectance model. Most of the proposed models can be classified into two classes, Lambertian and Non-Lambertian model. The Lambertian model, which is popular for capturing the intensity of the facial image effectively, has been widely used in 3D shape recovery. There are different methods to handle the model even using the same reflectance model. One of the most straightforward methods is linear subspace [1, 2], which makes out some basis images that can be used to represent the facial image with variable lighting and pose linearly, and then the 3D facial shape is obtained by an iterative algorithm. Another method is to express the facial surface (referred to as the reflectance function) in terms of spherical harmonics, through which the author draws the conclusion that the facial surface can act as a low-pass filter to the light signal, and it can capture more than 87.5 percent of the energy even when only the first order approximation is used. With the spherical harmonics representation, [3] proposes a reconstruction algorithm from a single image using a single reference face shape. As discussed above, the facial surface acts as a low-pass filter under the Lambertian assumption, it behaves unsatisfactorily when handling the high-frequency component such as cast shadows and specularities. Therefore some shape reconstruction methods exploit No-Lambertian model to capture

Z. Sun et al. (Eds.): CCBR 2011, LNCS 7098, pp. 42–49, 2011.

the rapidly changing section of image, [4] proposes a Non-Lambertian reflectance model using tensor-splines, through which they can simulate the high-frequency composition well. However, it takes the intensity of shadow as 0 and doesn't make full use of facial symmetrical structure. The intensity of shadow is a small positive integral due to the DC component added in the image. So the estimated error may be very great. In this paper, we propose a reflectance model which not only can approximate the shadows and specularities well but also can simulate the DC composition well. We also use the symmetry of face to increase the number of the input images. Another mentionable method used in this paper is a mean to obtain height from the normal field in [5, 8], by which we can get a facial 3D shape satisfying a certain integrability and smoothness.

This paper is organized as follows: In section 2, we will propose a reflectance model and illustrate the existence of DC component in image, we will then show the capability of our model to capture specularities and DC component. In section 3, we will propose a reconstruction algorithm based on the assumption of facial symmetry. In section 4, we will apply our method to face relighting and shape recovery. And finally the section 5 is the sum-up about this paper.

2 Reflectance Model

2.1 Reflectance Model

If we consider the intensity of the pixel I as a function of the light direction, we can write it as $I = f(s_1, s_2, s_3)$ where $s = (s_1, s_2, s_3)$ is a unit vector, now we can expand it with Taylor's series as follows:

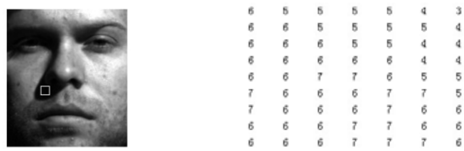
$$E{=}f(0,0,0) + f_x(0,0,0)s_1 + f_y(0,0,0)s_2 + f_z(0,0,0)s_3 + \cdots \tag{1}$$

where $f(0,0,0)$, $f_x(0,0,0)$, $f_y(0,0,0)$, $f_z(0,0,0)$;$\cdots$ are associated with the object's normal, the incident light intensity, and the albedo to the corresponding point. If the incident light intensity is fixed, all of these coefficients are considered as constants.

The Lambertian reflectance Model can be seen as a special case of Eq.1, where only the linear terms are considered.

Image usually can be added with an extra constant intensity due to the diffuse reflection and imaging system itself, i.e. a picture signal often contains a DC component. As illustrated in Fig.1, the face in the white block are in the shadow region, according to the Lambertian rule, their intensities should be 0, but the values are not 0 but relatively small integer as shown in (b). In other words, the image intensity is added with a constant value i.e. DC component we called above. In fact face can not only give diffuse reflection but also specular reflection. So it is essential to have the nonlinear terms in Eq.1 been kept to approximate the specular reflection. In this paper, the second order terms are kept. So we can get the reflectance model as follows:

$$E{=}\sum_{k+l+m\le 2} T_{klm}(s_1)^k (s_2)^l (s_3)^m \tag{2}$$



(a) (b)

Fig. 1. Facial image. (a) facial image with white block (b) intensities of pixels in white block.

However, the vector $\vec{s}$ is unit and the second order part can contain $f(0,0,0)$, we can write the above formula as

$$E = \sum_{1 \le k+l+m \le 2} T_{klm} (s_1)^k (s_2)^l (s_3)^m \tag{3}$$

Now, we have obtained Eq.3 as our reflectance model. From the following section we can find it can capture the DC component and the specular reflection well.

2.2 Fitting Compared

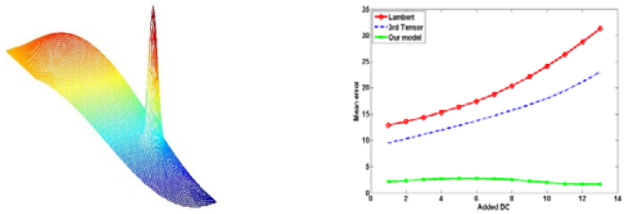
From the previous section we know that image can be added with a DC component, but its magnitude which is related with the digitalization system and the imaging ambient conditions is uncertain. In this section, we mainly illustrate the effectiveness of our model to capture specularities and DC component. As shown in the Fig.2, the standard error estimated by Lambertian model and the third order tensor [4] increases as the DC component increase, while stays relatively constant at a small value when our model is used. Typically, the Lambertian model has the largest error, the third tensor takes the 2nd place, and our model has the least error.

3 Shape Recovery

Zhao introduced symmetric constraint method to reconstruct the 3D shape of the symmetrical objects [7] and he can obtain object's 3D shape from single image. However, the method can't work properly when the object has cast shadow or specularity. In this paper, strictly symmetric face is assumed at first to obtain its normal field, then an image is picked up to modify the normal field, at last the height field(3D shape) is obtained from the modified normal.

3.1 Symmetry

Generally speaking, the two types of geometrical symmetry discussed mostly are central symmetry and axial symmetry. In this section, we mainly focus on axial symmetry in R^3. For any axisymmetric objects, we can make the axis pass the original through a coordinate transformation, such that the lines between symmetric points are perpendicular to the axial plane, i.e. y-z plane. Then we can get $z(x, y) = z(-x, y)$,



(a) (b)

Fig. 2. Synthetic example (a) synthesis example (b) fitting error

where $z(x, y)$ represents the height of the object at (x, y), so $n_1(x, y) = -n_1(-x, y)$, where $n_1(x, y)$ is the first component of normal at (x, y). In this section, we assume face is symmetry in both geometrical shape and surface reflectance property. Then we can draw the conclusion that the intensity at (x, y) with (s_1, s_2, s_3) as its incident light direction is equal to the intensity at $(-x, y)$ with light direction $(-s_1, s_2, s_3)$. In Fig.3, (a) and (b) are two images from Yale Face Database B, The light direction of (a) is(-95, 0), and (b) is(95, 0) separately, (c) is right half of (a) with a mirror left-right transformation. (d) is left half of (b), (e) is a synthetic image whose left half is from (a) and right half from (b). (c) and (d) are almost the same except in the regions where specular reflection is happened. We attribute this difference to the nonlinear terms in the Eq.3. The mean Euclidean distance between (c) and (d) is 0.3649, and their correlation coefficient is 0.9223. This means that if the direction of the light turns to the symmetrical direction, the new image can be obtained just from the old one. The high correlation between (c) and (d) also illustrate that the linear terms play a major role in Eq.3. This consists with the conclusion that the linear estimators of reflective function can capture more than 87.5 percent of the energy [2].

Based on the above analysis, the symmetry of face in this paper can be used to augment the gallery (facial) set with meaningful images. For any input image with a light direction (s_1, s_2, s_3), we can safely draw a method to synthesize the image with light direction $(-s_1, s_2, s_3)$: Interchanging the left half with right half of the original image. It means that we can double the input images on the premise of $s_1 \neq 0$.

3.2 Shape Recovery

Based on the above symmetry assumption, we can just reconstruct the 3D shape of the half-face, and this can reduce the computational time to a certain degree. However, face may be some departing from symmetry, it is necessary to make some amendment after getting the symmetric normal. There are 9 coefficients in the reflectance model determined by Eq.3. As discussed in the previous section, we can derive another image from each input image, so if we want to solve the coefficients we need 4 input images at least. In this paper, more than 5 images are used to gain a reliable result. Note that the application of symmetry is to synthesis images with symmetric light direction, so we require the light directions of the input images should not be symmetry, i.e. all the first

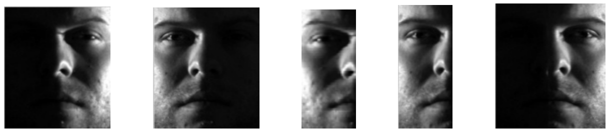


Fig. 3. Symmetry (a) (-95,0) (b) (95,0) (c) right half of (a) with mirror transform (d) left half of (b) (e) Synthetic image

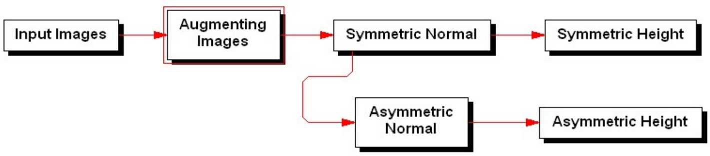


Fig. 4. Algorithm flow chart

component of the light directions should not be opposite number, only in this case can the symmetry assumption be fully used. The reconstruction algorithm in this paper mainly consists of three acts, (1) global normal computation, (2) normal field modification, (3) shape (height) recovery.

It is a simple process to solve the normal vector field from the input images. Similar to the method in [4], 10 linear equations can be gotten on the basis of Eq.3 at any pixel, and then the coefficients in Eq.3 can be obtained by solving these equations, at last the direction that makes Eq.3 reach its maximum can be taken as its normal direction.

Right now, the normal field we've gotten is a strictly symmetric field. However, to a certain degree, face may be departing from symmetry, so it is essential to make some adjustment in the normal field. So we pick out one image that without shadows and specularities firstly, then we make an amendment based on the image. The amendment is achieved by solving the following optimization problem:

$$\min_{\vec{n}} \int_{\Omega} (\left\| \vec{n} - \vec{n_1} \right\|_{L^2}^2 + \lambda (I - \rho \vec{n}\vec{s})^2) dxdy \tag{4}$$

Where $\vec{n_1}$ is the normal before modifying, ρ satisfies:

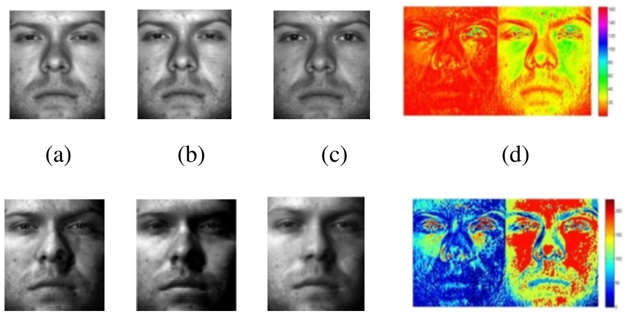
$$\rho \vec{n_1} \vec{s} = I(x, y) \tag{5}$$

In order to get a height field that satisfies some conditions as smoothness and integrability from the modified normal field, we adopt the method proposed in [5], although another reliable method is also proposed in [8]. Firstly, from the normal vector field, we can obtain the gradient field of the facial height as follows:

$$z_x = -\frac{n_1}{n_3}, \; z_y = -\frac{n_2}{n_3}, \; \vec{n} = (n_1, n_2, n_3) \tag{6}$$

Let:

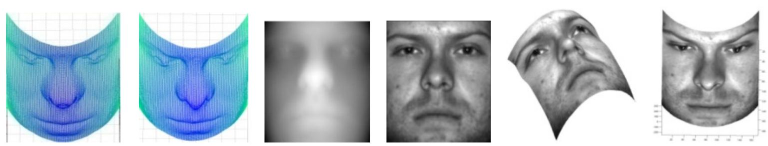
$$\tilde{c}(w) = \frac{-jw_1 c_x(w) - jw_2 c_y(w)}{w_1^{\ 2} + w_2^{\ 2}} \tag{7}$$



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 5. Relighting comparison. (a) our method (b) 3rd tensor (c) ground truth (d) the errors (e) without symmetry hypothesis (f)3rd tensor (g)symmetry hypothesis. (h) SMQT of (d).



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

Fig. 6. Shape recovery. (a) symmetric shape (b) asymmetric shape (c) facial height (d) one input image (e) shape with texture (f) shape with texture.

where $\{c_x\}$, $\{c_y\}$ are the Fourier coefficient of z_x and z_y , $w=(w_1,w_2)$ is a two-dimensional index. Then we can get the integrable height field only by performing the inverse 2D Fourier Transform on the coefficients $\tilde{c}(w)$.

Finally, we make a summary for our reconstruction algorithm. As shown in Fig.4, firstly, we augment the number of input images with symmetry assumption, then we obtain a facial symmetric normal field with the proposed reflectance model, in this step, we assumed that Eq.3 reaches maximal value at its normal. With the obtained field we can figure out facial symmetric height field, and the result will be presented in the following section. Because face may be not strictly symmetry, we have to adjust the symmetric normal to get a more accurate facial height, i.e. facial 3D shape.

4 Experimental Results

4.1 Face Relighting

In this section, we apply our method to face relighting. Firstly, we obtain face images with illumination direction (0,0,1) by the 3rd tensor and the our model without symmetry postulate, they are presented in Fig.5. We can see that (a) and (b) are much similar to the ground truth except in some specular regions. The left half of (d) is the

Fig. 7. Shape from varied reflectance models. Top-bottom: Lambertian, 3rd tensor, our model.

visualization of deviation between (a) and (c), while the right half is that between (b) and (c). (h) is the regularized results of (d) with the method called successive mean quantization transform (SMQT) [6]. From (d) and (h) we can find that images obtained by our method are closer to the ground truth than 3rd tensor. Also from (h), we can see that the DC component contained in image signal should not be neglected. (e), (f), (g) is the relighting results taking (40,30) as the direction of illumination. Unlike (a), (b), (c), the direction of (e), (f), (g) is not consisted in the Yale B Database, so we can't draw a parallel between the experimental results and the ground truth, but we can also see that the results are quite according with the truth. However, the relighting images are not very good in the shadows due to lack of input images. Comparing (e) with (g), we can find that the symmetry hypothesis can marginally reduce the vagaries of shadows, and it is useful to reconstruct 3D facial shape.

4.2 Shape Recovery

In Fig.6, a 3D symmetric facial shape reconstructed by the method in this paper is shown in (a) and a asymmetric shape from symmetry hypothesis is presented in (b). Regarding them as a whole, quite good agreement between experimental results and the real facial shape is obtained. However, some deficiencies are also existed in the reconstructed shape. Take nose for example, because shadows and specularities often happen near the nose, the reconstructed shape would probably deviate from the proper value. From (b) we can hardly find that the 3D facial shape is not symmetrical. And the correlation coefficient of left half and right half is 0.9901 which implies the retouched part is quite small. (c) is the height field reconstructed from input images, and (d) is one of the five input images. (e) and (f) are 3D facial shapes overlaid with an input image at different poses.

In order to illustrate the effectiveness of our reflectance model in the reconstruction algorithm, the model is replaced with Lambertian and 3rd tensor model and the corresponding experiments are performed. Some results are presented in Fig.7. We can find that the performance of our model to simulate the interaction of light and facial surface is better than 3rd tensor model but more or less the same with Lambertian model.

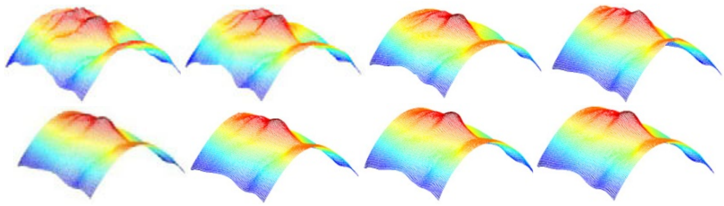


Fig. 8. Shapes from varied numbers of images. Left-right(up-down) 6,11,16,21,26,31,36,41.

As shown in Fig.8, Our reconstructed algorithm can obtain a quite good result (except in the region near the lips) even when only 6 input images are used, and we attributed this inaccuracy to the lack of input images. We can find that the facial shape becomes more and more accurate as the number of input images increases.

5 Conclusion

We proposed a reflectance model to simulate the common photo-effects (e.g. shadow, specularity) and process the DC component contained in image signal. Different from previous work, the symmetric assumption was used to augment the input images rather than being used as a constraint for modeling. Our experiments showed that the proposed method could reduce the effect of shadow to some extent, and could achieve good performance for shape reconstruction.

References

1. Georghiades, A.S., Belhumeur, P.N., Kriegman, D.J.: From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose. IEEE Transactions on Pattern Analysis and Machine Intelligence 23, 643–660 (2001)
2. Basri, R., Jacobs, D.W.: Lambertian Reflectance and Linear Subspaces. IEEE Transactions on Pattern Analysis and Machine Intelligence 25, 218–233 (2003)
3. Kemelmacher-Shlizerman, I., Basri, R.: 3D Face Reconstruction from a Single Image Using a Single Reference Face Shape. IEEE Transactions on Pattern Analysis and Machine Intelligence 33, 394–405 (2011)
4. Kumar, R., Barmpoutis, A., Banerjee, A., Vemuri, B.C.: Non-Lambertian Reflectance Modeling and Shape Recovery of Faces Using Tensor Splines. IEEE Transactions on Pattern Analysis and Machine Intelligence 33, 553–566 (2011)
5. Frankot, R.T., Chellappa, R.: A Method for Enforcing Integrability in Shape from Shading Algorithms. IEEE Transactions on Pattern Analysis and Machine Intelligence 10, 439–451 (1988)
6. Nilsson, M., Dahl, M., Claesson, I.: The Successive Mean Quantization Transform. In: IEEE International Conference on Acoustics, Speech and Signal Processing, 2005. Proceedings(ICASSP 2005), vol. 4, pp. 429–432 (2005)
7. Zhao, W.Y., Chellappa, R.: Symmetric Shape-from-Shading Using Self-ratio Image. International Journal of Computer Vision 45, 55–75 (2001)
8. Kovesi, P.: Shapelets Correlated with Surface Normals Produce Surfaces. In: Tenth IEEE International Conference on Computer Vision (ICCV 2005), vol. 2, pp. 994–1001 (2005)