SHAPE RECONSTRUCTION FOR COLOR OBJECTS USING SEGMENTATION AND PHOTOMETRIC STEREO

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ABSTRACT

Objects whose shapes we want to estimate may have not a single color but mostly multi-colors. This may make it difficult to estimate their shapes using the existing photometric stereo methods in a straightforward manner. In this paper we combine segmentation with photometric stereo to reconstruct shapes for multi-color objects. For this purpose, our previous photometric stereo method that uses two images is extended to use three images, with modifications in the application of boundary conditions. The three images are segmented in color and the resulting segmented images are normalized in each region in intensity, based on the assumption that the three lighting directions are apart enough from each other. The modified shading images are used to reconstruct the object's shape. Experiments using synthesized images clearly show the usefulness of our method.

1. INTRODUCTION

Shape-from-shading has long been studied [1], [2], [3], producing a variety of approaches, called local [4], minimization [5], [6], linear [7], [8], propagation [9], [10], and deformable model [11]. These approaches that use a single shading image appear to be limited in numerical stability and, as a result, accuracy in shape or surface normal. On the other hand, photometric stereo [12] appears much more promising, since the distribution of surface normal can uniquely be determined from three shading images. Klette et al. present algorithms to convert it to the shape or height distribution [13], [14], based on Frankot and Challappa's [15]. It appears that the resulting shape is not necessarily accurate especially in rapidly changing image parts. In addition the height information of the shape is not available by their methods.

The object has been assumed in most cases to have the homogeneous reflective properties. Actually, however, many objects do not have them; for example, they may have multiple colors. In this case the color images have to be decomposed into color components, such as *RGB, HSV*, *YCbCr* or *Lab*, to estimate the shape. Unfortunately the difference in color may results in different shadings, which may result in a shape different from the actual one.

In this paper, first, we extend our previous photometric method [16] to the case of three shading images and improve it in the application of boundary conditions. We may not be able to get enough shading information by using two light directions depending on the object. Use of the solid boundary condition is crucial to obtain good shape in our method. Then, color segmentation is carried out for image parts with significant color differences. When the lighting directions are made apart from each other enough, a part of the object in each segmented region may well be considered to face right to the light. In this case the images may be able to be normalized to unity in each of the regions to reconstruct the shape of the object. Computer experiments are given to show the usefulness of our method.

2. RELATION TO ESTIMATE SHAPE

In the shape reconstruction we use the consistency between three NxN pixels images $I_i(x,y)$, i=1,2,3, and the appropriate reflectance maps $R_i(p,q)$:

$$R_i(p,q) = I_i(x,y) \tag{1}$$

where x,y=1,…,N and it is assumed that the images are normalized to unity. Let **P** and $\mathbf{S}_i$, i=1,2,3, be the surface normal of the shape $z(x,y)$ and the light directions, respectively:

$$\mathbf{P} = (p,q,1)^T \Big/ \sqrt{p^2+q^2+1} \tag{2}$$

$$\mathbf{S}_i = (s_{i,x}, s_{i,y}, s_{i,z})^T \Big/ \sqrt{s_{i,x}^2+s_{i,y}^2+s_{i,z}^2}\ ,\ i=1,2,3 \tag{3}$$

where p=-$\partial z/\partial x$ and q=-$\partial z/\partial y$. Then, for the *Lambertian* surface, the reflectance maps, normalized by the *albedo*, are given by the scalar products of **P** and $\mathbf{S}_i$:

$$R_i(p,q) = \frac{ps_{i,x}+qs_{i,y}+s_{i,z}}{\sqrt{p^2+q^2+1}\sqrt{s_{i,x}^2+s_{i,y}^2+s_{i,z}^2}} \tag{4}$$

When p and q are given by

$$p = z(x-1,y)-z(x,y),\ q = z(x,y-1)-z(x,y) \tag{5}$$

R_i can be regarded to be functions of $z(x,y)$, $z(x\text{-}1,y)$ and $z(x,y\text{-}1)$. Let the functions $f_i(x,y)$ be defined by

$$f_i(x,y) \equiv I_i(x,y) - R_i(p,q),\ i = 1,2,3 \tag{6}$$

Applying the Jacobi's iterative method to these functions gives the iterative relations:

$$\begin{aligned} -f_i^{(n-1)}(x,y) &= \left(\frac{\partial f_i(x,y)}{\partial z(x,y)}\right)^{(n-1)} \left(z^{(n)}(x,y) - z^{(n-1)}(x,y)\right) \\ &+ \left(\frac{\partial f_i(x,y)}{\partial z(x-1,y)}\right)^{(n-1)} \left(z^{(n)}(x-1,y) - z^{(n-1)}(x-1,y)\right) \\ &+ \left(\frac{\partial f_i(x,y)}{\partial z(x,y-1)}\right)^{(n-1)} \left(z^{(n)}(x,y-1) - z^{(n-1)}(x,y-1)\right) \end{aligned} \tag{7}$$

where n is the number of iterations. Eq. (7) can be rewritten in matrix form as

$$-\mathbf{f}_i^{(n-1)} = \mathbf{g}_i^{(n-1)}(\mathbf{z}^{(n)} - \mathbf{z}^{(n-1)}),\ n=1,2,\ldots,\ i=1,2,3 \tag{8}$$

where $\mathbf{f}_i$ are vectors of N^2 elements of $f_i(x,y)$, $\mathbf{z}$ is a vector of N^2 elements of $z(x,y)$, and $\mathbf{g}_i$ are matrices of N^2xN^2 elements that are made of the first derivatives of $f_i(x,y)$ with respect to $z(x,y)$, $z(x\text{-}1,y)$ and $z(x,y\text{-}1)$. The three relations in Eq. (8) are combined to a single relation as:

$$-\mathbf{F}^{(n-1)} = \mathbf{G}^{(n-1)}\left(\mathbf{z}^{(n)} - \mathbf{z}^{(n-1)}\right) \tag{9}$$

$$\mathbf{F} = \left[\mathbf{f}_1^T, \mathbf{f}_2^T, \mathbf{f}_3^T\right]^T \tag{10}$$

$$\mathbf{G} = \left[\mathbf{g}_1^T, \mathbf{g}_2^T, \mathbf{g}_3^T\right]^T \tag{11}$$

Following the least square error procedure, the shape is iteratively estimated as follows:

$$\mathbf{z}^{(n)} = \mathbf{z}^{(n-1)} - \left(\mathbf{G}_2^{(n-1)}\right)^{-1} \mathbf{F}_2^{(n-1)},\ n = 1,2,\ldots, \tag{12}$$

$$\mathbf{G}_2 = \mathbf{G}^T\mathbf{G} \tag{13}$$

$$\mathbf{F}_2 = \mathbf{G}^T\mathbf{F} \tag{14}$$

where the iteration is begun with null values $\mathbf{z}^{(0)} = \mathbf{0}$.

On the two boundary lines of $x=N$ and $y=N$, p and q are given by the shape $\mathbf{z}$ being estimated. But, on the other two boundary lines of $x=1$ and $y=1$, they are not. In this paper, assuming that the object rests on a stand, we modify the shading images. That is, we surround them with uniform shading parts that correspond to the flat shape with $z=0$, and add the shading lines between the images and the added parts, where the shading values are determined by the vertical walls of the stand along the four boundary lines and the light directions.

3. SEGMENTATION

The shape-from-shading or photometric stereo method is based on the assumption that the reflective properties are homogeneous over the entire object of interest, implying that the object has a single color. When that is not the case, the color differences are reflected on the component images, although the magnitudes vary depending on the transformation to be used. An example is shown in Fig. 1, where the light-gray container has a blue label region painted on it. If the label part is the same as the surrounding container part in brightness, then the *V*-component image of *HSV* is not affected by the color difference, even if the two parts have different colors. But this cannot be expected in general.

(a) *R* (b) *G* (c) *B* (d) *Y* (e) *V* (f) *L*

Fig. 1. Color component images for the light-grayed container with square blue label pained, where *Y*, *V* and *L* are components of *YCbCr*, *HSV* and *Lab*, respectively.

To cope with this problem, we follow the procedure:
(i) segmentation of the images in color
(ii) normalization of the segmented images in brightness in each image region, and
(iii) reconstruction of the shape from the modified images.

As for the segmentation, a region-growing method is applied using an error that depends on the magnitude of color difference. We notice that image parts with more similar colors may be needed to segment to a lesser degree, and that different color image parts may be neglected if they are small in area, such as the lettering parts in Fig. 1. As for the normalization, our method requires a part of the object within a segmented region faces right to one of the lights. If the lighting is restricted in direction, any part of the object within a segmented region possibly may not face right to any of the lights. Then we cannot know what value the segmented images are normalized to. This may also be the case when the segmented regions are too small in area.

4. COMPUTER EXPERIMENTS

A plastic container, shown in Fig. 1, and a plastic penguin doll were used. Their shapes were measured using a laser range scanner; the container and the doll are 16.45mm and 14.25mm in height, respectively. Assuming the Lambertian surface and using their color images, shading images were generated, which consist of 64x64 pixels for the container and 63x63 for the doll. In this case, the *Y* component image in Fig. 1 is used for the container, while the *V* component one is used for the doll. As shown in Fig. 2, the *V* component image appears to have minimal intensity differences in one of the two segmentation regions.

(a) *V* (b) *L* (c) *Y*

Fig. 2. Three intensity images of the penguin doll whose colors are shallow blue for the hat, dark blue for eyes, green for nose, light gray for belly, pink for the tie, yellow for feet and blue for the rest including face.

First, results for the container are summarized in Fig. 3. Two views of the measured shape are given in (a), and the shading images generated for three light directions are given in (b) to (d), where the three rectangular image parts of the blue color have the maximal value of 68 of 255. The periodical pattern noise is due to the errors occurred in transforming the three-dimensional measured data to the data on the two dimensional grid. It is seen in (e) that the estimated shape has serious distortions in the rectangular region with the maximal height of 33.9, about twice the given one. The color segmentation was carried out for the rectangular part, and the resulting three segmented images were normalized in intensity, as shown in (f) to (h). The shape obtained from the modified images by using the existing method [13], [14] is shown in (i) and that obtained by using our method is shown in (j). Comparison of the results in (i) and (j) shows the superiority of our method. In addition our method lets us know the maximal height of the object of 15.7 or about 95.3% of the given one, which the existing method does not. The relative shape error after matching the estimated shape to the given one through shifting and magnifying operations in height is 20.4% for the result in (e) and 2.2% for that in (j).

The results for the doll are shown in Fig. 4 in the same way as the container. The doll has several different colors but its *V*-component image has almost two regions in terms of the intensity, as may be seen in Fig. 2. The shading images in (b) to (d) reflect the color differences on the magnitudes of shading. It is seen that the shape obtained from these images does not represent many of the fine details of the doll, as shown in (e), and that its maximal value of 104.4 is much greater than the real one. The segmentation and normalization minimizes the effects of the color differences in the three shading images, as shown in (f) to (h). Our method reconstructs almost the same shape as the given one from these modified images, as shown in (j), where the shape has the maximal height of 12.6 or 88.6% of the given one, and its relative shape error is 7.0% in contrast with 12.4% for that in (e). On the other hand, the existing method gives a fairly degraded shape with no information on the attained height of the shape.

5. CONCLUSIONS

In this paper we introduced segmentation to reconstruct good shapes for multi-color objects. For this purpose, our previous photometric stereo method was modified with an improvement in the boundary conditions. In the method, regions of different colors are color-segmented and the segmented images are normalized to unity in each region, to reconstruct the shape. Experiments using synthesized images show the usefulness of our method.

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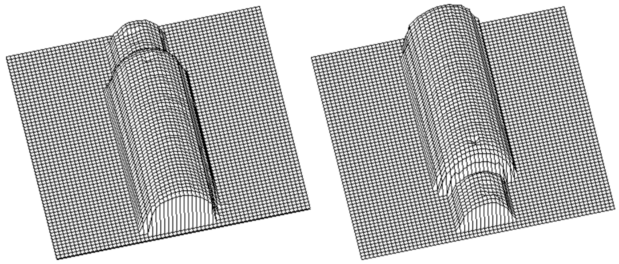
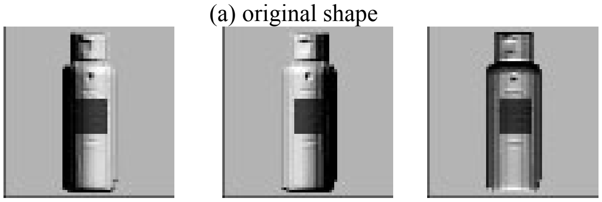
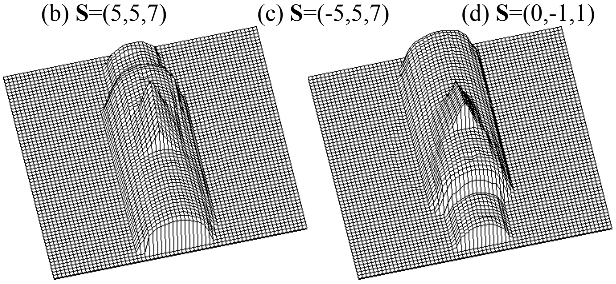


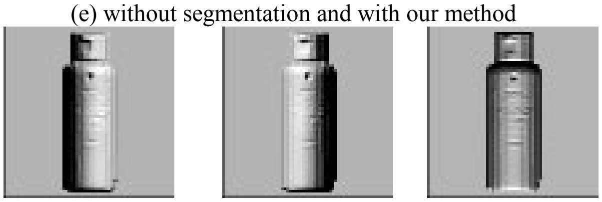
(a) original shape



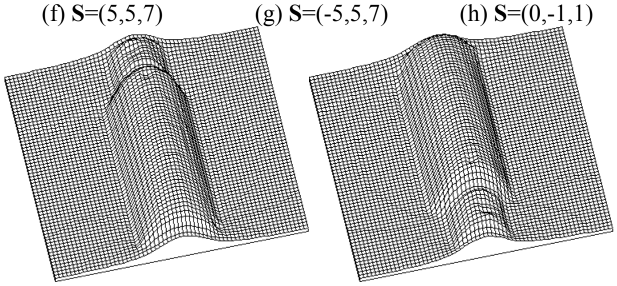
(b) **S**=(5,5,7) (c) **S**=(-5,5,7) (d) **S**=(0,-1,1)



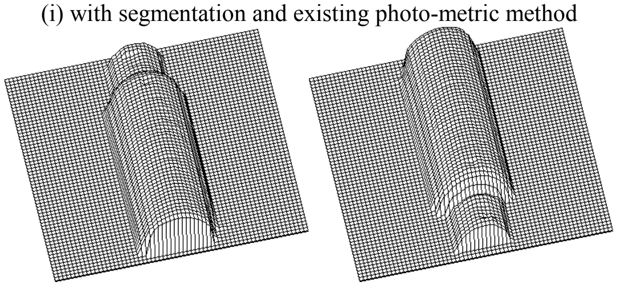
(e) without segmentation and with our method



(f) **S**=(5,5,7) (g) **S**=(-5,5,7) (h) **S**=(0,-1,1)

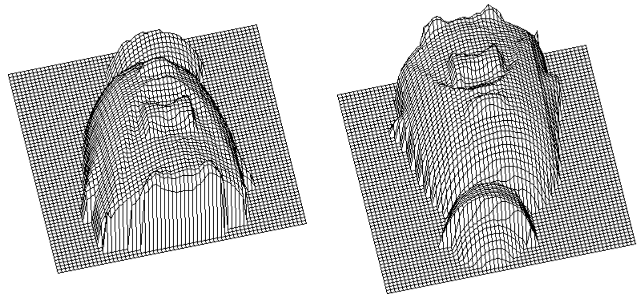


(i) with segmentation and existing photo-metric method

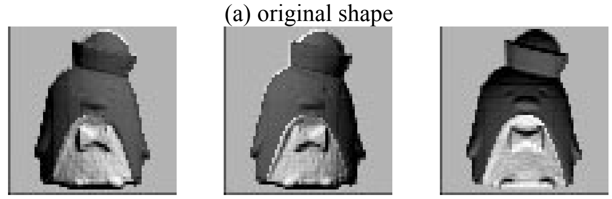


(j) with segmentation and our method

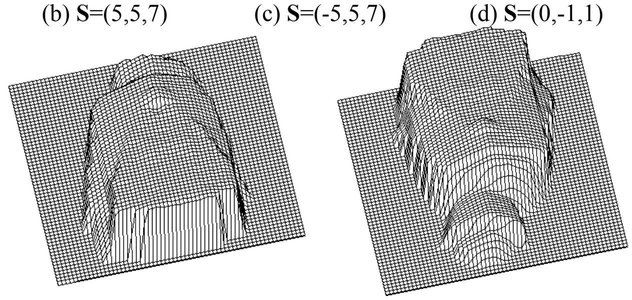
Fig. 3. Experimental results for a light-gray container with blue square label painted.



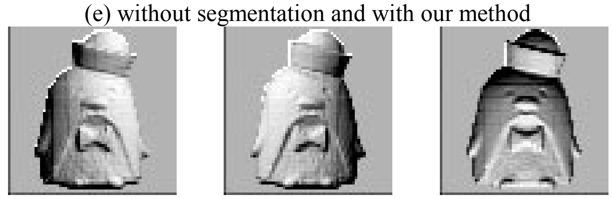
(a) original shape



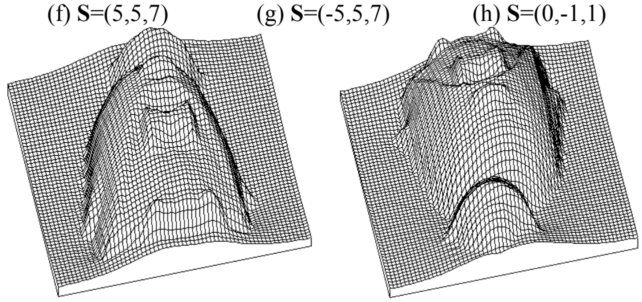
(b) **S**=(5,5,7) (c) **S**=(-5,5,7) (d) **S**=(0,-1,1)



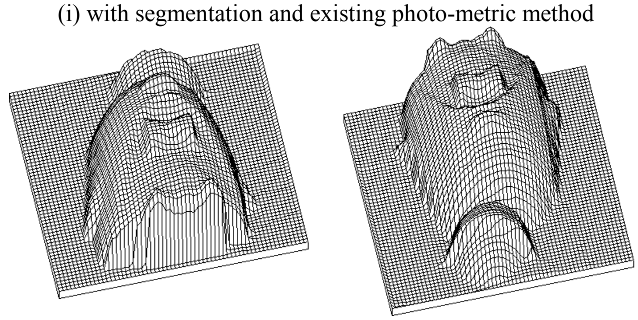
(e) without segmentation and with our method



(f) **S**=(5,5,7) (g) **S**=(-5,5,7) (h) **S**=(0,-1,1)



(i) with segmentation and existing photo-metric method



(j) with segmentation and our method

Fig. 4. Experimental results for a multi-color doll.