One Shot Photometric Stereo from Reflectance Classification

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Abstract: 3D reconstruction of object shape is one of the most important problem in the field of computer vision. Especially, estimation of normal orientation of object surface is useful for photo-realistic image rendering. For this estimation, the photometric stereo is often used. However, it requires multiple images taken under different lighting conditions in the same pose, and thus, we cannot apply it to moving objects in general. In this paper, we propose a one-shot photometric stereo for estimating surface normal of moving objects with arbitrary textures. In our method, we estimate surface orientation and reflectance property simultaneously. For this objective, reflectance data set is used for decreasing DoF (Degree of Freedom) of estimation. In addition, we classify reflectance property of an input image into limited number of classes. By using the prior knowledge, our method can estimate surface orientation and reflectance property, even if input information is not sufficient for the estimation.

1 INTRODUCTION

In the field of computer vision, 3D reconstruction is one of the most important problems. In ordinary case, several numbers of images are taken under different imaging condition, and then, 3D shape is reconstructed from these images. In general, stereo method from multiple cameras is used for 3D reconstruction(Agarwal et al., 2011; Newcombe et al., 2011). In these methods, correspondences are detected from images, and 3D shape is reconstructed from the correspondences(Hartley and Zisserman, 2000). In particular, multi-baseline stereo method with bundle adjustment is widely used for 3D reconstruction(Agarwal et al., 2011). Furthermore, dense 3D reconstruction by using a moving camera is also proposed(Newcombe et al., 2011).

The 3D reconstruction is useful for obtaining 3D shape of objects, since we need just cameras. However, the accuracy of results is often not sufficient for recovering surface orientation. The surface orientation can be estimated by differentiating 3D shapes, and thus we need very accurate 3D shapes for obtaining accurate surface orientations. The surface reconstruction is important for synthesizing realistic 3D graphics because photometric property, such as shading, on object depends mostly on surface orientations. Thus, accurate estimating methods of surface orientation are required.

The photometric stereo method(Chen et al., 2011; Anderson et al., 2011) is widely used for surface orientation estimation. The method can estimate surface orientation directly from a set of images taken under different lighting conditions. In ordinary case, a camera and a target object are fixed and just lighting condition changes for the estimation.

Although the method works well for static scenes, it cannot work for dynamic scenes, since images are taken under not only different lighting conditions but also different poses in the case of dynamic scenes. Thus, we cannot reconstruct surface orientation of dynamic scenes from these images.

For reconstructing 3D surface of dynamic scenes, we need to obtain multiple images under different lighting conditions simultaneously. For this objective, some methods are recently proposed. Chen et al.(Chen et al., 2011) proposed image demultiplexing method for photometric stereo. In this method, special periodic patterns are projected from projectors to target scene simultaneously. By demultiplexing an observed image, we can obtain multiple images taken under different lighting from a single image. Although the method works well even if the target scenes change dynamically, it does not work when scene include complex texture. Anderson et al.(Anderson et al., 2011) proposed a method using multiple colored lights. In this method, a single image is divided into multiple images illuminated under different conditions by using color information. Furthermore, Brostow et al.(Brostow et al., 2011) ex-

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pand the method for color objects. Fyffe et al.(Fyffe et al., 2011) also proposed one shot stereo using multi spectral (multi-band) lighting. Although they estimate surface normal and reflectance simultaneously, their method needs 6 band light sources. In addition, their method can estimate only RGB reflectance.

In this paper, we propose a new one shot photometric stereo method for reconstructing dynamic 3D surfaces. In this method, we use multiple lights which have different spectrum to each other. The spectral components are not only ordinary red, green and blue, but also the other kinds of colors. By using the multiple colors, much larger number of information than the number of unknown parameters, e.g. surface orientation and reflectance, can be used for estimating the unknown parameters. Furthermore, we achieve simultaneous estimation of surface orientation and reflectance from small number of light sources by using reflectance classification. By this classification, DoF of reflectance in a whole image is drastically reduced, and thus, we can estimate reflectance and surface orientation more efficiently.

2 PHOTOMETRIC STEREO

Photometric stereo for surface reconstruction is widely studied and various methods were proposed. Although the photometric stereo was applied to complex reflection models(Brostow et al., 2011) in recent years, we need to estimate additional parameters in order to deal with complex reflection models. Thus, in this paper, we consider a simple reflection model for surface reconstruction.

2.1 Reflection Model

We first explain basic photometric stereo for surface reconstruction. In this paper, we assume that reflection of surface can be described by Lambert model, in which observed intensity I can be described by a surface normal $\mathbf{n}$ and lighting direction $\mathbf{s}$ as follows:

$$I = \max(E\rho\mathbf{n}^\top\mathbf{s}, 0) \tag{1}$$

where E indicates a radiance of the light and ρ indicates a reflectance of object surface. If there is no shadow in the scene, Eq.(1) can be rewritten as follows:

$$I = E\rho\mathbf{n}^\top\mathbf{s} \tag{2}$$

If a light source is sufficiently far from the scene, we can describe all the intensities in an image by using a single lighting direction $\mathbf{s}$ linearly, which is called infinite light reflection model. The infinite light reflection model is widely used for photometric analysis since it simplifies problems drastically and enhance the stability of method. Thus we in this paper use the infinite light reflection model.

2.2 Reconstruction of Normal Orientation

We next consider surface reconstruction from images taken under different lighting conditions. Let $\mathbf{s}_i$ denote a lighting direction for i-th image. Then, the intensities of M images can be described as follows:

$$\begin{bmatrix} I_1 \\ I_2 \\ \vdots \\ I_M \end{bmatrix} = \begin{bmatrix} E_1\mathbf{s}_1^\top \\ E_2\mathbf{s}_2^\top \\ \vdots \\ E_M\mathbf{s}_M^\top \end{bmatrix} \rho\mathbf{n} \tag{3}$$

where I_i and E_i are an intensity and a radiance for i-th image. If the lighting information E_i and $\mathbf{s}_i$ is calibrated, a surface orientation $\mathbf{n}$ can be estimated linearly by the least means square method as follows:

$$\rho\mathbf{n} = \begin{bmatrix} E_1\mathbf{s}_1^\top \\ E_2\mathbf{s}_2^\top \\ \vdots \\ E_M\mathbf{s}_M^\top \end{bmatrix}^+ \begin{bmatrix} I_1 \\ I_2 \\ \vdots \\ I_M \end{bmatrix} \tag{4}$$

where $\mathbf{A}^+$ is the pseudo inverse of $\mathbf{A}$ and $\mathbf{A}^+ = (\mathbf{A}^\top\mathbf{A})^{-1}\mathbf{A}^\top$. The norm of a surface orientation $\mathbf{n}$ is equal to 1, and thus, ρ and $\mathbf{n}$ can be separated easily.

In this estimation, DoF of estimated parameters is 3 and they are a reflectance and two parameters of surface. Although surface orientation $\mathbf{n}$ has 3 variables, DoF of it is 2 because a norm of it is constrained. Therefore, we can estimate these parameters from 3 or more than 3 images taken under different illuminations. It indicates that we cannot estimate the parameters from a single image by the photometric stereo method.

3 ONE SHOT PHOTOMETRIC STEREO

3.1 Intensity Representation by Light Spectrum

In this paper, we expand the photometric stereo for multi-band lighting. In this section, we describe observed intensity from a viewpoint of spectrum. Let $r(\lambda)$ denotes a reflectance spectrum, $e(\lambda)$ denotes a light spectrum and $x(\lambda)$ denotes a spectral response of an observing camera. In this case, an observed intensity I can be described as follows:

$$I = E\int e(\lambda)r(\lambda)x(\lambda)d\lambda\mathbf{n}^\top\mathbf{s} \quad (5)$$

where E denotes radiance of light, and, $\mathbf{n}$ and $\mathbf{s}$ indicates surface orientation and lighting direction. A reflectance ρ can be defined as follows:

$$\rho = \int e(\lambda)r(\lambda)x(\lambda)d\lambda \quad (6)$$

Thus, Eq.(5) is equivalent to Eq.(1). Note that, reflectance ρ includes not only reflectance spectrum but also light spectrum and spectral response of camera in this paper.

3.2 Multi-band Imaging under Multi-band lighting

As descried in the previous section, we can obtain different equations from a single image when we use multiple lights which have different spectrum. Therefore, we can reconstruct surface normals from a single image. For this objective, we first consider the case where there are some light sources which have different light spectrum to each other. When the scene is observed by multiple sensors which have different spectral response, observed intensity I_j of j-th sensor can be described as follows:

$$I_j = E_i\sum_i\int e_i(\lambda)r(\lambda)x_j(\lambda)d\lambda\mathbf{n}^\top\mathbf{s}_i \quad (7)$$

where e_i indicates a light spectrum of i-th light and x_j indicates a spectral response of j-th sensor. The reflectance ρ_{ij} under i-th light for j-th sensor can is defined as follows:

$$\rho_{ji} = \int e_i(\lambda)r(\lambda)x_j(\lambda)d\lambda \quad (8)$$

By using the reflectance ρ_{ij}, Eq.(7) can be rewritten as follows:

$$I_j = E_i\rho_{ji}\mathbf{n}^\top\mathbf{s}_j \quad (9)$$

When E_i is equal to 1, we finally obtain simultaneous equations as follows:

$$\begin{bmatrix} I_1 \\ \vdots \\ I_M \end{bmatrix} = \begin{bmatrix} \rho_{11} & \cdots & \rho_{1N} \\ & \vdots & \\ \rho_{M1} & \cdots & \rho_{MN} \end{bmatrix} \begin{bmatrix} \mathbf{s}_1^\top \\ \vdots \\ \mathbf{s}_N^\top \end{bmatrix} \mathbf{n} \quad (10)$$

If we can solve the simultaneous equations, we can estimate the surface orientation $\mathbf{n}$ from a single image.

As described above, we may think that we can estimate surface orientations from a single multi-band image. However, we cannot do it unfortunately, because the number of variable such as reflectance increases when the number of bands increases as shown in Eq.(10). Thus, we cannot obtain unique surface orientations from a multi-band image without any additional constraint.

3.3 Photometric Stereo with Reflectance Database

In order to solve Eq.(10) for estimating surface orientation, we add other constraints. We first consider a constraint on reflectance of object surface. Reflectance parameters are determined by reflectance spectrum $r(\lambda)$. It is known that arbitrary spectrum can be represented by linear summation of limited number of bases. The fact indicates that reflectance can also be described by small number of parameters. In this section, we assume that a set of reflectance of the object can be obtained beforehand. However, the object is non-rigid and its surface normals change in each time instant, and thus we have to estimate them simultaneously. Under this assumption, Eq.(10) can be rewritten as follows:

$$\begin{bmatrix} I_1 \\ \vdots \\ I_M \end{bmatrix} = \mathbf{R}(s) \begin{bmatrix} \mathbf{s}_1^\top \\ \vdots \\ \mathbf{s}_N^\top \end{bmatrix} \mathbf{n} \quad (11)$$

where $\mathbf{R}(s)$ is a matrix which represents a set of reflectance determined by a parameter s.

In this equation, the number of unknown variables is 3, i.e. two parameters of a surface normal $\mathbf{n}$ and a parameter s, if we know lighting direction. Thus, we can estimate these variables from 3 or more than 3 band images.

For representing a manifold of reflectance, we use reflectance database. This database consists of a set of reflectance of target scene, and then, we should just choose a proper reflectance from the database for parameter estimation. In this method, the database efficiently works for estimating the surface orientation, although we need to prepare the database beforehand.

3.4 Smoothness Constraint

We next add smoothness constraint with surface orientation. In ordinary case, object surface is approximately smooth, and thus, surface orientations among neighbor pixels should be similar to each other. Therefore, we define a cost function about smoothness E_s^{xy} at pixels (x,y) as follows:

$$E_s^{xy} = \sum_{l=x-1}^{x+1}\sum_{m=y-1}^{y+1}||\mathbf{n}^{xy} - \mathbf{n}^{lm}|| \quad (12)$$

When E_s is minimized at all pixel, object surface become smooth.

3.5 Minimization of Cost Function

In the previous sections, we defined some constraints for surface orientation estimation. By combining these constraints, we can finally obtain a cost function for surface orientation estimation as follows:

$$E = \sum_x \sum_y (||I_j^{xy} - \hat{I}_j^{xy}(\mathbf{n}, s)||^2 + wE_s^{xy}) \quad (13)$$

where w is a weight and I_j^{xy} is an observed intensity at pixel (x, y) for j-th band sensor. $\hat{I}_j^{xy}(\mathbf{n}, s)$ is a reconstructed intensity from estimated parameters $\mathbf{n}$ and s. By minimizing the equation, we can estimate a surface normal $\mathbf{n}$ and a reflectance $\mathbf{R}(s)$ simultaneously. However, the minimization is not so easy because $\mathbf{R}(s)$ is not linear and continuous.

In order to minimize the function, we use separated estimation. In this estimation, we minimize only first term pixel by pixel as follows:

$$E_1^{xy} = ||I_j^{xy} - \hat{I}_j^{xy}(\mathbf{n}, s)||^2 \quad (14)$$

In this estimation, we select a reflectance from the database and estimate surface orientation $\mathbf{n}$ as a result of LM solution of Eq.(10). After that, we evaluate selected reflectance set by Eq.(14). A reflectance which provides the lowest E_1 is the estimated parameters and $\mathbf{n}$ estimated by this parameter is the result of estimation.

After that, we estimate surface orientation with smoothness constraint. In this estimation, reflectance parameter s is fixed. In addition, we define the estimation weight as follows:

$$w^{xy} = 1 - \frac{E_1^{xy2}}{E_i^{xy2} + \sigma} \quad (15)$$

where σ determines distribution of weight. Figure 1 shows this function when $\sigma = 1$. This weight describes the reliability of s. By using the weight, we define a cost function as follows:

$$E_2 = \sum_x \sum_y (w^{xy} ||I_j^{xy} - \hat{I}_j^{xy}(\mathbf{n}, s)||^2 + wE_s^{xy}) \quad (16)$$

By using this function, surface orientation is estimated from the smoothness constraint when reliability of s is low. This cost function is just a linear equation, and thus it can be solved by the LMS method. After this orientation estimation, reflectances are finally chosen by using the estimated orientations, and thus orientations and reflectances are estimated with smoothness constraint.

By this proposed method, we can estimate reflectance and surface orientation simultaneously from a single multi-band image.

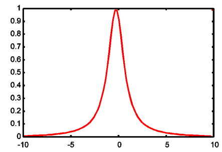


Figure 1: Weight function $1 - \frac{x^2}{x^2+1}$.

4 REFLECTANCE ESTIMATION USING REFLECTANCE CLASSIFICATION

4.1 Reflectance Representation by Linear Combination of Bases

We next consider the case where reflectance properties are unknown completely. We do not utilize the particular reflectance database for a target object, and thus, we should use other prior knowledge. For this objective, a general reflectance database(Kohonen et al., 2005) can be used. The general reflectance database includes various reflectance properties in natural environment, and thus, we can choose appropriate reflectance property from the database. However, this database includes a lot of reflectances, thus, it is not so easy and requires large computational cost to choose proper reflectance.

In order to avoid the problem, we compress the database. In general, it is known that most of the reflectance property in natural environment can be represented linearly by a small number of bases. Therefore, we compress the database by using a principal component analysis (PCA). By using the linear bases from the PCA, reflectance properties in the natural environment can be represented by linear combination of about 5 principal bases. Therefore, we can estimate arbitrary reflectance property in natural environment by estimation of only small number of coefficients for each bases. In this paper, the number of bases is described by K.

4.2 Reflectance Classification

As described in the previous section, we can represent and estimate arbitrary reflectance property from small number of parameters. However, if we do not have sufficient number of spectral band, we cannot estimate reflectance property and surface normal orientation simultaneously. For example, when we have 3 band image, we cannot estimate reflectance and surface normal because DoF of input image is 3 and it is smaller than the DoF of estimating parameters $2 + K$

(2 for surface orientation and K for reflectance).

In order to avoid the problem, we utilize a new prior knowledge. In general, a number of reflectance property in a object is limited. Therefore, we should estimate limited number of reflectance properties from a whole image. Under this constraint, we can estimate reflectance properties and surface orientation simultaneously from a single image. For example, when there are L kinds of properties in an input images which have N pixels, the DoF of estimating parameters are $KL+2N$. Therefore, we can estimate surface orientation from an M-band image when MN is larger than $KL+2N$.

4.3 Simultaneous Estimation of Surface Orientation and Reflectance

In order to minimize the cost function under above-mentioned constraint, we utilize RANSAC like optimization method. In this section, we explain detail of this optimization method.

At first, minimum number of points for estimating reflectance and surface orientation are chosen randomly , and then, the surface orientation and reflectance are estimated by minimizing a cost function. The cost function E_1 is defined as follows:

$$E_1 = \sum_i \sum_j ||I_{ij} - \mathbf{n}_i^\top \mathbf{s}_j R(\mathbf{c})||^2, ||\mathbf{n}_i|| = 1 \qquad (17)$$

where I_{ij} is the intensity of i-th point illuminated by j-th light, $\mathbf{c}$ is a set of coefficients of reflectance and $R(\mathbf{c})$ indicates reflectance obtained from $\mathbf{c}$. When the set of pixels have the same reflectance, E_1 becomes very small and proper surface normals $\mathbf{n}_i$ are estimated. On the other hand, the cost E_1 cannot become small if the reflectance properties of a set of pixels are different from each other. Therefore, we choose candidates of reflectance when the cost E is smaller than a threshold θ_1. Note, DoF of estimated parameters is $L+2O$ when O denotes number of points and DoF of input image is MO. Thus, O satisfies $L/(M-2)$.

We next confirm the candidate reflectance from the previous step by using consensus. In this step, surface orientation for every pixel are estimated by using candidate reflectance $\hat{R}(\mathbf{c})$, and then, the candidate is evaluated as follows:

$$E_2 = \delta \sum_k \sum_j ||I_{kj} - \mathbf{n}_k \mathbf{s}_j \hat{R}_j(\mathbf{c})||^2 \qquad (18)$$

$$\delta(x) = \begin{cases} 1 & \text{if } x < \theta_2 \\ 0 & \text{otherwise} \end{cases} \qquad (19)$$

where θ_2 is a threshold. When the evaluation value E_2 is larger than a threshold θ_3, reflectance $\hat{R}$ is chosen as reflectance of the target object.

By applying the process iteratively, a set of reflectance is obtained. At last, we optimize surface orientation by using the estimated reflectance. In this step, the following cost functions are minimized pixel by pixel

$$E_3 = \sum_j ||I_j - \mathbf{n}^\top \mathbf{s}_j \hat{R}_j^l(\mathbf{c})||^2 \qquad (20)$$

where $\hat{R}_j^l$ indicates j-th band reflectance of l-th reflectance property. The surface orientation $\mathbf{n}$ and a reflectance $\hat{R}$ which minimize the cost are selected as the final estimation results. By using the re-estimation step, we can correct error estimation in the first step, and thus, we can obtain proper orientation and reflectance for each pixel.

5 EXPERIMENTAL RESULTS FROM SPECIFIC DATABASE

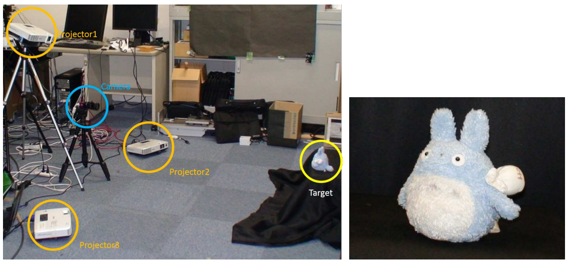
We estimated reflectance and surface orientation by the proposed method. We first show experimental results by using a specific reflectance database as described in **3.3**.

5.1 Environment

In this experiment, reflectance database was constructed from a target object, at first. After that, surface normal of the target object was estimated in different pose using the reflectance database. We used 3 projectors as light sources in the experiment. The projectors were set as shown in Fig.2(a) and emit red, green and blue lights simultaneously. Directions of the light sources from a target object were calibrated beforehand. A color camera is set in front of a target object as shown in Fig.2(a). The target object of this experiment is shown in Fig.2(b). The database of reflectance was constructed from surface orientation estimated by the standard photometric stereo method (which is not one shot method) and images taken under each single color light. Under this environment, surface orientation was estimated by the proposed method.

5.2 Reconstructed Result

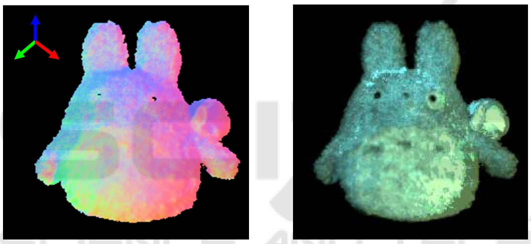
We first show an input image in Fig.3. This image was illuminated by 3 lights simultaneously. From the image, surface orientation was reconstructed as shown in Fig.4(a). In this figure, surface orientations are represented by color referring to the left top measure in the image. Fig.4(b) shows the estimated reflectance. In this figure, only diagonal components of $\mathbf{R}$ is shown by color.



(a) Experimental environment (b) Target object

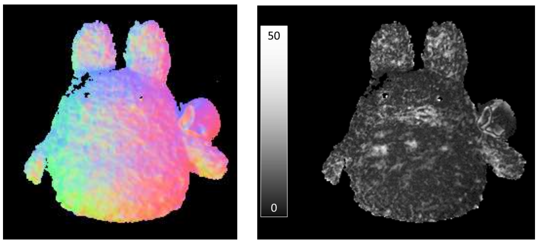
Figure 2: Experimental environment and target object.

Figure 3: Input image: The object was illuminated by 3 lights which have different spectrum to each other.



(a) Surface normal (b) Reflectance

Figure 4: Surface normal and reflectance obtained from the proposed method.



(a) Ground truth (b) Estimation error

Figure 5: Comparison between proposed method and ordinary method: (a) indicates the ground-truth of surface normals, and (b) indicates estimated error of our method.

In order to evaluate the proposed method, we compared the result with surface orientations reconstructed by the ordinary method. In the ordinary photometric method, 3 images are taken separately under different lighting conditions. The same light sources as the proposed method were used and they emit white light, respectively. The result of the ordinary method and the difference between the proposed method and the ordinary method is shown in Fig.5. In Fig.5(b), intensities of error image represent angles between surface normals estimated by these two methods. The average of angle errors was 14.7 degrees. The result indicates that our proposed method can reconstruct surface orientation accurately from a single image.

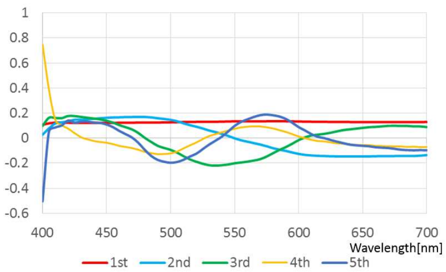


Figure 6: Five principal bases for representing arbitrary reflectance. The bases were computed by PCA from Munsell color data set.

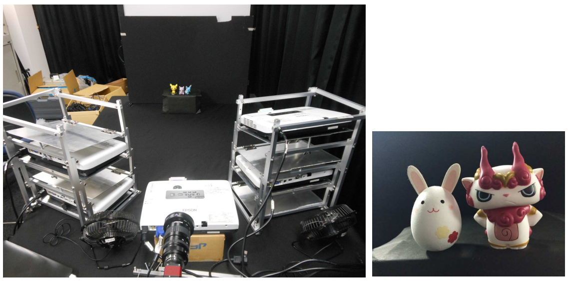
6 EXPERIMENTAL RESULT BY LARGE SCALE DATABASE

6.1 Environment

We next show experimental results using large scale database. In this experiment, The Munsell color data set(Kohonen et al., 2005) was used for reflectance database. From the database, 5 principal bases were computed by PCA. A cumulative contribution ratio of these five bases was 99.1%. The spectrums of the reflectance bases are shown in Figure—6 shows spectral reflectance of each principal bases. An arbitrary reflectance is represented by combining the bases.

Experimental environment for taking input images are shown in Fig.7. In this experiment, 5 projectors were used as light sources. The each projector equipped different spectrum band pass filters. Spectrum distribution of the filters are shown in Fig.8. In order to obtain multi-band images, a single gray scale camera and 5 band pass filters were used instead of a real multi-band camera. Spectrum distribution of each band pass filter is correspond to a filters for light sources, and thus, we can separate multi-band image to single band image illuminated by a light source easily.

Input images were taken with changing band-pass filters. Figure 9 shows examples of input images for each band. In this figure, intensities in each spectrum band is shown as images (a), and image (b) shows observed result by an ordinary RGB camera. The image



(a) Environment (b) Target objects

Figure 7: Experimental environment and target objects: Five projectors were set in front of target objects. The projectors equipped different spectral band-pass filters.

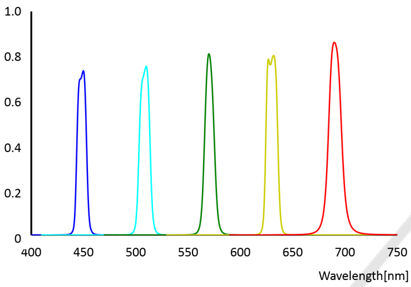


Figure 8: Spectral distributions of band pass filters for light sources.

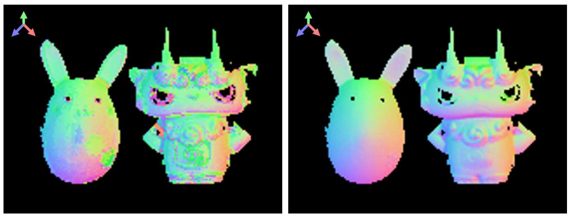
(a) Intensities on each spectrum band

(b) Observed image by RGB camera

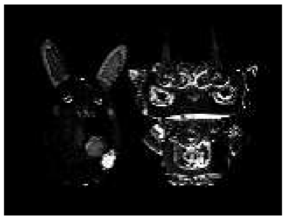
Figure 9: Input multi-band image: Images (a) indicate intensities on each spectrum band shown in Fig.8 and image (b) shows observed image by ordinary RGB camera.

(b) was not used for estimation, and thus, a 5 band image at (a) was used for estimation by our proposed method.

From the images and the 5 principal bases, surface normal and reflectance distribution of each pixel were estimated by the proposed method.

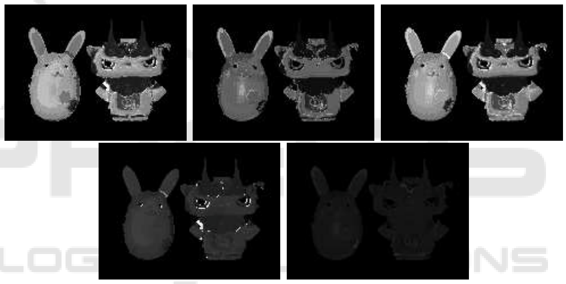


(a) Estimated surface (b) Ground truth

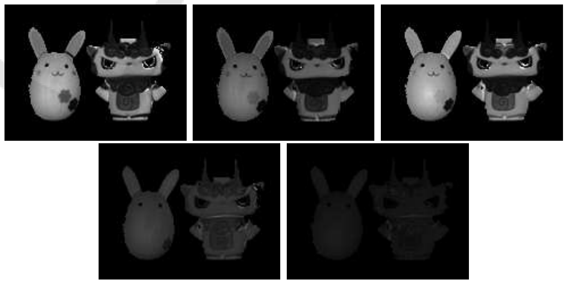


(c) Estimated errors

Figure 10: Surface orientation estimation result: (a) shows estimated result by our proposed method and (b) shows ground truth estimated from normal photometric stereo. Image (c) shows angle between estimated result and ground-truth.



(a) Estimated reflectance on each spectrum band.



(b) Ground truth

Figure 11: Reflectance estimation result: images (a) show result by our method and images (b) show ground truth from ordinary photometric stereo.

6.2 Estimated Results

Figure 10 shows estimated surface orientation by the proposed method. In this figure, (a) shows estimated result by our method, (b) shows ground truth from an ordinary photometric stereo, and (c) shows angles between estimated result and ground truth. From these results, the surface orientation can be estimated roughly except depth and image edge. At the depth edge, the orientation estimation could not work well because reflectance of the input image was changed drastically. In this case, the reflectance cannot be represented by the combination of principal bases, and thus, reflectance and orientation estimation could not work well.

Figure 11 shows estimated reflectance by the proposed method. In this figure, the estimated reflectance (a) was computed from estimated coefficients of bases, and the ground truth (b) was estimated from ground-truth orientation and input intensities in each band. In this result, our estimated results are similar to the ground truth reflectance. As similar to the orientation estimation, the estimated result is not stable at image/depth edge by the above mentioned reason. However, the reflectance can also be estimated in whole image roughly. The results show that the proposed method can estimate not only surface orientation, but also reflectance.

7 CONCLUSION

In this paper, we proposed a one-shot photometric stereo for estimating surface orientations with arbitrary textures. In our method, we used multiple lights with different light spectrum and a multi-band camera. In order to simplify the reflectance estimation, we used a reflectance database. By using the database, reflectance estimation can be achieved by the selection of reflectance and estimation of small number of coefficients. In addition, we utilized reflectance classification, so that the DoF of estimation in whole image is decreased drastically. Therefore, our method can estimate reflectance and surface orientation simultaneously from smaller number of color band than existing methods. Experimental results show that our method can reconstruct surface from a single multiband image. The method is useful for reconstructing surface of non-rigid moving objects and it can be applied to synthesizing real objects into 3D graphics.

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