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Shape Modification from Endoscope Images by Regression Analysis

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Abstract

The VBW (Vogel-Breuß-Weickert) model is proposed as a method to recover 3-D shape under point light source illumination and perspective projection. However, the VBW model recovers relative, not absolute, shape. Here, shape modification is introduced to recover the exact shape. Modification is applied to the output of the VBW model. First, a local brightest point is used to estimate the reflectance parameter from two images obtained with movement of the endoscope camera in depth. A Lambertian sphere image is generated using the estimated reflectance parameter and VBW model is applied for a sphere. Regression analysis is introduced to improve the surface gradients, where linear coefficients can be obtained using true values of gradient parameters with a generated sphere. Depth can then be recovered using the modified gradient parameters. Performance of the proposed approach is confirmed via computer simulation and real experiment.

Keywords: *Endoscope Image, VBW Model, Regression Analysis, Shape Modification, Reflection Factor*

1. Introduction

Endoscopy allows medical practitioners to observe the interior of hollow organs and other body cavities in a minimally invasive way. Sometimes, diagnosis requires assessment of the 3-D shape of the observed tissue. For example, the pathological condition of a polyp often is related to its geometrical shape. Medicine is an important area of application of computer vision technology. Many approaches are based on stereo vision [1]. However, the size of the endoscope becomes large and this imposes a burden on the patient. Here, we consider a general purpose endoscope, of the sort still most widely used in medical practice.

Shape recovery from endoscope images is considered. Shape from shading (SFS) [2] and Fast Marching Method (FMM) [3] based SFS approach [4] are proposed. These approaches assume orthographic projection. An extension of FMM to perspective projection is proposed in [5]. Further extension of FMM to both point light source illumination and perspective projection is proposed in [6]. Recent extensions include generating a Lambertian image from the original multiple color images [7-8]. Application of FMM includes solution [9] under oblique illumination using neural network learning [10]. Most of the previous approaches treat the reflectance parameter as a known constant. The problem is that it is impossible to estimate the reflectance parameter from

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only one image. Further, it is also difficult to apply point light source based photometric stereo [11] [12] in the context of endoscopy.

Recently, the Vogel-Breuß-Weickert (VBW) model [13], based on solving the Hamilton-Jacobi equation, has been proposed to recover shape from an image taken under the conditions of point light source illumination and perspective projection. However, the result recovered by the VBW model is relative. VBW gives smaller values for surface gradient and height distribution compared to the true values. That is, it is not possible to apply the VBW model directly to obtain exact shape and size.

This paper proposes a new approach to improve the accuracy of polyp shape determination as absolute size. The proposed approach estimates the reflectance parameter from two images with small camera movement in the depth direction. A Lambertian sphere model is synthesized using the estimated reflectance parameter. The VBW model is applied to the synthesized sphere and shape then is recovered. Surface gradient parameters are obtained by ellipsoid fitting for the height distribution of Z which is recovered from VBW model. Obtained gradient parameters are used as input for the regression analysis. While the true values of the corresponding gradient parameters are used for the output of regression analysis. The proposed approach is evaluated via computer simulation and real experiments and it is confirmed that the obtained shape is improved.

2. VBW Model

The VBW model [13] is proposed as a method to calculate depth (distance from the viewer) under point light source illumination and perspective projection. The method solves the Hamilton-Jacobi equations [14] associated with the models of Faugeras and Prados [15]. Lambertian reflectance is assumed.

The following processing is applied to each point of the image. First, the initial value for the depth $Z_{default}$ is given using Eq.(1) as in [16].

$$Z_{default} = -0.5 \log(If^2) \tag{1}$$

Where I represents the normalized image intensity and f represents the focal length of the lens.

Next, the combination of gradient parameters which gives the minimum gradient is selected from the difference of depths for neighboring points. The depth, Z, is calculated from Eq. (2) and the process is repeated until the Z values converge. Here, (x,y) are the image coordinates, Δt is the change in time, (m,n) is the minimum gradient for (x,y) directions, and $Q = f / \sqrt{x^2 + y^2 + f^2}$ is the coefficient of the perspective projection.

$$\begin{aligned} Z(x,y) &= Z(x,y) + \Delta t \exp(-2Z(x,y)) \\ &- \Delta t \left(\frac{If^2}{Q} \sqrt{f^2 (m(x)^2 + n(y)^2) + (xm(x) + yn(y))^2 + Q^2} \right) \end{aligned} \tag{2}$$

Here, it is noted that the shape obtained with the VBW model is given in a relative scale, not an absolute one. The obtained result gives smaller values for surface gradients than the actual gradient values.

3. Proposed Approach

3.1. Estimating Reflectance Parameter

When uniform Lambertian reflectance and point light source are assumed, image intensity depends on the dot product of surface normal vector and the light source direction vector subject to the inverse square law for illuminance.

Measured intensity at each surface point is determined by Eq. (3).

$$E = C\frac{(\mathbf{s} \cdot \mathbf{n})}{r^2} \tag{3}$$

Where E is image intensity, **s** is a unit vector towards the point light source, **n** is a unit surface normal vector, and r is the distance between the light source and surface point.

The proposed approach estimates the value of the reflectance parameter, C, using two images acquired with a small camera movement in the depth direction. It is assumed that C is constant for all points on the Lambertian surface. Regarding geometry, it is assumed that both the point light source and the optical center of lens are co-located at the origin of the (X,Y,Z) world coordinate system. Perspective projection is assumed.

The actual endoscope image has the color textures and specular reflectance. Using the approach proposed by [17] the original input endoscope image is converted into one that satisfies the assumptions of a uniform Lambertian gray scale image.

The procedure to estimate C is as follows.

Step 1. If the value of C is given, depth Z is uniquely calculated and determined at the point with the local maximum intensity [18]. At this point, the surface normal vector and the light source direction vector are aligned and produce the local maximum intensity for that value of C.

Step 2. For camera movement, ΔZ, in the Z direction, two images are used and the difference in Z, Z_{diff}, at the local maximum intensity points in each image is calculated. Here the camera movement, ΔZ, is assumed to be known.

Step 3. Let $f(C)$ be the error between ΔZ and Z_{diff} . $f(C)$ represents an objective function to be minimized to estimate the correct value of C. That is, the value of C is the one that minimizes $f(C)$ given in Eq. (4).

$$f(C) = (\Delta Z - Z_{diff}(x, y))^2 \tag{4}$$

3.2. Regression Analysis for Shape Modification

The size and shape recovered by the VBW model are relative. VBW gives smaller values for surface gradient and depth compared to the true values. Here, modification of surface gradient and improvement of the recovered shape are considered. First, the surface gradient at each point is modified by a regression analysis. Then the depth is modified using the estimated reflectance parameter C and modified surface gradient parameters $(p, q) = (\frac{\partial Z}{\partial X}, \frac{\partial Z}{\partial Y})$ by regression analysis. Here, the regression analysis estimates the linear coefficients of regression model and modifies each of the surface gradient parameters for the recovered result by VBW model. Using the estimated C, a sphere image is synthesized with uniform Lambertian reflectance. The VBW model is applied to this synthesized sphere. Ellipsoid is assumed under the consideration to treat a sphere. Equation is written as Eq.(5) where x and y represent the image coordinates corresponding to the world coordinates (X,Y), z represents the depth (height) information) obtained from VBW. Coefficients S, T, U can be obtained using n sampled points of ellipsoid using linear least squares as shown in Eq.(6) to Eq.(8). Transforming Eq.(5) gives Eq.(9) and gradient parameters (p,q) are given by Eq.(10).

$$Sx^2 + Ty^2 + Uz^2 = 1 \tag{5}$$

$$\begin{pmatrix} x_1^2 & y_1^2 & z_1^2 \\ x_2^2 & y_2^2 & z_2^2 \\ \vdots & \vdots & \vdots \\ x_n^2 & y_n^2 & z_n^2 \end{pmatrix} \begin{pmatrix} S \\ T \\ U \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \tag{6}$$

$$L = \begin{pmatrix} x_1^2 & y_1^2 & z_1^2 \\ x_2^2 & y_2^2 & z_2^2 \\ \vdots & \vdots & \vdots \\ x_n^2 & y_n^2 & z_n^2 \end{pmatrix}, m = \begin{pmatrix} S \\ T \\ U \end{pmatrix}, n = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \tag{7}$$

$$m = (L^T \cdot L)^{-1} \cdot L^T \cdot n \tag{8}$$

$$z = \sqrt{\frac{1 - Sx^2 - Ty^2}{U}} \tag{9}$$

$$p = \frac{\partial z}{\partial x} = \frac{1}{2}\left(\frac{1 - Sx^2 - Ty^2}{U}\right)^{-\frac{1}{2}} \cdot \left(-\frac{2Sx}{U}\right) = -\frac{Sx}{U}\left(\frac{1 - Sx^2 - Ty^2}{U}\right)^{-\frac{1}{2}},$$

$$q = \frac{\partial z}{\partial y} = \frac{1}{2}\left(\frac{1 - Sx^2 - Ty^2}{U}\right)^{-\frac{1}{2}} \cdot \left(-\frac{2Ty}{U}\right) = -\frac{Ty}{U}\left(\frac{1 - Sx^2 - Ty^2}{U}\right)^{-\frac{1}{2}} \tag{10}$$

The estimated gradients, (p,q), and the corresponding true gradients for the synthesized sphere, (p,q), are given respectively as input vectors and output vectors to the regression analysis. Suppose when we assume the 3rd order polynomial for the relation between the original gradient parameter and the corresponding true gradient parameter, the regression model becomes Eq.(11) and four coefficients a to d are obtained using linear least squares of Eq.(12) to Eq.(14) with n samples points on the Lambertian sphere.

$$y = ax^3 + bx^2 + cx + d \tag{11}$$

$$Ax = y \tag{12}$$

Where

$$A = \begin{pmatrix} x_1^3 & x_1^2 & x_1 & 1 \\ x_2^2 & x_2^2 & x_2 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ x_n^3 & x_n^2 & x_n & 1 \end{pmatrix}, x = \begin{pmatrix} a \\ b \\ c \\ d \end{pmatrix}, y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \tag{13}$$

$$x = (A^T A)^{-1} A^T y \tag{14}$$

Here x is assumed to be gradient parameter p or q, and y is assumed to be modified gradient parameter p or q. Substituting coefficients a to d into Eq.(11) can obtain the modified gradient parameters p or q. Gradient parameter p and q are obtained with numerical difference taken for the recovered result z of VBW. For the real endoscope image, these parameters are used to this regression model for the modification.

In the case of endoscope images, preprocessing is used to remove specular points and to generate a uniform Lambertian image based on [17].

Next, the VBW model is applied to the this Lambertian image and the gradients, (p,q), are estimated from the obtained Z distribution.

The estimated gradients, (p,q), are input to the regression analysis and modified estimates of (p,q) are obtained as output from the regression analysis.

Recall that the reflectance parameter, C, is estimated from f (C), based on two images obtained by small movement of endoscope in the Z direction.

The depth, Z, is calculated and updated by Eq.(15) using the modified gradients, (p,q), and the estimated C, where Eq.(15) also is the original equation developed in [6].

$$Z = \sqrt{\frac{CV\,(-px - qy + f)}{E\,(p^2 + q^2 + 1)^{\frac{1}{2}}}} \tag{15}$$

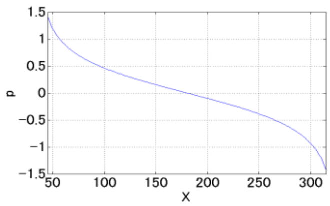
Again, $(p,q) = (\partial Z / \partial X, \partial Z / \partial Y)$, E represents image intensity, f represents the focal length of the lens and $V = \dfrac{f^2}{(x^2 + y^2 + f^2)^{\frac{3}{2}}}$ (we call the coefficient of perspective projection).

4. Experimental Results

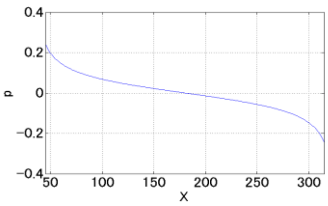
4.1. Regression Analysis

Sphere image is synthesized with the center coordinate (0,0,15) and radius r=5mm, focal length f=10mm and image size=9mm for each. Gradient parameters (p,q) are obtained with ellipsoid fitting for the obtained height distribution of z. This ellipsoid fitting is important to estimate reliable coefficients of *n-th* order polynomial. Ellipsoid fitting can also correspond to the difference of aspect ratio of imaging device.

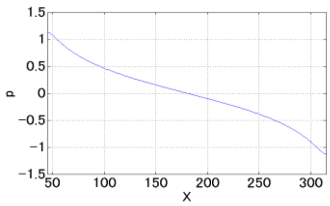
VBW model was applied to a sphere image and ellipsoid fitting was applied to the result by VBW. Obtained gradient parameters were given as input data while the corresponding true gradient parameters were given as output data of regression analysis. 3rd order regression analysis was applied and the coefficients a to h were obtained as a = -39.7316, b = -3.8192e-14, c = 6.9932, d = 1.6263e-18, e = -39.7316, f = 9.0206e-13, g = 6.9932, h = -2.6102e-17, respectively. These coefficients were used in Eq.(11) and gradient parameters were modified. Cross section of true parameter p is shown in Figure1 (a), parameter p before modification is shown in Figure 1 (b), while parameter p after modification using regression analysis is shown in Figure 1 (c).



(a) True p



(b) p Obtained by VBW



(c) Modified p

Figure 1. Cross Section of Surface Gradient Parameter

It is shown that regression analysis performed good modification of gradient parameters and it is confirmed that the regression analysis using a Lambertian sphere works well.

Other order number of n in polynomial used in regression analysis is also investigated via simulation. Mean error was evaluated for the height z in each case with substituting the modified (p,q) into Eq.(15). The result by VBW and that after each case of 1st to 5th regression analysis are shown in Table 1, where the number of percentage is the proportion to the radius r=5mm of a sphere.

Table 1. Mean Error of *Z* [mm]

VBW Model	1st-order Regression	2nd-order Regression	3rd-order Regression	4th-order Regression	5th-order Regression
3.6343(72.5%)	0.3635(7.3%)	0.3635(7.3%)	0.3221(6.4%)	0.3203(6.4%)	0.3203(6.4%)

Table 1 shows every case of regression analysis with different order polynomials gives improvement than the result of VBW. 1st and 2nd order regression gave some difference but 3^{rd,} 4th and 5th order regressions did not give much difference. From these observations, 3rd order regression analysis is useful and recommended to the modification.

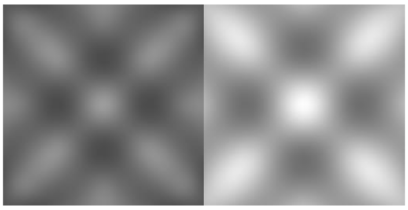
4.2. Computer Simulation

Computer simulation was performed for two synthesized images with a small difference z to confirm the performance of the regression analysis.

Synthesized cosine curved surfaces were used, one with center located at coordinates (0, 0, 12) and the other with center at (0, 0, 15). Common to both, the reflectance parameter, C, is 120, the focal length f is 10mm and the waveform cycle is 4mm and the ± amplitude is 1mm. Image size is 5mm×5mm and pixel size is 256×256 pixels. The synthesized image whose center is located at (0, 0, 12) is shown in Figure2 (a) and the one with center located at (0, 0, 15) is shown in Figure2 (b).

The reflectance parameter C was estimated according to the proposed method and gradient was modified using 3rd order regression analysis in section 4.1. After gradient parameters, (p,q) were modified, depth Z were updated using Eq.(15). The graph of the objective function, $f(C)$, is shown in Figure3 and the true depth is shown in Figure4 (a). The estimated C was 119 (compared to the true value of 120). The estimated Z_{diff} was 2.9953 (compared to the true value of 3).

The result recovered by VBW for Figure2(a) is shown in Figure4(b). The modified values of depth, using the regression analysis and Eq. (15), are shown in Figure4(c). Table.2 gives the mean errors in surface gradient and depth estimation. The percentages given in the Z column represent the error relative to the amplitude of maximum - minimum depth (=2mm) of the cosine synthesized function.



(a) Center : (0,0,12)   (b) Center : (0,0,15)

Figure 2. Cosine Model

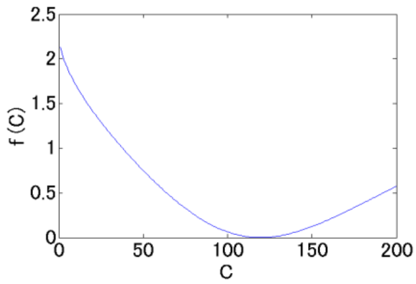
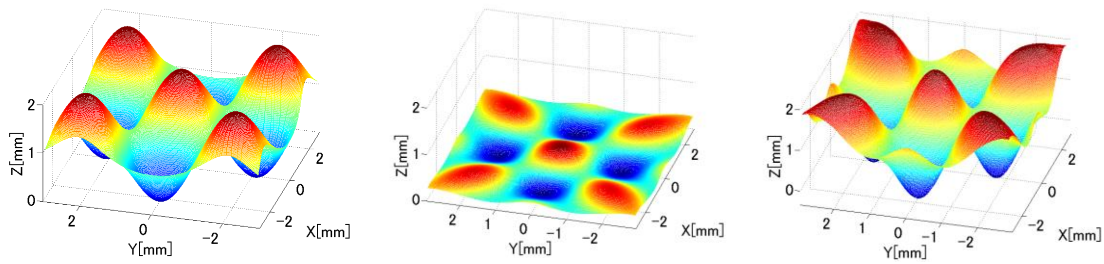


Figure 3. Objective Function *f*(*C*)



(a) True *Z* (b) *Z* by VBW (c) Modified *Z*

Figure 4. Results

Table 2. Mean Error

	p	*q*	*Z*[mm]
VBW	23.0406	23.0406	0.8611(43.1%)
Proposed	0.3259	0.3259	0.1823(9.1%)

It is confirmed that the shape is improved with modification in the proposed approach from Figure4. This means that regression analysis modified (p,q) for each point and Z are modified correctly. In Table 2, Depth estimation is improved to a mean error of 9.1% from 43.1%. Regression analysis improved shape for an object with absolute size and shape. Total processing time was 7 seconds.

Another experiment was performed under the following assumptions. The reflectance factor, C, is 590, the focal length, f, is 10mm and the object is a sphere with radius 5mm. The centers for two positions of the sphere were set at (0, 0, 15) and (0, 0, 17) respectively. The image size was 9mm×9mm with pixel size 360×360 pixels. Here, 4% Gaussian noise (mean 0, variance 0.02, standard deviation 0.14142) is added to each of the two input images. Evaluations for 6% (mean 0, variance 0.03, standard deviation 0.17320) and 10% (mean 0, variance 0.05, standard deviation 0.22360) Gaussian noise are shown in Table 3, as well.

Table 3. Mean Error of Z for Different Gaussian Noise

	4%	6%	10%
VBW	3.2007(64.0%)	3.2917(65.8%)	3.3607(67.2%)
Proposed	0.4380(8.8%)	0.4817(9.6%)	0.5630(11.3%)

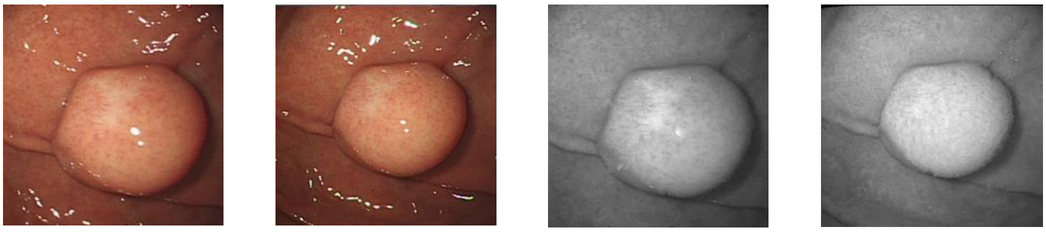
In all three cases, Gaussian noise of 4%, 6% and 10%, the proposed approach reduced the mean error in Z significantly compared to the original VBW model. This suggests modification using the regression analysis is robust to noise and is applicable to real imaging situations, including endoscopy.

4.3. Real Image Experiments

Two endoscope images obtained with camera movement in the Z direction are used in the experiments. VBW was applied to one of the images which was first converted to a uniform Lambertian image. After estimating the reflectance parameter C, coefficients of regression model were obtained using a sphere model with the estimated value of C.

Surface gradients, (p,q), were modified with the 3rd order regression model then depth, Z, was updated at each image point. The focal length, f = 10mm, the image size 5mm× 5mm, and camera movement, ΔZ = 3mm, were assigned to the same known values as those in the computer simulation.

The two endoscope images are shown in Figure5(a) and (b). The generated Lambertian images are shown in Figure5(c) and (d), respectively. The objective function, $f(C)$, is shown in Figure6. The result from the VBW model is shown in Figure7(a) and the modified result is shown in Figure7(b).



(a) Endoscope 1 (b) Endoscope 2 (c) Lambert 1 (d) Lambert 2

Figure 5. Endoscope Image and Generating Lambert Image

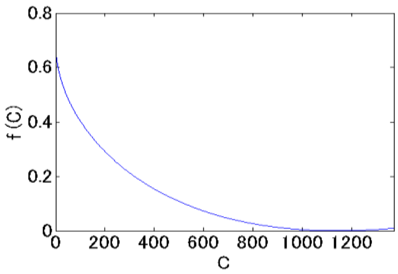
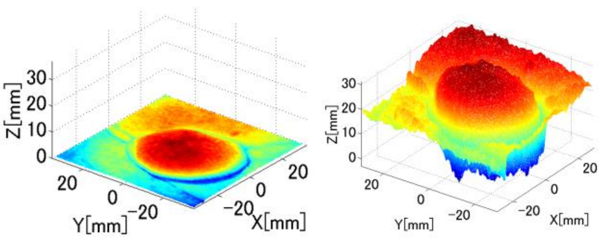


Figure 6. Objective Function *f*(*C*)



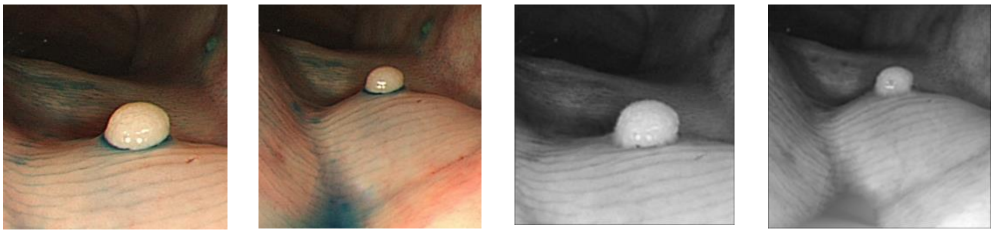
(a) Z by VBW (b) Modified Z

Figure 7. Result for Endoscope Images

The estimated value of the reflectance parameter, C, was 1141 from Figure6. The difference in depth, Z, at the local maximum point was 1 [mm] for the camera movement Z_{diff} between two images. In Figure5(c)(d), specularities were removed compared to Figure5(a)(b). The converted images are gray scale with the appearance of uniform reflectance. Figure7(b) gives a larger depth range than Figure7(a). This suggests depth estimation is improved. The size of the polyp was 1cm and the processing time for shape modification was 12 seconds.

Although quantitative evaluation is difficult, medical doctors with experience in endoscopy qualitatively evaluated the result to confirm its correctness. Different values of the reflectance parameter, C, were estimated in different experimental environments. The absolute size of a polyp is estimated based on the estimated value of C. Accurate values of C lead to accurate estimation of the size of the polyp. The estimated polyp sizes were seen as reasonable by the medical doctor. This qualitatively confirms that the proposed approach is effective in real endoscopy.

Another experiment was done for the endoscope images shown in Figure8(a)(b). The generated gray scale Lambertian images are shown in Figure8(c)(d), respectively. Here the focal length is 10mm, image size is 5mm×5mm, pixel size is 256×256 and ΔZ was set to be 10mm. The graph of $f(C)$ is shown in Figure9. The VBW result for Figure8(d) is shown in Figure10(a), while that for the proposed approach is shown in Figure10(b).



(a) Endoscope 1 (b) Endoscope 2 (c) Lambert 1 (d) Lambert 2

Figure 8. Endoscope Image and Generating Lambert Image

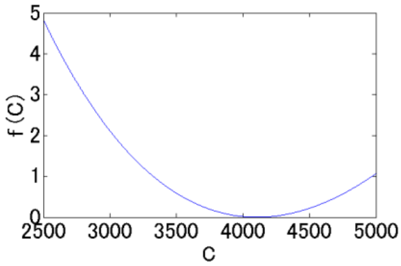
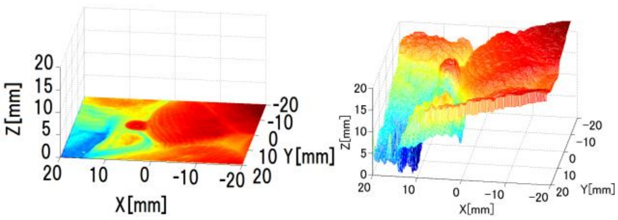


Figure 9. Objective Function *f*(*C*)



(a) *Z* by VBW (b) Modified *Z*

Figure 10. Result for Endoscope Images

C was estimated as 4108 from Figure9. Figure10(b) shows greater depth amplitude compared to Figure10(a). The estimated size of the polyp was about 5mm. This corresponds to the convex and concave shape estimation based on a stain solution. Total processing time was 12 seconds.

5. Conclusion

This paper proposed a new approach to improve the accuracy of absolute size and shape determination of polyps observed in endoscope images.

Coefficients of regression model are obtained for a Lambertian sphere and surface gradient parameters were modified for the result where VBW model is applied for endoscope images. Thus VBW model was used to estimate a baseline shape. Modification of gradients with the regression analysis improved the accuracy of shape and absolute size was obtained via modification. Estimation of the reflectance parameter C was achieved under the assumption that two images are acquired via small camera movement in the depth, Z, direction. The approach was evaluated both in computer simulation and with real endoscope images. Results confirm that the approach improves the accuracy of recovered shape to within error ranges that are practical for polyp analysis in endoscopy. Further research includes an extension to endoscope video with scene understanding and realizing faster processing time.

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