FULL PAPER

Manual/Automatic Colorization for Three-Dimensional Geometric Models utilizing Laser Reflectivity

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While laser scanners can produce a high-precision 3D shape of a real object, appearance information of the object has to be captured by an image sensor, such as a digital camera. This paper proposes a novel and simple technique for colorizing 3D geometric models based on laser reflectivity. Laser scanners capture the range data of a target object from the sensors. Simultaneously, the power of the reflected laser is obtained as a by-product of the range data. The reflectance image, which is a collection of laser reflectance depicted as a grayscale image, contains rich appearance information about the target object. The proposed technique is an alternative to texture mapping, which has been widely used to realize photo-realistic 3D modeling but requires strict alignment between range data and texture images. The proposed technique first colorizes a reflectance image based on the similarity of color and reflectance images. Then the appearance information (color and texture information) is added to a 3D model by transferring the color in the colorized reflectance image to the corresponding range image. Some experiments and comparisons between texture mapping and the proposed technique demonstrate the validity of the proposed technique.

Keywords: Reflectance image, Colorization, Laser scanner, 3D modeling, Virtual reality

1. Introduction

In the field of computer vision, three-dimensional (3D) geometric modeling of real objects is one of the essential techniques. This modeling has many applications, such as landscape surveying, digital archiving of cultural heritages, and virtual reality. At the same time, texture mapping, which projects texture images onto the surface of a 3D model, has been widely used to display a 3D model with high realism. However, since color images and the 3D geometric model are generally captured by different sensors, such as a digital camera and a laser scanner, respectively, strict calibration between these sensors is required to map color information precisely on the 3D geometric model.

In this paper, we propose a new technique using laser reflectivity to add color to a 3D geometric model. A laser scanner obtains the range image of a target based on the properties of the laser projected onto the surface. At the same time, the laser reflectivity, which represents the power of the reflected laser, is obtained as a by-product of the distance value. Each pixel in the range image has a corresponding reflectance value. In other words, the range image and the reflectance image are precisely aligned.

By taking advantage of the characteristics of the reflectance image, our proposed technique achieves highly realistic 3D modeling with only a single color image [1]. The key scheme is to

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colorize the reflectance image based on its similarity with a color image, then transfer the color information to the 3D geometric model. This paper presents some experimental results using a laser scanner, and quantitative evaluations of the proposed technique by comparing it with texture mapping to demonstrate the validity of the proposed technique.

Whereas previous methods have been developed to assign color information to 3D models by projecting corresponding camera images, this paper proposes a novel colorization technique for 3D geometric models. The major contribution of our approach is to extend a conventional monochrome image colorization technique so that it can be applied to range and reflectance images. To our best knowledge, no studies have addressed colorization for 3D geometric models scanned with laser scanners by utilizing reflectance attribute except for the proposed method.

The rest of this paper is organized as follows. In Section 2, an overview of the previous approaches will be presented. In Sections 3, we will propose a new colorization technique for a 3D geometric model using a reflectance image. In Section 4, we carry out some experiments using a laser scanner, and verify the performance of the proposed technique.

2. Related Work

Texture mapping[2], which is a fundamental technique for creating a photo-realistic 3D model, has been widely used in the field of computer vision. In some applications, it maps a color image on a range image and creates a colored 3D model. Usually range and color images are captured from different viewpoints by two independent sensors, such as a laser scanner and a digital camera. Therefore, it is necessary to determine the correspondence between range and color images in order to map color information on the 3D geometric model precisely.

For aligning a 3D model and a color image, Yoshida et al.[3] proposed an alignment technique by assigning several matching points between range and color images manually. Neugebauer et al.[4] proposed a similar technique that calculates suitable camera parameters according to the interactive selection of corresponding points between 3D range data and a 2D color image.

In contrast, techniques that align range and color images automatically have been developed by several researchers. Viola et al.[5] proposed a technique that utilizes statistical characteristics of both images. Stamos et al.[6] also proposed a method that extracts several planes from range data and edges in color images, and then calculates the intersection lines of the planes and the edges. Some approaches that compare a 2D image contour with a silhouette image of the 3D geometric model have been proposed. Iwakiri et al.[7] proposed a real-time texturing method that aligns the color image and the silhouette image of a 3D geometric model from a virtual camera. Lensch et al.[8] also proposed a silhouette-based algorithm that determines the camera transformation based on an XOR-operation between the silhouette image of a 3D model and the color image.

Registration techniques that exploit reflectance images have also been studied. The reflectance image, obtained by most laser scanners as a by-product of the range image, has a similar appearance to a color image. Therefore, some approaches make use of reflectance images for registration between a 2D image and a 3D geometric model for texture mapping. Boughorbal et al.[9] utilized the similarity between the reflectance image and the intensity image based on the $\chi^2$-metric. Umeda et al.[10] proposed a technique to determine relative relations between a range sensor and a color sensor based on the gradient constraint between reflectance and color images. On the other hand, local features in both images are effective to estimate the correspondence between reflectance and color images. Kurazume et al.[11] proposed a calibration method for texture mapping that minimizes the error between edges extracted from reflectance and color images by using the robust M-estimator. Boehm et al.[12] utilized the scale-invariant feature transform (SIFT) [13] to estimate extrinsic parameters by matching them in reflectance and color images. Inomata et al.[14] proposed a SIFT-based technique that calculates not only the extrinsic parameters but also the intrinsic parameter and distortion of the camera lens simultaneously. This method uses
Soft-matching that retains correct matches while removing false matches between reflectance and color images according to the similarity of the appearances based on Bhattacharyya distance.

All the methods mentioned above assume that color images which correspond to range images are captured. However, in some cases, it is difficult or almost impossible to provide color images perfectly, for example, in dark and wide areas. The proposed technique in this paper gives a solution for providing a colored 3D model even in these conditions.

3. Colorization for 3D Geometric Models with Reflectance Images

In this section, we show our algorithm for adding color information to 3D geometric models by applying the image colorization technique to reflectance images [1]. The basic idea behind the proposed technique is as follows. Since reflectance and range images are fundamentally and precisely aligned, we first colorize the reflectance image by using its similarity with a color image, then transfer the color to the 3D geometric model.

The proposed technique does not require precise calibration between the color and range images. Such calibration is required for conventional texture mapping. Thus, the gaps or discontinuities in appearance due to calibration errors can be avoided even if several images must be registered on a model. Moreover, the appearance of the entire surface of a model can be assigned from a partial view of the model if the appearance does not change significantly or have a repetitive pattern in the entire model.

In the following sections, we introduce the details of the proposed technique: characteristics of the reflectance image, assigning color seed points in the reflectance image based on a local similarity between the color and reflectance images, and colorizing the reflectance image based on the seed points.

3.1 Reflectance image

A time-of-flight range sensor, such as a laser scanner, obtains range data by measuring the round-trip time of a laser pulse reflected by an object. Fig. 1(a) shows an example of a range image acquired by a 3D laser scanner[15]. On the other hand, the most range sensors provide the strength of the reflected laser pulse (reflectivity). Fig. 1(b) shows a reflectance image that depicts reflectance values as a grayscale image. As mentioned above, an unique reflectance value is determined for each pixel in the range image. In other words, the range image and the reflectance image are fundamentally aligned.

3.2 Image colorization

Image colorization is a technique for adding color to a monochrome image and has been used in some specific applications, such as coloring monochrome movies or creating color-coded images for electron photomicrograph or X-ray imaging. Since adding color values to a monochrome image has no clearly defined procedure, the current approaches attempt to estimate all colors based on clues given as seed points manually[16][17][18] or automatically[19][20][21].

Yatziv et al.[17] proposed a fast image colorization technique using Dijkstra’s distance[22]. This technique estimates the color at each pixel in a grayscale image by calculating a weighted average of Dijkstra’s distances from each seed point which has chromatic information. Dijkstra’s distance is computed considering changes in luminance in the monochrome image. If the change in luminance from the seed point is small, the chromatic information at the seed point is mainly copied to the pixel. More precisely, if the color is described in YCbCr color space, the color of Y
Figure 1. Range and reflectance images

each monochrome pixel is estimated using Dijkstra’s distance as follows:

\[ c_i = \frac{\sum_{j \in \Omega} w(i, j) c_j}{\sum_{j \in \Omega} w(i, j)} \]  \hspace{1cm} (1)

\[ w(i, j) = r_{ij}^{-\alpha} \]  \hspace{1cm} (2)

\[ r_{ij} = \min \sum_{k=1}^{n-1} |Y_{p_{k+1}} - Y_{p_k}|_{p_{k+1} \in N(p_k), p_k = i, p_0 = j} \]  \hspace{1cm} (3)

Where, \( c_i \) is the estimated color value (CbCr) in pixel \( i \), \( \Omega \) is a set of seed points which have color information, \( r_{ij} \) is Dijkstra’s distance from pixel \( i \) to pixel \( j \), \( \alpha \) is a gain parameter that controls the effect of weighting function \( w(i, j) \) based on Dijkstra’s distance, and \( Y_{p_k} \) and \( N(p_k) \) are the intensity and the neighbor pixels of the pixel \( p_k \).

Equation (2) indicates that the seed point, which has a small Dijkstra’s distance to the target pixel, is preferentially selected to colorize the monochrome pixel in the grayscale image. In contrast, a seed point which has a Dijkstra’s path with large luminance change contributes little to the color estimation of the monochrome pixel.

### 3.3 Colorization of range image using reflectance image

Based on the image colorization technique described above, we propose a new colorization technique for a 3D geometric model utilizing a reflectance image and a color image. The basic idea of the proposed technique is as follows; since reflectance and range images are fundamentally and precisely aligned, we colorize the reflectance image using its similarity with a color image at first, then transfer the color to the range image. In the following sections, we introduce our techniques, which determines correspondences in reflectance and color images using HOG features[23].

#### 3.3.1 Assignment of seed points in a reflectance image

We colorize a reflectance image obtained by a laser scanner based on Yatziv’s method [17] shown in Section 3.2. To colorize it, we first assign seed points that have chromatic information in the reflectance image. We adopt the following two approaches for assigning seed points.
In the manual assignment, a 3D geometric model is colorized according to the human instruction. Several seed points are selected manually in the reflectance image, and color information in the color image is assigned to these seed points.

In order to assign color seed points automatically, Simple Linear Iterative Clustering (SLIC) [24] and Histograms of Oriented Gradients (HOG) features [23] are utilized. SLIC proposed by Achanta et al. [24] is a technique to divide an image into small segments with similar size called “superpixels”. Each segment extracted by SLIC holds pixels that have similar intensity or color. HOG is proposed by Dalal et al. [23] for pedestrian detection in camera images. HOG is able to describe local object appearances robustly according to the distribution of gradient orientation of the intensity.

First, we divide the reflectance and color images into small segments with SLIC, and then the local features are extracted by applying HOG to small regions around the segments (Fig. 2). Note that we apply Canny edge detection to the reflectance and color images to compare the outlines of objects for HOG feature extraction. Finally, based on the similarities of HOG features between the small regions in the reflectance and color images, the correspondences of the regions in both images are determined. Seed points in the reflectance image are chosen at the center of the segmented regions, and the chromatic information is copied from the center of the corresponding regions to the color image.

Here, in order to exclude mismatches between reflectance and color images as much as possible, we adopt 2-step corresponding determination technique: First, we find the most similar 5 corresponding points in a color image to each point in a reflectance image with a large HOG window to get global correspondence, and then select the suitable one from the 5 correspondences with a small HOG window which can describe the appearances in detail. Here, we consistently defined the window size as around 20% and 10% of input images for large and small HOG windows, respectively. We also eliminate correspondences whose feature similarities are too low.

3.3.2 Colorization of reflectance image using range image

Based on the color seed points given by the method described above, the reflectance image can be colorized with conventional colorization techniques used for monochrome images. These techniques are quite effective. However, it is sometimes difficult to colorize a reflectance image properly because the reflectance values indicate intensities on the surfaces of target objects under a single-frequency light source, and the object boundaries in the reflectance image are rather indistinct due to the lack of sufficient appearance information in comparison with the camera image.

In contrast, a range image includes the structural edges of target objects as jump edges that can be detected easily. Focusing on the fact that the range and reflectance images are precisely aligned, we can use the jump edges in the range image as additional edges for colorization of the reflectance image.
Consequently, we developed a new colorization technique extending Yatziv’s method [17] so that edges not only in the reflectance image but also in the range image are considered simultaneously for colorization of the reflectance image.

To take these edges in the range image into account, we define a new energy function using an exponential function instead of Eq. (3) as follows (See Appendix.A).

\[ r_{ij} = \min_{p_k} \sum_{k=1}^{n-1} |Y_{p_{k+1}} - Y_{p_k}| \left| e^{D_{p_{k+1}} - D_{p_k}} \right|_{p_{k+1} \in N(p_k), p_i = i, p_j = j} \]  

Where, \( D_{p_k} \) is an intensity value at pixel \( p_k \) in a range image. Dijkstra’s distance is computed by considering the changes in intensity in the monochrome reflectance image and the range image.

If no clear edge exists along the path from a seed point to a target pixel in both the reflectance and the range images, Dijkstra’s distance becomes small and the chromatic information at the seed point affects the color estimation of the target pixel significantly. In contrast, the seed point with large Dijkstra’s distance due to jump edges in the reflectance and/or the range image slightly influences the color estimation.

3.3.3 Proposed method

The proposed colorization techniques for a 3D geometric model are summarized as follows. Note that the YCbCr color space is used in this paper, however, the proposed technique works in other color spaces such as YUV or \( l\alpha\beta \).

Method 1: Manual assignment of seed points

(i) Acquire range and reflectance values and a color image by a laser scanner and a digital camera, respectively.
(ii) Create range and reflectance images in which gray values of each pixel are proportional to the measured range and reflectance values.
(iii) Assign seed points in the reflectance image manually according to the correspondence between the reflectance and the color images.
(iv) Apply the proposed colorization technique in Eqs. (1), (2), and (4) using range and reflectance images, and obtain a colorized reflectance image. Luminance \( Y \) in the colorized reflectance image is determined by a reflectance value.
(v) Transfer the color value of each pixel in the colorized reflectance image to the corresponding range image and construct a colorized 3D model from the range image.

Method 2: Automatic assignment of seed points

To assign seed points automatically, we roughly determine the correspondence between reflectance and color images using HOG features.

To do so, (iii) in the method 1 is replaced as follows.

(iii) Divide reflectance and color images in small segments using SLIC, and determine the correspondence between segments according to HOG features. Then, assign the color information to the center pixel of each segment in the reflectance image from the corresponding region in the color image.

4. Experiments

4.1 Experiments with LIDAR

This section introduces the results of the colorization experiments. Range and reflectance images are obtained by the 3D laser measurement robot[15]. This robot captures surrounding range and reflectance data by rotating the laser scanner (SICK, LMS151) on a rotary table. Color images are taken by a digital camera (Fujifilm, FinePix S7000) by hand. In the experiments, the parameter
α is set as $\alpha = 6$, and the number of superpixels is determined for each image experimentally so that we can get small super pixels enough to describe the appearance pattern on target objects in it. Range and reflectance images are quantized to 255 levels with the linear normalization (See Appendix.B).

Figure 3 shows three experimental conditions: a simple environment with two road cones of different colors (scene 1), a complex environment with a human and other objects (a table and chairs) (scene 2), and a house made of red bricks (scene 3). Figure 4 shows the range and reflectance images of these scenes captured by the measurement robot.

First, we assigned seed points to the reflectance images in Fig. 4(b) manually (Fig. 5) and automatically (Fig. 6). Note that only 10% correspondences are shown in Fig. 6 for visibility. Figures 5(a) and 6(b) show the seed points in the reflectance image in both methods. Colorized reflectance images are shown in Fig. 5(b) and Fig. 6(c), respectively. Figure 7(a) is the 3D mesh model constructed from the range image shown in Fig. 4(a). Figures 7(b)(c) show the 3D mesh model colorized by the method 1 (manual) and the method 2 (automatic), respectively. It is clear that the proposed methods successfully add color information to the surface of the 3D geometric models without accurate pose estimation.

Next, we carried out the experiments using a reflectance image and a color image taken in scene
2 (Fig. 3(b)). Similar to the experiments in the scene 1, we assigned seed points manually (Fig. 8) or automatically (Fig. 9). Figures 8(a) and 9(b) show assigned seed points in both methods. Colorized reflectance images are shown in Fig. 8(b) and Fig. 9(c), respectively. We also colorized Fig. 9(b) by applying Yatziv’s method[17] which doesn’t use range information, and the result is shown in Fig. 9(d). Figures 9(c)(d) show that the proposed methods successfully prevent these color seeds from spreading extremely by considering jump edges in a corresponding range image. The colorized 3D model for scene 2 is shown in Fig. 10. Figures 10(a)-(c) are the 3D mesh model constructed from the range image (Fig. 4(c)), the 3D mesh model colorized by the method 1.
From these results, we verified that the proposed methods are capable of creating colorized 3D geometric models in more complex scenes.

Finally, we carried out experiments in scene 3 (Fig. 3(c)). In this experiment, we colorized an entire 3D geometric model of a house made of red bricks with a partial view of the house shown in Fig. 3(c). The entire 3D geometric model is created from four range and reflectance...
images shown in Figs. 4(e)(f). Figure 11 shows colorized reflectance images using the method 1 manually, and the method 2 automatically. The colorization results of the 3D geometric model (Fig. 12(a)) in scene 3 are shown in Figs. 12(b)(c). Note that while the manual assignment can give color seed points to the regions which don’t appear in the picture if an operator assigns all the correspondences, the automatic assignment maps color seeds only to objects with similar appearances in the picture, for instance, a house and trees. This causes color-less regions in Fig. 11(c). To overcome this problem, we can use multiple pictures from different viewpoints and obtain additional color seed points by finding correspondences among reflectance images and the pictures. Figure 12(d) demonstrates the colorization result using three color images taken from different viewpoints with the proposed method 2, and you can see that the colorized regions increased. Consequently, we successfully colorized the entire geometric model using a partial view of the target house.

4.2 Quantitative evaluation

We demonstrate the validity of the proposed colorization technique for photo-realistic 3D modeling in comparison with texture mapping. In this experiment, range and reflectance images are acquired with the ShapeGrabber system (with scan head SG-100 on a PLM300 linear displacement mechanism) and FARO Focus3D (FARO) and as shown in Fig. 13 and Fig. 17, respectively. We first assign several color seed points manually with the human instruction (proposed method 1, Fig. 14(a) and Fig. 18(a)), and automatically according to the correspondence between the reflectance image and the color image with SLIC and HOG features (proposed method 2, Fig. 14(b)-(e) and Fig. 18(b)(c)). Second, colorization of the reflectance images is performed based on the color seed points. The colorization results are shown in Fig. 15(a)-(c) and Fig. 19(a)-(c). Finally, the color information in the colorized reflectance images is transferred to each corresponding 3D point (Fig. 16(a) and Fig. 20(a)), and the colorized 3D models are constructed as shown in Fig. 16(b)(c) and Fig. 20(b)-(d).

In an experiment with the cat model shown in Fig. 13, we colorized the entire model using the proposed methods. Note that we used only one texture image (Fig. 13(c)), and colorized
the back side of a target object by assigning seed points using a typical front side texture (Fig. 14(d)(e)). These experimental results show that the proposed methods successfully add color information to the surface of the 3D geometric models without accurate pose estimation from only a partial view of the target object.

In another experiment with the building model shown in Fig. 17, we demonstrate the validity of the proposed colorization method by comparing it with the Yatziv’s method. Fig. 19(a)(b) show the colorization results using the proposed method and the Yatziv’s method based on color seeds in Fig. 18(a). Since the proposed method can prevent color seeds from diffusing too much by detecting abrupt changes in geometry, the buildings are colorized appropriately based on the seed points even when reflectance values are quite similar between adjacent buildings. In contrast, the Yatziv’s method allowed some color seeds to spread excessively and gave the colors over the adjacent buildings (Fig. 19(b)). The proposed method also colorized most of the building facades correctly, but some parts were assigned inappropriate colors due to mismatches between the reflectance image and texture image. This experiment is rather challenging since these images were taken from distant viewpoints and their appearances are not similar in some regions. However, this result shows that we need to improve the performance of the automatic color seed assignment even more.

Additionally, we created/measured texture-mapped 3D geometric models (Fig. 16(d)[14] and Fig. 20(e)) to compare the performances between the proposed method and texture mapping. In the comparison of Fig. 16(b)(c) with Fig. 16(d), and Fig. 20(b)(c) with Fig. 20(e), the qualities of 3D models constructed by the proposed methods are as good as those of texture mapping. We also carried out quantitative evaluations of the proposed methods. In YCbCr color space normalized 0 to 255, the differences of color values in the colorized reflectance images and the texture images at each pixel are also calculated in Cb and Cr channels, and the root mean square (RMS) errors between the texture image (Fig. 16(d) and Fig. 20(e)) and colorized reflectance images (Fig. 16(b)(c) and Fig. 20(b)-(d)) are shown in Table 1. Note that YCbCr space represents color as brightness and two different color signals, and the RMS errors in Cb and Cr channels are affected slightly by the change of brightness, such as the cast shadow in Fig. 13(c). Since the RMS errors are within 3.12% and 5.35% of the color ranges of the texture images respectively, the proposed methods are as useful as conventional texture mapping techniques for creating photo-realistic 3D models.

5. Conclusion

In this paper, we proposed a new colorization technique for a 3D geometric model using the laser reflectivity. The proposed technique adds color information on the surface of a 3D geometric model by colorizing the reflectance image manually or automatically. Automatic colorization is easy but needs adequate correspondence between the reflectance and color images. In contrast, manual colorization gives a colored model even if the correspondence is slight between the images.

Precise calibration between color and range images is not required, even though it is indispensable for conventional texture mapping. Thus, gaps or discontinuities in appearance can be avoided even if several images must be registered on a model. Moreover, the appearance of the entire surface of a model can be assigned from a partial view of the model, if the appearance does not change significantly in the entire model.

In addition, we carried out a quantitative evaluation of the proposed colorization techniques in comparison with texture mapping to demonstrate their validities. The results show that the proposed techniques are able to create photo-realistic 3D models by colorizing reflectance images based on several color seed points, and the qualities of 3D models constructed by the proposed techniques are as good as those of texture mapping.
Acknowledgment

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Figure 12. Colorization of the entire 3D geometric model
Figure 13. Range, reflectance, and texture images of a target cat model

Figure 14. Seed point assignment to the cat model. (a) Seed points applied manually (Proposed method 1). (b) The correspondences between Fig. 13(b) and Fig. 13(c). (c) Seed points applied automatically based on the correspondences (Proposed method 2). (d) Seed point assignment for the back side using a typical front side texture. We can assign proper seed points even when the back side texture images are not available. (e) Seed points applied automatically using a typical pattern texture (Proposed method 2).

References


Figure 15. **Colorization results of the cat model.** (a), (b) and (c) are colorized reflectance images based on Fig. 14(a) (Proposed method 1) and Figs. 14(c) and (e) (Proposed method 2), respectively.


Figure 16. 3D models constructed by the proposed methods and texture mapping with the cat model.


Figure 17. Range, reflectance, and texture images of target buildings.

Figure 18. **Seed point assignment to the building model.** (a) Seed points applied manually (Proposed method 1). (b) The correspondences between Fig. 17(b) and Fig. 17(c). (c) Seed points applied automatically based on the correspondences (Proposed method 2).

Figure 19. **Colorization results of the building model.** (a),(b) Colorized reflectance image based on Fig. 18(a) with Proposed method 1 and Yatziv’s method respectively. (c) Colorized reflectance images based on Fig. 18(c) with Proposed method 2.
Figure 20. 3D models constructed by the proposed methods and texture mapping with the building model

Table 1. RMS errors in Cb and Cr color space

Cb and Cr ranges are 113-214 and 50-126 in Fig. 13(c), and 109-148 and 110-162 in Fig. 20(d). RMS errors between the texture images (Fig. 16(d) and Fig. 20(d)) and colorized reflectance images (Fig. 16(b)(c) and Fig. 19(a)-(c)) are computed by calculating the differences of color values in the texture images and colorized reflectance images at each pixel.

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<th>Back (Fig. 16(b): lower)</th>
<th>Front (Fig. 16(c): upper)</th>
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<td>2.16</td>
<td>2.28</td>
<td>2.26</td>
</tr>
<tr>
<td></td>
<td>2.74</td>
<td>2.46</td>
<td>2.15</td>
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<td></td>
<td>5.28%</td>
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<tr>
<td></td>
<td>5.27%</td>
<td>2.86%</td>
<td>2.50%</td>
<td>3.02%</td>
</tr>
</tbody>
</table>
Appendix A. Cost function for colorization

Color information from a seed point should be diffused within a single object, and should not be spread over different objects. To do so, we emphasize a gap in a depth image rather than a reflectance image and use an exponential cost function for a depth image. To demonstrate the validity of the exponential cost function, we also carried out an experiment with the cost function weighted by the difference of reflectance values instead of Equation (4). The formulation is as follows:

\[
    r_{ij} = \min \sum_{k=1}^{n-1} \left\{ \kappa |D_{p_k+1} - D_{p_k}| + 1 \right\} |Y_{p_k+1} - Y_{p_k}|
\]  

(A1)

Where, \( \kappa \) denotes a gain parameter to control the effect of the depth data for color estimation. You can see the colorization results using Yatziv’s method in Fig. 9(d), exponential weight in Fig. 9(c), and difference weight in Fig. A1. As shown in Fig. 9(d), Yatziv’s method which considers only reflectance data couldn’t prevent some color seeds from spreading too much, especially an abdominal region of the person sitting on a chair. We tried to colorize this region appropriately with Equation (A1) changing the parameter \( \kappa \) (Fig. A1(a) and (b)). When \( \kappa \) is small, the colorization result was almost the same as that of Yatziv’s method. On the other hand, although bigger \( \kappa \) enabled us to colorize the abdominal region appropriately, the cost term of depth data became more dominant than that of reflectance data and some color seeds diffused too much ignoring edges in a reflectance image. This can be seen in an left arm of the person on a chair. In contrast, the exponential cost function could successfully detect abrupt changes in geometry, which are object boundaries, and prevent undesirable color diffusions over different objects (Fig. 9(c)).

![Colorization result with small \( \kappa \) (\( \kappa = 1 \))](image1.png)  
(a) Colorization result with small \( \kappa \) (\( \kappa = 1 \))  
![Colorization result with large \( \kappa \) (\( \kappa = 100 \))](image2.png)  
(b) Colorization result with large \( \kappa \) (\( \kappa = 100 \))

Figure A1. Colorization with a cost function weighted by a difference of reflectance using Fig. 9(b)

Appendix B. HOG feature based on raw/normalized reflectance data

Although reflectance data is quantized to 256 levels, HOG feature still can be extracted stably. In order to extract HOG feature, the gradient orientation calculated at each pixel in an input image is discretized in large intervals, and the histogram at each cell is computed robustly by casting a weighted vote for the corresponding bin according to the gradient and strength of each pixel within the cell.

To demonstrate it, we extracted HOG features with 8 bins (45 degree/per a bin) and 8 × 8 cells from raw and normalized range images individually and compared the difference. As shown in Fig. B1, the extracted HOG features changed slightly.
Figure B1. **HOG extraction based on reflectance data in scene 1.** (a) and (b) visualize extracted HOG features from normalized and raw reflectance values, respectively.