Integrated Color Matching Using 3D-distance for Local Region Similarity

Ran Shu, Ho-Gun Ha, Dae-Chul Kim, and Yeong-Ho Ha
School of Electronics Engineering, Kyungpook National University, Daegu, South Korea

Abstract

Color consistency in stereoscopic content is important for 3D display systems. Even with stereo cameras of the same model and with the same hardware settings, complex color discrepancies occur when acquiring high quality stereo images. Global matching can reduce global color discrepancies, but it is not sufficient with local color discrepancies due to different objects having different reflections and imaging models where a more exhaustive and precise process is needed. Therefore, the local matching method is added for reducing local color discrepancies. In this paper, we propose an integrated color matching method that uses an estimated 3D-distance for the stage of local matching. The distance between the current pixel and the target local region is computed using depth information and the spatial distance in the 2D image plane. The 3D-distance is then used to determine the similarity between the current pixel and the target local region. The overall algorithm is as follows. First, the cumulative histogram matching is introduced for reducing global color discrepancies. Then, the proposed local color matching is established for reducing local discrepancies. Finally, a weight-based combination of global and local matching is computed. Experimental results show the proposed algorithm has improved global and local error correction performance for stereoscopic contents with respect to other approaches.

Introduction

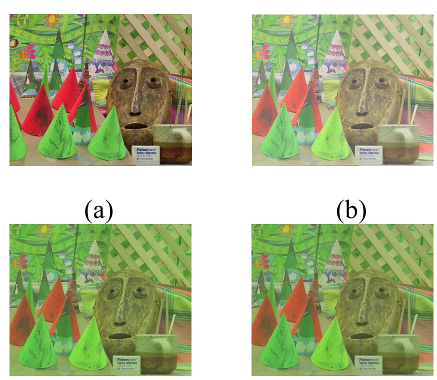
Movies and televisions with 3D technology can provide users with improved viewing experience over traditional 2D technology thanks to high interactivity and photorealistic image quality. Recent research on 3D visual systems, such as three dimensional television (3DTV)[1], and free viewpoint television (FTV)[2], these technology are emphasized to fulfill the demand of experiencing 3D perception than previous 2D video systems. In the current 3DTV system, synchronized left and right stereo images are presented respectively to two eyes for acquiring 3D scene. Therefore, the color consistency of stereoscopic images is important for perceiving 3D scene and reducing visual discrepancies.

Color discrepancies in stereoscopic images are introduced due to three different reasons. The first kind of discrepancy is introduced by using non-calibrated stereo cameras, and it can be recovered by calibrating camera to the same settings. Discordant radiometric characteristics of cameras also mainly induce global color discrepancies, and this global error can be recovered by global matching approaches. Finally, local errors are introduced by the different angle of incidence of light on each camera. However, global matching methods cannot recover this kind of error, because different objects have different reflections and imaging models, needing a more accurate correction method.

Many approaches have been proposed for color matching, mainly divided in global matching and local matching. Previous global matching approaches include those proposed by Chen using histogram matching[3], and Fecker derived a mapping function from the cumulated histograms of both images[4]. Also, Hwang used a key point detector[5] and Doutre proposed a block matching algorithm[6] for modeling transformation rules of color correction. Mantiuk suggested the use of adaptive tone mapping[7], Cherdhirunkorn proposed a multispectral imaging technique[8], and Reinhard used a general color transfer method[9]. These global matching does not search correspondences between image pairs, so their runtimes are very short. Yet, local color error is left untouched.

Local matching methods are tailored to reduce local color error. Wang assumed that every pixel in a region segmented by meanshift color segmentation[10] has the same color distortion characteristics. Therefore, one color transformation rule is presented for each corresponding segmented region. Yet, this assumption is not correct, because the objects in natural images mostly have different color distributions. Yu proposed a hybrid color matching method[11] which can correct some local errors and maintain the color distribution well, because the color transformation rule is different for each pixel and the color mapping functions for each pixel are based on the relationship with the target local region. This relationship is based on the color distance and the spatial distance between the current pixel and all the target local regions. Yet, the use of the spatial distance alone is not correct. The spatial distance can just measure the 2D-distance on the image plane, while different objects with short image plane distance may have very different depths, thus leading to a failure in discrimination. Fig. 1 shows this error.

Figure 1 shows the results of the histogram matching and the hybrid method. The histogram matching can correct the global



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

***Figure 1**. The local error is retained by uncorrected spatial distance. (a) the reference image, (b) the distorted image, (c) the Chen's histogram matching method, (d) the Yu's hybrid method.*

color discrepancies while local color discrepancies such as the mask and the green cone region are obviously untouched. The hybrid method can reduce the local color error in the mask region, but the local color error in the cone region is retained due to the failure of using the spatial distance for measuring the reality distance between the current pixel and sample features, because neighborhood regions of the cone is almost regions of mask or red cones, so the color correction on the cone is effected a lot by the color of mask or red cones and resulted color discrepancies in green cone region. Therefore, the proposed local color matching uses the 3D-distance measure for reducing the local color discrepancies.

In this paper, a local matching method based on 3D-distance is proposed for measuring region similarity. The used of a 3D-distance allows us to distinguish objects or regions with different depth and short spatial distance. The organization of the remainder of this paper is as follows. Firstly, Yu's hybrid method is introduced. Then, the proposed color matching is presented. Finally, experimental results are shown.

Previous color matching method

The same types of stereo cameras are well calibrated at first. Then, color discrepancies in stereo image can be categorized to global and the local color discrepancies. Therefore, Yu proposed a hybrid color matching method for reducing the global and the local discrepancies, simultaneously. Global color discrepancies are corrected by the modified histogram matching method, and local color discrepancies are reduced by a local matching method.

Global matching method

The chosen algorithm for the global matching is histogram matching and it tries to adapt the color distributions between stereo images. This method is only based on statistical distributions and does not use the spatial position information of pixels. Yu proposed a modified histogram matching method based on the luminance image. Then, histogram matching for each color channel is processed after luminance matching.

Local matching method

Global color discrepancies between stereo images can be corrected by global color matching method that images are treated as a whole process and corrected by finding a color transfer function or mapping table, but local color discrepancies are retained due to different objects or even same object may has the different reflection and imaging models, which puts requirements for a more deliberate correction. Therefore, different color correction functions are presented for pixels of different positions in the local region. In the previous method proposed by Yu, which correspondence points are firstly searched and filtered in order to determine color correspondence. In this method, it is important to store spatial position of each color correspondence, because a transformation rule for the current pixel is generated by using a weighting of spatial and color distance to color correspondences. In this paper, the proposed local matching method use two measures those called the 3D-distance and the color distance to find the target local region for correcting the current pixel. Figure 2 shows the concept of measures for controlling the effect of the color correction in the local matching. However, the current pixel is corrected by all color correspondences, but proper color correspondences those are nearby the current pixel may have the

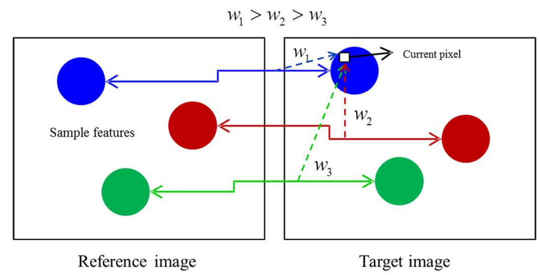


Figure 2. *The concept of measures for weighting color correction functions in local matching.*

same color correction function introduce the biggest effect to the current pixel, while the unrelated color correspondences introduce little or no effect to the current pixel. Therefore weighting functions for each pixel are $w_1, w_2, ..., w_k$ which is determined by the color and spatial distance to each color correspondence. Finally, local color discrepancies in the distorted image are corrected by the target local region, and the color distribution of local regions is retained by using different mapping functions for different pixels.

In the first step, SIFT is used for finding corresponding features in stereo images, and RANSAC(RANdom SAmple Consensus) is added to reduce the outliers of corresponding features[12]. Figure 3 shows the SIFT features in the reference and the target image, and the corresponding features after RANSAC

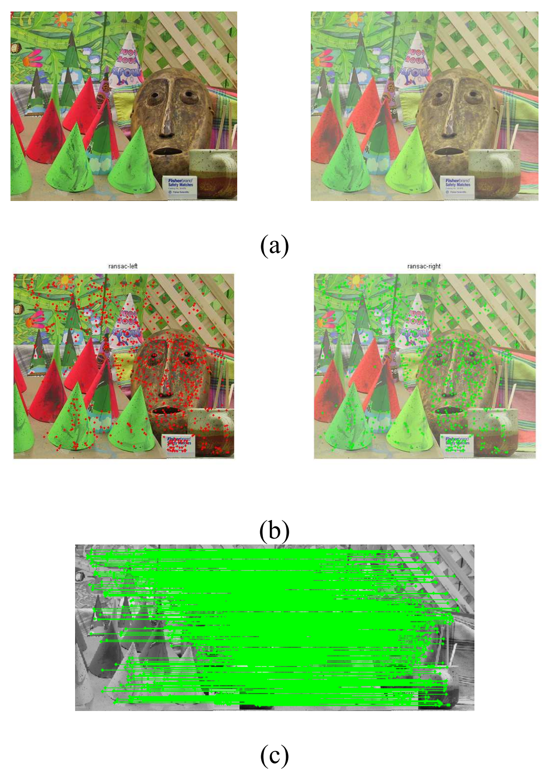


Figure 3. *The corresponding SIFT features between reference and distorted image are detected by SIFT. (a) Left is the reference image and the right is the distorted image, (b) detected corresponding features by SIFT method, (c) the corresponding features between stereo images.*

are also presented. But SIFT features are mainly dark corner points those are lack of the color information, therefore, sample feature stage is introduced. An initial SIFT feature is extracted and 8 neighboring candidate pixels are defined. Then, SND (Sum of Normalized Difference) between the left candidate temple and the right candidate temple is calculated, and the candidate temple is presented by the window centering at the candidate pixel. And the acquisition method of the sample feature which is selected from the candidate pixel. The SND of the *k*-th candidate feature is calculated at Eq. (1).

$$LUM_{(i,j)} = \frac{1}{3}\left(R_{(i,j)} + G_{(i,j)} + B_{(i,j)}\right)$$

$$m_{R,k} = \frac{1}{h \cdot w}\sum_{i=1}^{h}\sum_{j=1}^{w} LUM_{R,(i,j)}$$

$$m_{D,k} = \frac{1}{h \cdot w}\sum_{i=1}^{h}\sum_{j=1}^{w} LUM_{D,(i,j)}$$

$$SND_k = \frac{1}{h \cdot w}\sum_{i=1}^{h}\sum_{j=1}^{w}\left(\left|LUM_{R,(i,j)} - LUM_{D,(i,j)} - m_{R,k} + m_{D,k}\right|\right) \quad (1)$$

where k means the *k*-th corresponding feature. If the SND is lower than a threshold value, this *k*-th candidate feature is added to the sample feature set. Finally, a CD-LUT (Color Difference Look-up Table) is calculated which contains the color difference between each pair of sample feature and the color difference is calculated in XYZ color space.

The spatial distance and the color distance between the current pixel and the sample features are collected for weighting the CD-LUT. The previous method can introduce a local error if objects get a short spatial distance in the image plane, because the spatial distance cannot present the accurate information for determining the weighting function to the current pixel. Therefore, the proposed local matching method can distinguish objects with short spatial distance in the image plane. It is presented by using the 3D-distance which measures the reality distance between the current pixel and sample features. The 3D-distance is calculated using the spatial distance and the depth distance between the current pixel and the sample features. Figure 4 shows the situation of the failure local correction by the previous method, that there are two sample features with the short spatial distance to the current pixel. Therefore, the current pixel gets same weighting from them, which causes the failure local color correction. Figure 5 shows the flowchart of the proposed integrated color matching method.

Proposed integrated color matching

In this paper, the global matching is presented by a cumulative histogram matching method proposed by Fecker, that a more accurate result can be presented. Firstly, the stereo image

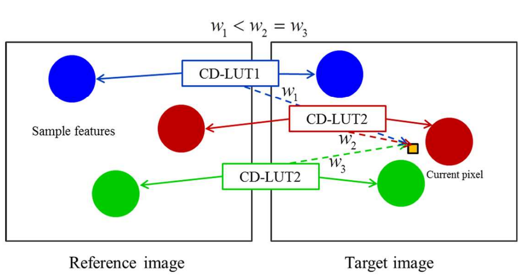


***Figure 4**. The situation of the failure local correction by the previous method.*

pairs have no rapid change on the chrominance and the luminance variation. Therefore, the cumulative histogram matching method can be used in stereo pairs. The histogram matching works on a stage of shifting the target histogram to the reference histogram. For this reason the characteristics of the reference histogram can be not modified. But the cumulative histogram matching proposed a method by deriving a mapping function from cumulative histograms of both images. Therefore, the characteristics of the reference histogram can be retained. Then the proposed local matching uses the 3D-distance for determining local region similarity is introduced as follows.

Extraction of roughly depth information

The depth distance between the current pixel and the sample feature is calculated for obtaining 3D-distance. Klaus presented a segment-based stereo matching method[13], and it can obtain a robust disparity plane. Firstly, this method utilized a mean-shift color segmentation method[14] on the reference image for extracting color homogenous regions. Then, reliable correspondences are calculated by a self-adapting dissimilarity measure which uses the local window-based matching method. Next, the corresponding disparity plane is derived by applying a novel robust plane fitting method and a consecutive refinement step. Finally, the disparity map is generated by approximating optimal disparity plane assignment. Figure 6 shows the resulting depth map, which the depth information of each pixel are used for 3D-disatance calculation.

Proposed 3D-distance calculation

3D-distance can be used as one measure to find the adjacent sample feature for correcting the current pixel. The spatial distance in the image plane can just present a distance which means the horizontal distance between two points in the image plane. Therefore, two objects with the short spatial-distance may carry a long 3D-distance. Figure 7 shows the ideal of the spatial-distance and the 3D-distance between two points. Then, the 3D-distance can be used for find the adjacent sample feature in the same object or region.

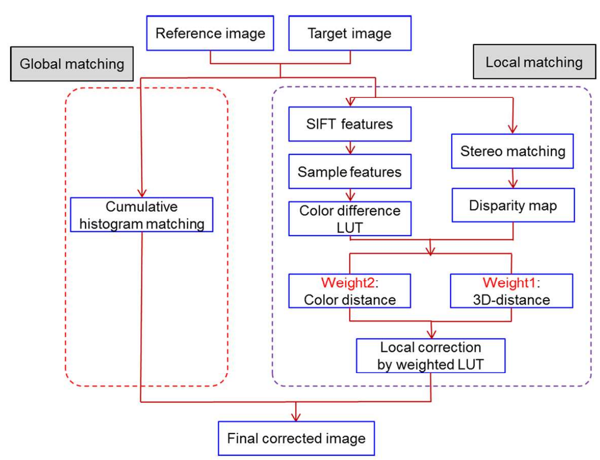


***Figure 5**. The flowchart of the proposed integrated color matching method.*

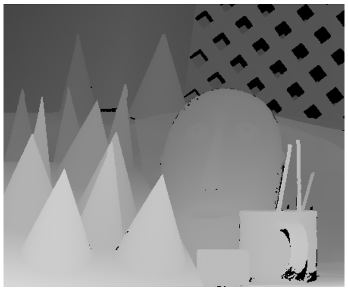


***Figure 6**. The depth disparity map(parameters setting in mean shift: h_r =7, h_s=10, M=30).*

Stereo images have the information of the depth for each pixel, and it can be used for calculating the 3D-distance between sample features and the current pixel. In other words, the current pixel can be corrected by the adjacent local region in the reference image. Therefore, the first measure for detecting the adjacent sample feature is the 3D-distance. The 3D-distance is calculated from the spatial distance in the image plane and the depth distance between two pixels. Because the spatial distance is orthogonal to the depth distance, the 3D-distance D_{3d} can be calculated by the Pythagoreans theorem as follows.

$$D_{3d} = \sqrt{D_{spatial}^2 + D_{depth}^2} \tag{2}$$

The spatial distance and the depth distance between current pixel and sample feature are calculated as follows:

$$\begin{aligned} D_{spatial} &= \frac{\sqrt{\left(i_{current} - i_{sample}\right)^2 + \left(j_{current} - j_{sample}\right)^2}}{T_{spatial}} \\ D_{depth} &= \frac{\left| dep_{\left(i_{current}, j_{current}\right)} - dep_{\left(i_{sample}, j_{sample}\right)} \right|}{T_{depth}} \end{aligned} \tag{3}$$

where $\left(i_{current}, j_{current}\right)$ is the current pixel, and $\left(i_{sample}, j_{sample}\right)$ is the sample feature, dep is the depth value, and $T_{spatial}, T_{depth}$ is the value for normalizing the spatial distance and the depth distance to 1.

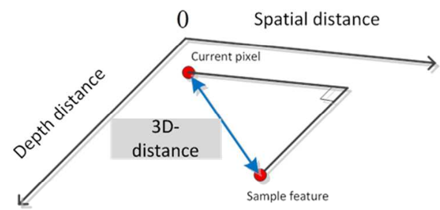
Local color correction by weighted CD-LUT

All pixels of distorted image are corrected by CD-LUT in the local matching step, and the local error can be reduced by the local matching. CD-LUT stands color differences between all sample feature pairs, but adjacent sample features and unrelated sample features give different effect for the current pixel. Therefore, two measures are considering for giving the different weight to different CD-LUT, which means CD-LUT of different sample features have different weight for correcting the current pixel. Two measures are the 3D-distance and the color distance between the current pixel and sample features. The weighting of the 3D-distance between two points which means the bigger weighting has the closer 3D-distance.

$$w_{(i,j),k,3d} = -\frac{\left(D_{(i,j),k,3d}\right)}{\max\left(D_{(i,j),k,3d}\right)} + 1 \tag{4}$$

where (i, j) is the current pixel, k denotes the k-th sample feature. The weighting of the color-distance is presented in L*a*b* color space as follows.

(a)



(b)

***Figure 7**. The definition of the 3D-distance is presented. (a) the spatial distance between the current pixel and the sample feature in image, (b) the definition of the 3D-distance.*

$$\begin{aligned} w_{(i,j),k,c} &= \begin{cases} -\dfrac{\sqrt{C_{(i,j),k,c}}}{threshold_c} + 1, & if\ C_{(i,j),k,c} \le threshold_c \\ 0, & otherwise \end{cases} \\ C_{(i,j),k,c} &= \left(x(i,j) - x(i_k, j_k)\right)^2 + \left(y(i,j) - y(i_k, j_k)\right)^2 \\ &\quad + \left(z(i,j) - z(i_k, j_k)\right)^2 \end{aligned} \tag{5}$$

In equation (5) $C_{(i,j),k,c}$ is the color distance between the current pixel and the k-th sample feature. $threshold_{3d}$ is the threshold for excluding the sample feature with big color difference to the current pixel. The final weighting of the k-th sample feature to the current pixel is presented and is normalized to make the sum of weightings be 1.

$$w_{(i,j),k} = \frac{w_{(i,j),k,3d} \cdot w_{(i,j),k,c}}{\sum_{p=1}^{U} w_{(i,j),p,3d} \cdot w_{(i,j),p,c}} \tag{6}$$

In equation (6), U is the total number of sample features. Finally, the local correction resulting for the current pixel is presented as follows.

$$f_{K,local}(i,j) = f_K(i,j) + \sum_{k=1}^{U}\left(w_{(i,j),k} \cdot D_k\right) \tag{7}$$

where the color difference D_k is calculated by the CD-LUT of the k-th sample feature.

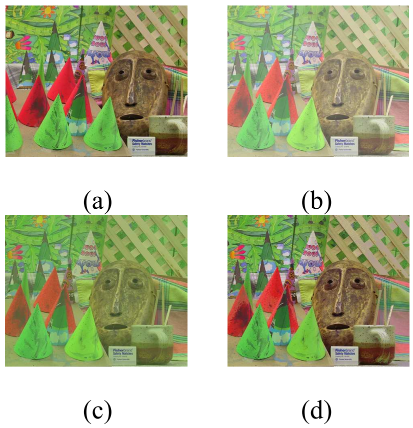


***Figure. 8**. The comparison of the previous hybrid method and the proposed method. (a) the reference image, (b) the distorted image, (c) the Yu's hybrid method, (d) the proposed method.*

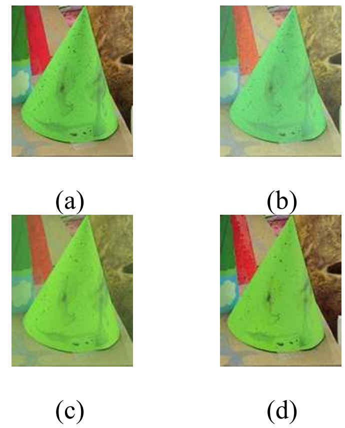


***Figure. 9**. Images are zoomed in for showing preference on the local regions. (a) the reference image zoomed in cone region, (b) the distorted image zoomed in cone region, (c) the Yu's hybrid method zoomed in cone region, (d) the proposed method zoomed in cone region.*

Combination of global and local matching

Final step is used for combination the effect of the global and local matching for each pixel in the distorted image. The global matching shows a fairly good result in reducing global color discrepancies, but the local region still retains local errors. As sample features are detected in the local region where get many feature information, such as face and so on. Therefore, local matching is used for reducing local color errors. Finally, corrected color is presented by a weight-based combination of the global and the local matching.

$$
\begin{aligned}
f_{K,local}(i,j) &= a \cdot w_{(i,j),\max} f_{K,local}(i,j) \\
&\quad + \left(1 - a \cdot w_{(i,j),\max}\right) f_{K,global}(i,j) \\
w_{(i,j),\max} &= \max\left(w_{(i,j),k,3d} \cdot w_{(i,j),k,c}\right) \\
a &= \begin{cases} -0.3, & \text{if } w_{(i,j),\max} \geq 0.95 \\ -0.1, & \text{otherwise} \end{cases}
\end{aligned}
\tag{8}
$$

where a is a scale factor which can control the effect of the local matching.

Experimental results

The evaluation of the proposed method is performed on 3 pairs stereo images, the global and the local discrepancies are added to 3 pairs of stereo images from the Middlebury stereo datasets[15] by Photoshop software. Those stereo images were captured by a well calibration stereo camera system. The proposed method shows the good performance on the correction of the global and local color discrepancies and it is compared to the previous hybrid color matching method. Figure 8 and 9 shows the resulting of the proposed method and the previous hybrid method. The local error such as the mask and the green cone can be found after the global matching, and the Yu's hybrid color matching method reduce the local color error on the mask region, but the cone is not corrected well. Finally, the color distribution of the cone is matched to the reference very similar. Figure 9 shows zoomed in results, we can see the color correction of the cone by proposed method is more similar to the reference image, and the global tone is closer to the reference image, and we measures the similarity of hue histograms[16] for evaluating the color correction performance. Table 1 shows the performance of the similarity of 3 pairs stereo images. Preference test of 3D images was also conducted. 5 levels of rating scale were provided to the 8 participants. Then, mean opinion scores (MOSs) were computed based on the ratings. The results are shown in table 2. The scores of the proposed method were generally higher than other methods

Table 1. Hue similarity of result images by various color matching methods.

	Histogram	Cumulative histogram	Hybrid matching	Proposed method
Dolls	0.5014	0.5217	0.4754	0.5431
Cones	0.2687	0.5969	0.3129	0.6193
Moebius	0.2582	0.5775	0.4286	0.6124

Table 2. MOSs of resulting images.

	Histogram	Cumulative histogram	Hybrid matching	Proposed method
Dolls	2.125	3.125	3.000	3.500
Cones	2.375	3. 250	2.750	3.500
Moebius	2.375	3.125	3.000	3.625

Conclusion and discussion

In this paper, we presented an integrated color matching based on a 3D-distance. The proposed method presents satisfying color matching results by combining global and the local matching. The algorithm first performs global matching by cumulative histogram matching. Then, local matching is performed by a pixel-wise correction method considering the CD-LUT of all sample features where the 3D-distance and the color distance are used for weighting the CD-LUT of each sample feature. Experimental results show that the proposed method has improved performance compared to previous approaches.

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Author Biography

Ran Shu received his B.S. degree in Information and Communication Engineering from Dongyang University, Yeongju, Korea, in 2011. Now he is M.S. candidate in Kyungpook National University. His research interests include image quality evaluation, color image enhancement.

Ho-Gun Ha received the B.S. and M.S. degrees in Electrical Engineering and Computer Science from Kyungpook National University, Daegu, Korea, in 2007 and 2009, respectively, where he has been pursuing the Ph.D. degree in the Color and Imaging Laboratory. His current research interests include image registration image compression, and color image processing.

Dae-Chul Kim B. S. and M. S. degrees in Electronic Engineering from Kyungpook National University, Daegu, Korea, in 2007 and 2010, respectively, and now is Ph. D. degree student in Electronic Engineering from Kyungpook National University. His main research interests are in color image processing and image processing.

Yeong-Ho Ha received the B. S. and M. S. degrees in Electronic Engineering from Kyungpook National University, Taegu, Korea, in 1976 and 1978, respectively, and Ph. D. degree in Electrical and Computer Engineering from the University of Texas at Austin, Texas, 1985. In March 1986, he joined the Department of Electronics Engineering of Kyungpook National University and is currently a professor. He served as TPC chair, committee member, and organizing committee chair of many international conferences held in IEEE, SPIE, and IS&T and domestic conferences. He served as president and vice president in Korea Society for Imaging Science and Technology (KSIST), and vice president of the Institute of Electronics Engineering of Korea (IEEK). He has been an IEEE member since 1986 and is now senior member of IEEE, a member of Pattern Recognition, and fellows of IS&T and SPIE. His main research interests are in color image processing, computer vision, and digital signal and image processing.