Journal of Imaging Science and Technology® 56(3): 030502-1–030502-7, 2012.

Color Image Quantization for Reduction of Quantization Contours and Preservation of Perceptually Sensitive Colors

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Abstract. *The conventional methods for color image quantization are aimed at obtaining the resulting image with a minimum mean squared error (MSE). Yet human perceptual satisfaction is not always related to the MSE. This article presents a color quantization method that uses a lightness enhancement factor for better representation of the gradation and a perceptual threshold for preservation of perceptually sensitive colors in the CIELUV color space. The experimental results show that the proposed method provides better visual quality when representing the gradation and better preserves the perceptually sensitive colors compared to the conventional methods even if the MSE of the proposed method is slightly higher than those of the conventional methods.* © *2012 Society for Imaging Science and Technology.*
[DOI: 10.2352/J.ImagingSci.Technol.2012.56.3.030502]

INTRODUCTION

Color image quantization is widely used in various applications, such as image compression,[1] image analysis,[2] image segmentation,[3] content-based image retrieval,[4] and image watermarking,[5] since large images are inefficient for transmission and storage. Color quantization methods can be broadly classified into uniform quantization and adaptive quantization.[6] Most of the algorithms in recent studies use adaptive quantization methods, because they lead to better results than those found for uniform quantization. Well-known adaptive quantization methods include median cut (MC),[7] variance based,[8] center cut,[9] octree,[10] principal analysis algorithm,[11] and Kekre's fast codebook generation (KFCG).[12,13] These methods start with a single cluster, which is recursively subdivided until the desired number of clusters is obtained. The algorithms are relatively simple and their execution times are fast, but most of them suffer from relatively high color distortion. Other methods use fuzzy C-means,[14] K-means,[15,16] competitive learning,[17,18] the Kohonen Self-Organized Feature Map neural network,[19] and self-information,[20] which are used to minimize color distortion. These methods show less color distortion, but have relatively high computational complexity as well as initialization issues. Yoon and Kweon proposed a quantization method based on human perception in order to obtain the optimal color pallet.[21] Their method results in good visual quality at the cost of high computational complexity.

When an image is quantized using the conventional methods, the unwanted contours in a quantized image often occur at the gradation areas where the lightness variation is usually larger than the chromaticity variation.[6] These visually annoying contours are called quantization contours and form visible edges that are absent from the original image. A feedback-based approach exists, which repeatedly performs re-quantization of the original image until the quantization contours are removed.[22] However, it is a very time-consuming process. The human visual system (HVS) is generally more sensitive to lightness than chromaticity.[23] The reason for this is associated with the characteristics of the retina.[24] The retina consists of rod and cone cells, which distinguish lightness and chromaticity respectively. We propose a lightness enhancement factor that puts more weight on the lightness than the chromaticity. Unfortunately, the RGB color space, in which most of the conventional methods operate, cannot be easily adapted to the HVS properties because it does not express colors as a combination of lightness and chromaticity. On the other hand, the CIELUV color space provides such a separation and allows us to perform a color quantization that separately considers the differences in lightness and chromaticity. The HVS is very sensitive to a color that is significantly different from the surrounding colors even if it occupies a relatively small region in an image. However, this property may be ignored by a quantization method aiming at minimum mean squared error (MSE). We also propose a perceptual threshold in order to prevent perceptually sensitive colors from being merged during the early stages of quantization. This article presents a new color quantization method based on a lightness enhancement factor for reducing the quantization contours and a perceptual threshold to preserve distinctive colors in the CIELUV color space.

PROPOSED METHOD

The proposed method is performed in the CIELUV color space.[25] This space is useful in providing perceptual uniformity. In order to obtain the CIELUV color space representation, the RGB values of an input image are transformed into the CIELUV color space by using the RGB primaries and the D65 standard white reference.[25] The CIELUV color

Received Jun. 2, 2011; accepted for publication Jun. 4, 2012; published online Oct. 22, 2012.
1062-3701/2012/56(3)/030502/07/$20.00

space has L^*, u^*, and v^* components. The L^* component is the lightness scaled from black to white. The u^* and v^* components are the coordinates for the red–green and yellow–blue channels, respectively. Unlike the RGB color space, each axis of the CIELUV color space has different expression ranges. The L^* component ranges from 0 to 100 with a width W_{L^*} (=101). The u^* component ranges from −134 to 220 with a width W_{u^*} (=355), whereas the v^* component ranges from −140 to 122 with a width W_{v^*} (=263).

The color difference between two colors in the CIELUV color space is calculated using the Euclidean distance

$$\Delta E^*_{uv} = [(\Delta L^*)^2 + (\Delta u^*)^2 + (\Delta v^*)^2]^{1/2}, \tag{1}$$

where ΔL^*, Δu^*, and Δv^* represent the difference between two colors in the L^*-axis, u^*-axis, and v^*-axis, respectively.

The Adaptive Uniform Quantization Based on Color Distribution

The main idea of our quantization method is based on a merging algorithm which reduces the number of cells until the number of cells contained in the original image reaches the quantization level. If we perform the merging algorithm without any preprocessing, it tends to result in high computational complexity and long execution time, since the CIELUV color space is divided into $W_{L^*} \times W_{u^*} \times W_{v^*}$ ($\fallingdotseq 9.43 \times 10^6$) cells. We introduce a preprocessing step that properly reduces the large number of cells before applying the merging algorithm. The uniform quantization method can be used for this preprocessing step,[6] but its results are not satisfactory because the histogram distribution is not considered. In this article, an adaptive uniform quantization method is proposed that considers the histogram distribution. We analyze the distribution of the histogram for L^*, u^*, and v^* components to normalize the number of divisions of the three components to 101. Inspired by the HVS,[23,24] we reduce the number of divisions in the u^* and v^* components, which in effect results in a finer division of the cells in the lightness axis compared to the chromaticity axes. Once the histogram of each component is divided by the number of each division, we can define the cells in the CIELUV color space with their representative values as the average values of the pixels contained in each cell. The method used to obtain the resultant cells using the adaptive uniform quantization is summarized as follows.

(1) From the given input image, calculate the range (width) of colors in each of the three axes from their corresponding histogram: $W^i_{L^*}$, $W^i_{u^*}$, and $W^i_{v^*}$.

(2) Obtain the normalized widths:

$$\begin{aligned} W^n_{L^*} &= W^i_{L^*}, \\ W^n_{u^*} &= W_{L^*} \times (W^i_{u^*}/W_{u^*}), \\ W^n_{v^*} &= W_{L^*} \times (W^i_{v^*}/W_{v^*}). \end{aligned} \tag{2}$$

(3) Calculate the initial numbers of cells for the adaptive uniform quantization: N_{L^*}, N_{u^*}, and N_{v^*},

$$\begin{aligned} N_{L^*} &= W^n_{L^*}, \\ N_{u^*} &= \alpha \times W^n_{u^*}, \\ N_{v^*} &= \alpha \times W^n_{v^*}. \end{aligned} \tag{3}$$

Note that $W^n_{u^*}$ and $W^n_{v^*}$ range from 0 to 100 and α ranges from 0 to 1. The number α is a parameter used to adjust the number of divisions in the u^* and v^* components. If the α value increases, the number of divisions in the u^* and v^* components increases. The value of α was set to 0.5 by trial and error; this value reduces the effects of the u^* and v^* components as they are compared to the L^* component. In this article, we use $N_{L^*} = 101$, $N_{u^*} = 51$, and $N_{v^*} = 51$. The total number of resultant cells (N_C) is about $N_{L^*} \times N_{u^*} \times N_{v^*}$ ($\fallingdotseq 2.6 \times 10^5$). Among these resultant cells, after quantization, cells with no or few pixels can exist. If a representative color value is assigned to this type of cell during quantization, the quantization error of an image can increase because another cell with a larger number of pixels may not have a chance to be selected as the representative color. Since the HVS performs an averaging operation within a small neighborhood,[21] an area with a small number of pixels does not affect overall image quality. We call a cell with no or few pixels that satisfies the condition

$$\frac{n(C_i)}{\sum_{i=1}^{N_C} n(C_i)} < N_{Th} \tag{4}$$

a noise cell, where $n(C_i)$ is the number of pixels in the cell C_i, N_C is the number of cells, and N_{Th} is an experimentally determined threshold. In this article, N_{Th} is set to 0.001, which corresponds to 0.1% of the total number of pixels in the image. If a cell is determined to be a noise cell, it is then merged with the neighboring cell with which it has the smallest color difference.

The Quantization Algorithm

After the adaptive uniform quantization is complete, we need to effectively reduce the number of cells until the initially set quantization level is reached. We can use the merging algorithm for this purpose. A basic merging algorithm consists of the following steps.

(1) Select the C-cell which is a cell that has the lowest number of pixels.
(2) Select the S-cell that has the smallest color difference from the C-cell.
(3) After merging the C-cell and the S-cell, calculate the new representative color value using the weighted average of the two cells.
(4) If the resulting number of the cells is the same as the quantization level, the algorithm terminates, otherwise repeat steps (1)–(4).

The color difference formula and the merging condition have significant influence on the results of the color quantization. In this article, we propose a new merging method by introducing a lightness enhancement factor for better representation of the gradation and a perceptual threshold for preservation of the perceptually sensitive colors.

The Weighted Color Difference Formula

The HVS properties for computer vision applications have been extensively researched. It is well known that the HVS is more sensitive to lightness than to chromaticity. Color television systems use the 4:1:1 sampling ratio, which is the ratio of the luminance signal sampling rate to the color difference signal sampling rates.[25] This attribute is employed when we calculate the color difference between two different colors, i.e.

$$(\Delta E^*_{uv})' = [(\Delta L^*)^2 + \beta^2((\Delta u^*)^2 + (\Delta v^*)^2)]^{1/2}, \quad (5)$$

where β is the lightness enhancement factor experimentally set to 0.3. When calculating the color difference, β determines which factor is more important, the lightness difference or the chromaticity difference. If the β value decreases, we give more weight to the lightness difference, which means that the quantization algorithm is more sensitive to a change in lightness. Otherwise, the opposite occurs. We determined the β value by trial and error. The results seem to concur with that of the sampling rate ratio for the television system mentioned above.

The quantization results using the new color difference formula with the lightness enhancement factor β are shown in Figure 1. The 128 color quantization result using Eq. (1) is shown in Fig. 1(b). We can see that there are quantization contours in the background. When we use the lightness enhancement factor, the background becomes smoother, as shown in Fig. 1(c), and is very similar to the original image shown in Fig. 1(a). The next issue is to find a method to preserve the visually sensitive colors, which correspond to the yellow disc seen in the middle of the flower in this image.

The Merging Algorithm Using a Perceptual Threshold

In order to preserve perceptually sensitive colors, we introduced a perceptual threshold to the merging algorithm. The HVS is very sensitive to a color that is significantly different from its surrounding colors, even if it occupies a relatively small region in an image. An experiment to distinguish the color difference in the perceptually uniform CIELUV color space has been performed and reported in Ref. 25. It was found that when the color difference is less than 1, it is barely perceptible. When the color difference is greater than 4, it is likely to be perceptible. The remaining color differences whose values are between 1 and 4 may or may not be perceptible. Accordingly, we applied the perceptual threshold P_{Th} to the merging algorithm in order to reflect these properties. If the color difference between the C-cell and the S-cell is less than P_{Th}, they merge with each other, otherwise the C-cell is selected as the final cell. Although the initial value of P_{Th} is set to 4, P_{Th} is adaptively increased depending on the quantization level. If the number of final cells is greater than the quantization level, P_{Th} is incremented by one each iteration until some of the selected final cells are freed for another merging. The pseudocode for this procedure is given in Algorithm 1.

Input: The cells remaining after implementation of the adaptive uniform quantization ($N_{L^*} \times N_{u^*} \times N_{v^*}$ cells)
Output: The cells according to the quantization level
Initialize perceptual threshold P_{Th} to 4 and the number of final_cell N_{final_cell} to 0
WHILE (The number of the cells != Quantization level) **THEN**
  IF (The color difference between C-cell and S-cell $< P_{Th}$) **THEN**
    Merge C-cell and S-cell
  ELSE
    IF ($N_{final\_cell} <$ Quantization level) **THEN**
      Assign C-cell as final_cell
      Add one to N_{final_cell}
      $N_{final\_cell} = N_{final\_cell} + 1$
    ELSE
      Add one to P_{Th}
      $P_{Th} = P_{Th} + 1$
      Remove all final_cell and set N_{final_cell} to 0
      $N_{final\_cell} = 0$
    END IF
  END IF
ENDWHILE

Algorithm 1: The Merging algorithm.

The proposed method combines the adaptive uniform quantization method, the weighted color difference formula, and a perceptual threshold adjusted merging algorithm. The resulting image from the proposed method is shown in Fig. 1(d). The gradation of the background is still smooth and the yellow disc in the flower is quite vivid. The resulting 128 color image looks similar to the original image when observed on a monitor.

EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the proposed method has been evaluated and compared to that of conventional methods with respect to a database consisting of 30 color images gathered from the Internet. Ten of the sample images in the database are shown in Figure 2. For a comparative study, we used two median cut (MC) based methods[7] on the RGB and CIELUV color spaces, abbreviated to MC (RGB) and MC (CIELUV), respectively, and an octree method.[10] The last comparative method used was KFCG,[12,13] which operates on the RGB color space. The MSE is commonly used to measure the effectiveness of a quantization method and is defined as[18]

$$\mathrm{MSE} = \frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W}\left\| I(h,w) - \hat{I}(h,w)\right\|^2, \quad (6)$$

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

Figure 1. 128 color quantization results: (a) original image, (b) CIELUV color difference formula, (c) weighted CIELUV color difference formula, and (d) proposed method.

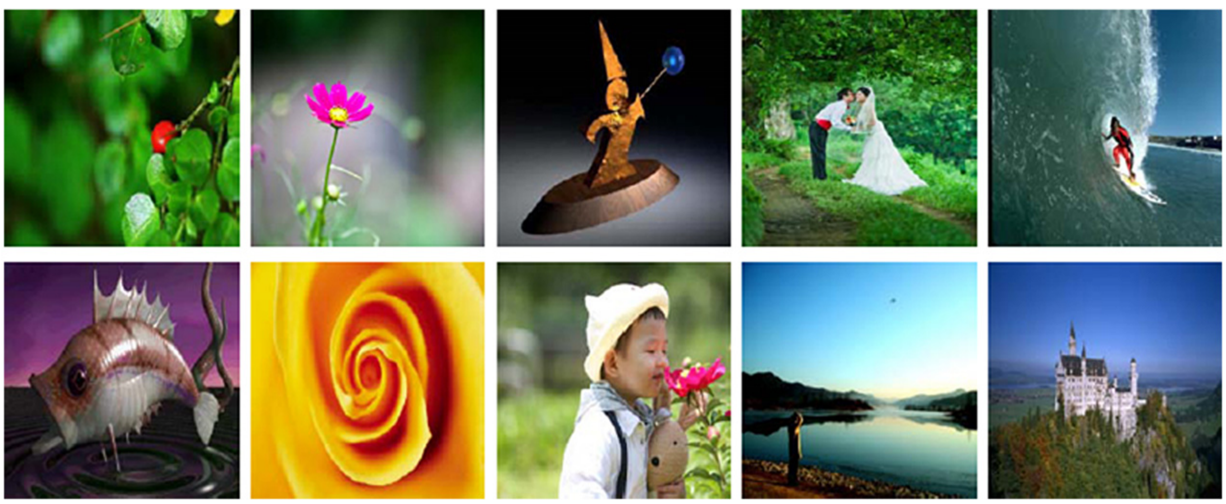

Figure 2. Sample examples of database images.

where I and $\hat{I}$ denote the original and quantized images with height H and width W, respectively. The MSE is usually calculated in the RGB color space.

For performance evaluation, each image in the database was quantized to 64, 128, 256, and 512 colors. The results of their MSEs are shown in the four graphs in Figure 3; their MSE averages and standard deviations are summarized in Tables I and II, respectively. In Fig. 3 and Table I, the KFCG has the lowest MSE value and the proposed method was in third place. It is expected in advance that the proposed method has some inherent limits in minimizing MSE, since the algorithm uses more representative colors values to represent a graded region more smoothly and to capture the small sensitive colors if they exist. In these cases, the proposed method uses a smaller number of colors to represent the remaining part of the image when compared to

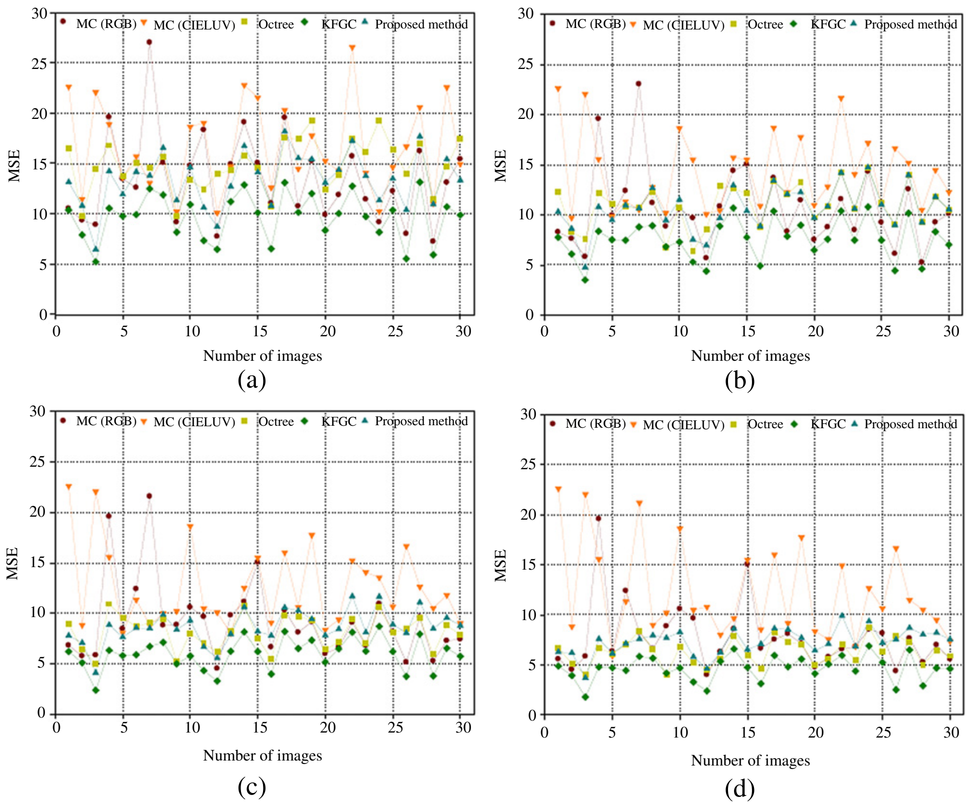

Figure 3. MSE comparison of database images: (a) 64 color quantization results, (b) 128 color quantization results, (c) 256 color quantization results, and (d) 512 color quantization results.

Table I. Average MSEs for various quantization levels.

Level	Quantization method				
	MC (RGB)	MC (CIELUV)	Octree	KFCG	Proposed method
512	7.73	12.26	6.27	**4.62**	7.26
256	8.75	13.03	8.14	**5.95**	8.63
128	10.2	14.66	10.84	**7.52**	10.63
64	13.24	17.4	14.85	**9.82**	13.59

Table II. Standard deviation of MSEs for various quantization levels.

Level	Quantization method				
	MC (RGB)	MC (CIELUV)	Octree	KFCG	Proposed method
512	2.66	4.42	1.24	1.21	**1.12**
256	2.71	4.02	1.64	**1.41**	1.45
128	3.01	3.96	2.41	**1.90**	1.97
64	3.57	4.56	2.32	**2.31**	2.65

other methods, which therefore leads to a potential increase in MSE. Table II shows that the standard deviation of the proposed method is similar to that of the KFCG and less than those of the other methods.

However, a smaller MSE in a quantized image does not guarantee better visual quality. The MSE alone is not sufficient to reflect the quantization contour, which can be quite irritating to human observers, or to assess any visual quality degradation from the color quantization. To assess the perceived quality of the quantized image, we used KFCG and the proposed method to produce flower and island 64 color images. The KFCG method was chosen

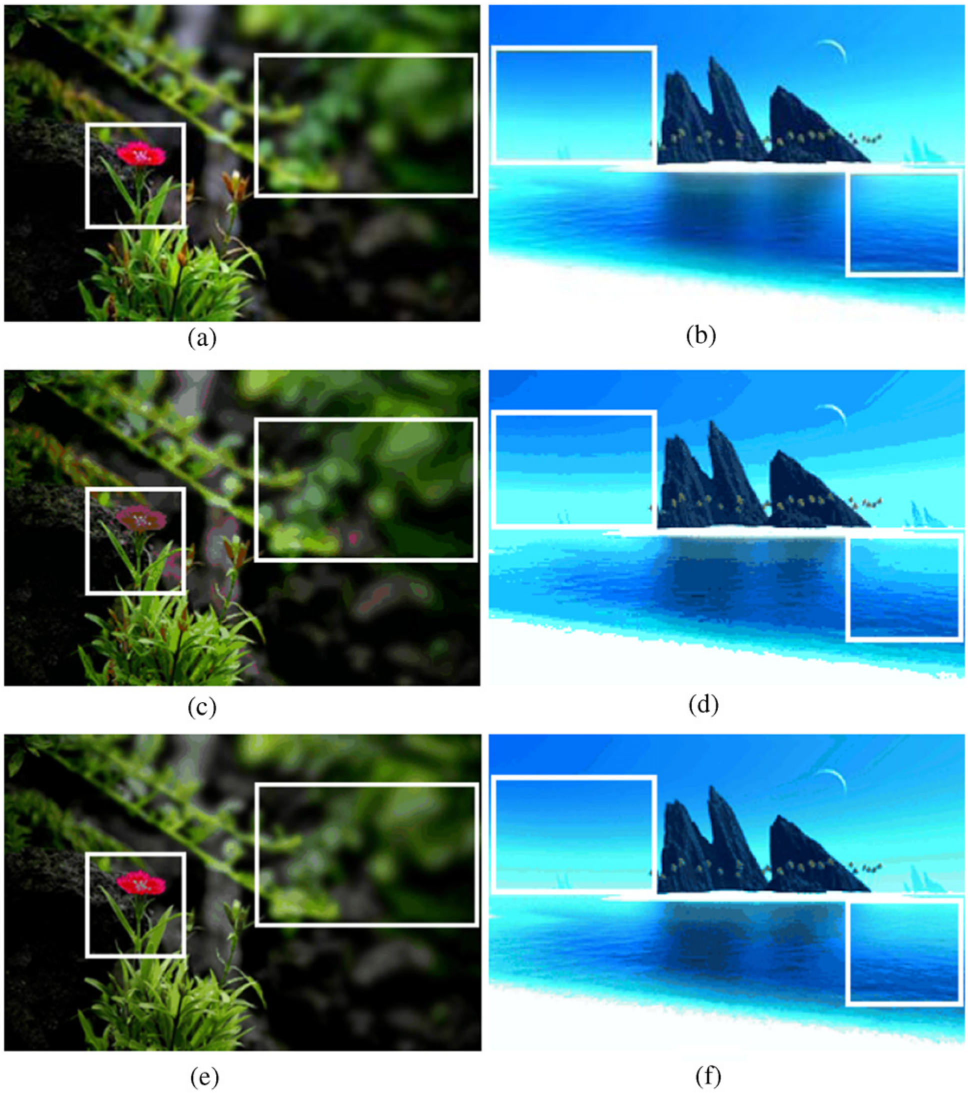

Figure 4. 64 color quantization results: (a) and (b) are original images, (c) and (d) are KFCG quantized images, and (e) and (f) are quantized images from the proposed method.

because it shows the best MSE performance and its visual qualities are better than the octree method and the two MC methods when visual tests on the quantized images are performed. The quantization results of the two methods are shown in Figure 4. In order to provide a better analysis regarding the visual contents of the quantized images, the rectangular parts of each image were enlarged and are shown in Figure 5. The KFCG quantized image shows visible contours on the background gradations and the red flower is not well represented in Figs. 4(c) and 5(c). When compared to the KFCG results, as can be seen in Figs. 4(e) and 5(e), the quantized images from the proposed method show a smoother background without visible contours and the color details of the red flower are well preserved. For the island shown in Figs. 4(d) and 5(d), the KFCG results do not appear to be natural due to the quantization contours. On the other hand, the image quality of the quantized images from the proposed method is quite good even with only 64-level quantization, as seen in Figs. 4(f) and 5(f). As discussed above, the lightness enhancement can lead to a smoother background. At the same time, the use of the perceptual threshold can preserve distinctive colors and prevent them from being merged.

CONCLUSIONS

We proposed a color image quantization method in the CIELUV color space. The method consists of a modified merging algorithm using a lightness enhancement factor weighted color difference formula to emphasize lightness as compared to chromaticity and a perceptual threshold for preservation of the perceptually sensitive colors occupying relatively small regions. Experimental results confirmed that the MSE may not be the best criterion to evaluate quantized results. The proposed method can obtain more satisfactory results in terms of the visual quality of an image, even with its slightly higher MSE.

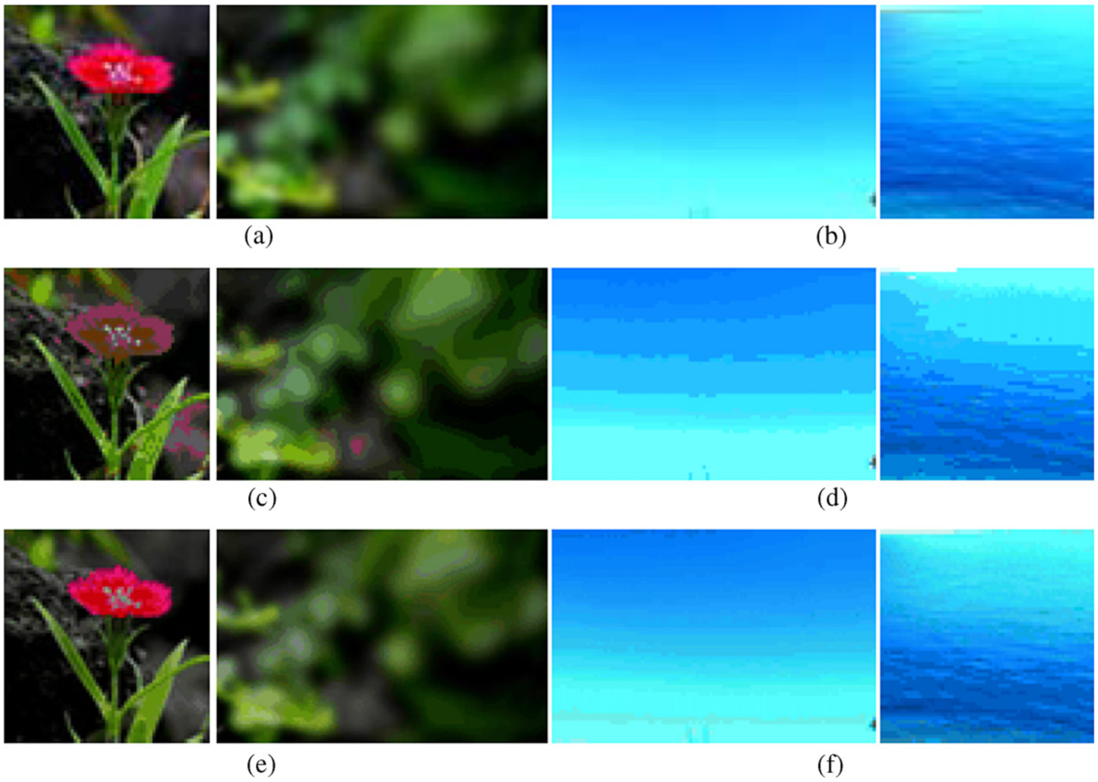

Figure 5. Enlarged images from Fig. 4: (a) and (b) are original images, (c) and (d) are those obtained using the KFCG method, and (e) and (f) are from the proposed method.

REFERENCES

[1] Y. Murakami, H. Manabe, T. Obi, M. Yamaguchi, and N. Ohyama, "Adaptive quantization in multispectral image compression for equalizing visual error distribution," J. Imaging Sci. Technol. **46**, 507–512 (2002).

[2] H. S. Wu, R. A. King, J. Barba, and J. Gil, "DCT basis decomposition coding of biomedical X-ray images using vector quantization," J. Imaging Sci. Technol. **41**, 158–165 (1997).

[3] H. B. Kekre, T. K. Sarode, and B. Raul, "Color image segmentation using Kekre's algorithm for vector quantization," Int. J. Comput. Sci. **3**, 287–292 (2008).

[4] E. L. van den Broek, P. M. F. Kisters, and L. G. Vuurpijl, "Content-based image retrieval benchmarking: utilizing color categories and color distributions," J. Imaging Sci. Technol. **49**, 293–301 (2005).

[5] P. Tsai, Y. C. Hu, and C. C. Chang, "A color image watermarking scheme based on color quantization," Signal Process. **84**, 95–106 (2004).

[6] L. Velho, A. C. Frery, and J. Gomes, *Image Processing for Computer Graphics and Vision*, 2nd ed. (Springer Verlag, Berlin, 2008).

[7] P. Heckbert, "Color image quantization for frame buffer display," Comput. Graph. **16**, 297–307 (1982).

[8] S. Wan, P. Prusinkiewicz, and S. Wong, "Variance-based color image quantization for frame buffer display," Color Res. Appl. **15**, 52–58 (1990).

[9] G. Joy and Z. Xiang, "Center-cut for color image quantization," Vis. Comput. **10**, 62–66 (1993).

[10] M. Gervautz and W. Purgathofer, *A Simple Method for Color Quantization: Octree Quantization in Graphic Gems* (Academic, New York, NY, 1990).

[11] X. Wu, "Color quantization by dynamic programming and principal analysis," ACM Trans. Graph. **11**, 348–372 (1992).

[12] H. B. Kekre and T. K. Sarode, "Vector quantized codebook optimization using k-means," Int. J. Comput. Sci. Eng. **1**, 283–290 (2009).

[13] H. B. Kekre, T. K. Sarode, and D. Mishra, "Coloring gray scale digital images using Kekre's fast code book generation algorithm," *Proc. Int'l. Conf. and Workshop on Emerging Trends in Technology* (ACM, New York, NY, 2010), pp. 498–501.

[14] Y. W. Lim and S. U. Lee, "On the color image segmentation algorithm based on the thresholding and the fuzzy c-means techniques," Pattern Recogn. **23**, 935–952 (1990).

[15] H. Kasuga, H. Yamamoto, and M. Okamoto, "Color quantization using the fast k-means algorithm," Syst. Comput. Jpn. **31**, 33–40 (2000).

[16] J. Dong and M. Qi, "A new algorithm for clustering based on particle swarm optimization and k-means," *Proc. 2009 Int'l. Conf. on Artificial Intelligence and Computational Intelligence* (IEEE, Piscataway, NJ, 2009), pp. 264–268.

[17] L. Law and Y. Cheung, "Color image segmentation using rival penalized controlled competitive learning," *Proc. 2003 Int'l. Joint Conf. on Neural Networks* (IEEE, Piscataway, NJ, 2003), pp. 108–112.

[18] M. E. Celebi, "An effective color quantization method based on the competitive learning paradigm," *Proc. 2009 Int'l. Conf. on Image Processing, Computer Vision, and Pattern Recognition* (CSREA, Las Vegas, NV, 2009), pp. 876–880.

[19] A. H. Dekker, "Kohonen neural networks for optimal colour quantization," Netw. Comput. Neural. Syst. **5**, 351–367 (1994).

[20] A. Pujol and L. Chen, "Color quantization for image processing using self information," *Proc. 6th Int'l, Conf. on Information, Communications and Signal Processing* (IEEE, Piscataway, NJ, 2007), pp. 1–5.

[21] K. J. Yoon and I. S. Kweon, "Human perception based color image quantization," *Proc. 17th Int'l. Conf. on Pattern Recognition* (IEEE, Piscataway, NJ, 2004), pp. 664–667.

[22] G. Joy and Z. Xiang, "Reducing false contours in quantized color images," Comput. Graph. **20**, 231–242 (1996).

[23] B. Rogowitz, "The human visual system: a guide for the display technologist," Proc. SID **24**, 235–252 (1983).

[24] M. Ebner, *Color Constancy* (John Wiley & Sons, New York, 2007).

[25] C. Poynton, *Digital Video and HDTV Algorithms and Interfaces* (Morgan Kaufmann, San Francisco, 2003).