Color image segmentation considering the human sensitivity for color pattern variations

Kuk-Jin Yoon, In-So Kweon
Robotics and Computer Vision Laboratory, Dept. of EECS, KAIST, Korea

ABSTRACT

Color image segmentation plays an important role in the computer vision and image processing area. In this paper, we propose a novel color image segmentation algorithm in consideration of human visual sensitivity for color pattern variations by generalizing K-means clustering. Human visual system has different color perception sensitivity according to the spatial color pattern variation. To reflect this effect, we define the CCM (Color Complexity Measure) by calculating the absolute deviation with Gaussian weighting within the local mask and assign weight value to each color vector using the CCM values. Weighted color vectors are used in K-Means algorithm and the shape and the center position of each cluster is formed according to the color distribution in the image. We adaptively determine optimal K value, which is the number of cluster, by using the statistics of the color complexity measure that implies the complexity of the color image. The experimental results show that proposed algorithm segments the color image preserving significant features while removing unimportant details.

Keywords: color image segmentation, *K-means* clustering, human color sensitivity.

1. INTRODUCTION

The goal of image segmentation is grouping the pixels that having similar feature in an image from the standpoint of human visual system. There are many techniques for gray image segmentation. But, because the color is multidimensional vector (typically two or three dimension), the segmentation techniques for gray images cannot be applied to the color images directly. Color image segmentation is more complicated problem than gray image segmentation.

Recently, many algorithms have been proposed to segment the color image 2, 7, 13, 18. They segment the image using coherency of color value or spatial distribution of color. These techniques could be categorized according to the processing domain that the segmentation is performed. Region growing based and merge and slit based algorithms 11, 21 are the methods that segment the image directly in the spatial image space. Clustering and histogram based techniques 2, 7, 10, 16 are the method that divide the specific feature space derived from a color image. In, this paper, we use the method that divides the specific feature space.

The most popular technique using the feature space is clustering based method. Although the histogram based techniques are proposed and show practical results 2, it is originally for the gray image that is one-dimensional. So it is not proper for multidimensional color data. The most common clustering technique is the *K-means* algorithm. It is known as a powerful method to deal with the large color pixel set to get the optimal clustering 16. In this scheme, each pixel is mapped to the one point in the feature space according to its feature (typically color). The feature points that having similar feature are grouping into the same cluster. Then, the each feature point has the cluster index and it is inversely mapped to the image space.

In the color image segmentation, it is most important to preserve the significant features and segment the image corresponding to the human visual perception. In this viewpoint, the initial methodologies of color image segmentation have some shortcomings. Because those methods only focused on the color value itself, they don't reflect the characteristics of the human visual system. First, the difference of two color points are treated as same regardless of where the points are located in a color space in the clustering process. As the result, clustering is formed neglecting the phenomenon that even if the Euclidean distances are same, the color dissimilarity may be different to the human visual system according to the location of color points in the color space 3.

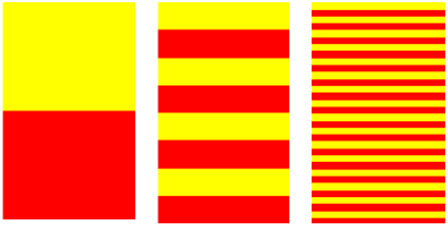


Fig. 1: Test Pattern of Color Perception to Spatial Color Pattern Variation

For this reason, uniform chromaticity scale was widely used for color image segmentation 7, 13, 16. Kehtarnavaz 10 select the uniform chromaticity scale color space to reflect the difference of the human visual color perception by using Euclidean distance between two color points accurately. Toninaga 14 also emphasized the selection of color space. Selection of the appreciate color space is crucial to the segmentation result because accuracy of color difference measure is related to the selected color space directly and the arrangement and the shape of clusters depend on the color space selected.

The other problem of conventional clustering based mythologies is that they do not consider the sensitivity of the human color perception that is depending on the spatial condition in the image domain. Human visual system shows different color perception sensitivity according to the spatial color pattern variation in the image domain 1, 4, 19. Fig. 1 shows some test pattern of color perception to spatial color pattern variation, which is similar to that of Wandell 1. As the color pattern variation increase, the sensitivity of human visual perception decreases. But, conventional approaches do not use spatial information at all. So, the cluster center positions, shapes in the color space are determined by the color values in the image only. As the result, the segmentation results do not coincide the human visual system. There may be undesirable region or some significant regions may be lost.

To include the spatial constraint, many approaches that consider the human visual system have been proposed. Pappas 17 proposed an adaptive clustering algorithm for image segmentation by generalizing the *K-means* clustering algorithm to include spatial constraint and to account for local intensity variation. But this algorithm is for the gray images. Kim et al. 6 and Chaddha et al. 9 proposed the activity function and distortion measure of color point based on human visual perception using simple masking operation.

In addition to these problems, the *K-means* algorithm has the fatal limitation: determination of K, number of cluster, value. That is very important for the accuracy of the segmentation and the efficiency of clustering processing. As the K value increase, the image will be over-segmented and the processing will need large computational power. On the contrary, if the K value is small, the image will be under-segmented and some significant region may be lost.

We propose a novel color image segmentation algorithm in consideration of human visual sensitivity for color pattern variations by generalizing *K-means* clustering. First, we define the CCM(Color Complexity Measure) by calculating the absolute deviation with Gaussian weighting within the local mask and assign weight value to each color vector using the CCM value. Weighted color vectors are used in *K-Means* algorithm and the shape and the center position of each cluster is formed according to the color distribution in the image. We adaptively determine optimal K value, which is the number of cluster, by using the statistics of the color complexity measure that implies the complexity of color image.

2. K-MEANS CLUSTERING

Basically, *K-means* algorithm is the technique that is based on the minimization of an object function, which is defined as the sum of the squared distances from all points in a cluster domain to the cluster center. The object function based on the least sum of square criterion is defined as like

$$J = \sum_{i=1}^{K} \sum_{C \in S_i} w(C) \left\| C - \overline{C}_{S_i} \right\|^2 \tag{1}$$

where $\overline{C}_{S_i}$ denotes the center of cluster S_i and K is the number of cluster. $w(C)$ is the weight factor of the point C.

When the data set $\boldsymbol{X}$ and the initial clusters are given, *K-means* clustering minimize the object function iteratively. This producer consists of the following steps.

Step 1. Choose K initial cluster centers $\overline{C}_{S_1}$, $\overline{C}_{S_2}$, …, $\overline{C}_{S_K}$.

Step 2. At the t^th^ iterative step, distribute the samples $\boldsymbol{X}=\{\boldsymbol{C}\}$ among the K cluster domains, using the relation

$$C \in S_i^t \ \ if \ \ \left\| C - \overline{C}_{S_i}^t \right\|^2 < \left\| C - \overline{C}_{S_j}^t \right\|^2 \tag{2}$$

for all $j=1, 2, \ldots, K, j\neq i$ where S_i^t denotes the set of points whose cluster center is $\overline{C}_{S_i}^t$. In other words, cluster S_i^t is composed of the points satisfying the following condition.

$$S_i^t = \left\{ C \mid \left\| C - \overline{C}_{S_i}^t \right\|^2 < \left\| C - \overline{C}_{S_j}^t \right\|^2 \right\} \tag{3}$$

for all $j=1, 2, \ldots, K, j\neq i$.

Step 3. From the result of step 2, compute new cluster centers $\overline{C}_{S_i}^{t+1}$, $i=1, 2, \ldots, K,$ such that the object function is minimized. The new cluster center that minimizes the object function is simply the center of mass of S_i^t. Therefore, the new cluster center is given by

$$\overline{C}_{S_i}^{t+1} = \frac{\sum_{C \in S_i^t} w(C) \times C}{\sum_{C \in S_i^t} w(C)} \tag{4}$$

Step 4. If all cluster centers does not change as the iteration step increases, the algorithm has converged and the procedure is terminated. Otherwise go to step 2.

The behavior of the *K-means* algorithm is influenced by the number of cluster specified, the choice of cluster centers and the geometrical properties of the data. Although no general proof of convergence exists for this algorithm, it was shown that *K-means* clustering that is based on that criterion converges to approximate the optimum solution theoretically and experimentally 16. Also, it was shown that the any clustering methods based on the least sum of square criterion gives the most separable clustering.

3. COLOR IMAGE SEGMENTATION ALGORITHM

We describe the core of proposed algorithm and implementation detail in this section. Fig. 2 shows the overall process diagram of proposed algorithm. Before the detailed explanation, we define some definitions.

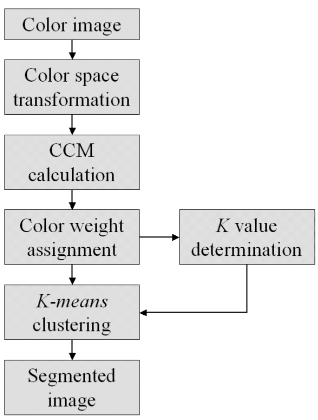


Fig. 2: Overall Process Diagram of Proposed Algorithm

3.1 DEFINITIONS

To measure the complexity of the pixel that are directly related to the color perception sensitivity of human visual system, we define the CCM(Color Complexity Measure) of a pixel located at *(i, j)* like follow

$$\varphi(i,j) = \iint_{x,y\in\Omega_{(i,j)}} G_\alpha\left(\left\|c(x,y)-\bar{c}(i,j)\right\|\right)dxdy \tag{5}$$

where G_α denotes the Gaussian weighting function and $\bar{c}(i,j)$ is an average color value within a local mask $\Omega_{(i,j)}$ centered at *(i, j)*. $\|\ \|$ denotes the color difference measure. This measures the color complexity about the interesting pixel by using the absolute deviation with Gaussian weighting. Large CCM value represent that there is high spatial color pattern variation in the local neighbor and small CCM value means that the pixel is located in the homogenous region. By using the CCM value, we can define the color weighting function as like

$$w(\varphi(i,j)) = \rho\left(\frac{\varphi(i,j)}{\iint_{x,y\in I}\varphi(x,y)dxdy}, \sigma\right) \tag{6}$$

where ***I*** represent the image domain. $\rho(x,\sigma)$ is the weighting function. We use Gaussian kernel as the $\rho(x,\sigma)$ according to the 20

$$\rho(x,\sigma) = k\cdot exp\left(-\frac{x^2}{2\sigma^2}\right) \tag{7}$$

where k is the normalizing constant. The weighting value is normalized to lie within [0,1]. The variance σ is the variance of the CCM values. Then, all of the pixels have its weight in an image domain. In color space, each point has the weight value that is the sum of the weights of the pixels, which is mapped to the point. So, the weight of the color vector, ***C***, in the specific color space is like

$$\Theta(C) = \iint_{x,y\in I} w(\varphi(i,j)\mid c(i,j)\equiv C)dxdy \tag{8}$$

3.2 COLOR SPACE SELECTION

Because the performance of segmentation methods based on clustering is directly related to the shape and the center position of each cluster, appropriate color space must be selected. Generally, the color difference is evaluated using the distance between two color points in a color space. The most common distance is Euclidean distance. So, we use CIELab color space, which is a uniform chromaticity color space. It is known that Euclidean distance of two colors is proportional to the difference that human visual system perceived in the CIELab color space.

Generally the image is composed of RGB color components. So we must convert RGB color components to CIELab color component. To do this, we first convert RGB to CIEXYZ using following equations.

$$\begin{aligned} X&=0.490\times R+0.310\times G+0.200\times B\\ Y&=0.177\times R+0.813\times G+0.011\times B\\ Z&=0.000\times R+0.010\times G+0.990\times B \end{aligned} \tag{9}$$

The conversion to CIEXYZ color to CIELab color is performed according to the following relation

$$\begin{aligned} L&=25\times (100\times Y/Y_o)^{1/3}-16\\ a&=500\times [(X/X_o)^{1/3}-(Y/Y_o)^{1/3}]\\ b&=200\times [(Y/Y_o)^{1/3}-(Z/Z_o)^{1/3}] \end{aligned} \tag{10}$$

3.3 COLOR DIFFERENCE MEASURE

It is important to represent the color difference between color points corresponding to the human visual perception accurately. In CIELab color space, small Euclidean distance between two color points is proportional to the difference that human visual system perceives. But, a large Euclidean distance has no meaning but only large difference in human visual system. Therefore, color difference in CIELab color space can be modeled as;

$$D(c(i,j),c(x,y)) = 1 - exp\left(-\frac{E(c(i,j),c(x,y))}{\gamma} \right) \quad (11)$$

where γ is the normalized factor(typically 14) and *E(c(i, j), c(x, y))* is the Euclidean distance in CIELab color space.

$$E(c(i,j),c(x,y)) = \sqrt{(L_{ij}-L_{xy})^2 + (a_{ij}-a_{xy})^2 + (b_{ij}-b_{xy})^2} \quad (12)$$

So, we use the equation (11) as the color difference measure. Fig. 3 shows the relation between color difference measure value vs. Euclidean distance in color space. Large Euclidean distance is saturated to 1 and has no significant meaning in comparing the color difference.

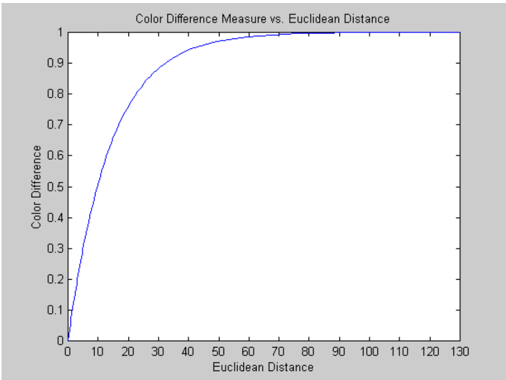


Fig. 3: Color Difference vs. Euclidean Distance in Color space.

3.4 CALCULATION OF COLOR WEIGHT

To assign a color weight to each pixel, we use a local mask centered at each pixel. We first calculate the average color within the mask. The average color is given by

$$\bar{c}(i,j) = \frac{1}{N} \sum_{x,y \in \Omega_{(i,j)}} c(x,y) \quad (13)$$

where *N* is the number of pixels in the local mask $\Omega_{(i,j)}$. Then we can calculate the CCM value by using the equation (5). Because we adapt the equation (11) as the color difference measure, equation (5) can be expressed as like

$$\varphi(i,j) = \iint_{x,y \in \Omega_{(i,j)}} G_\alpha\left(\| c(x,y) - \bar{c}(i,j) \| \right) dxdy = \sum_{x,y \in \Omega} G_\alpha \left(1 - exp\left(-\frac{E(c(x,y),c(i,j))}{\gamma} \right) \right) \quad (14)$$

After calculating the all CCM value of an image, we assign the weight value to each pixel color with the equation

$$w(\varphi(i,j)) = \rho\left(\frac{\varphi(i,j)}{\iint_{x,y \in I} \varphi(x,y)dxdy}, \sigma \right) = k \cdot exp\left[-\frac{1}{2\sigma^2} \left(\frac{\varphi(i,j)}{\iint_{x,y \in I} \varphi(x,y)dxdy} \right)^2 \right] \quad (15)$$

Finally, these weights are mapped to the color space according to the equation (8) to be used in *K-means* clustering.

3.5 K VVALUE DETERMINATION

We determine the K value, number of cluster, by using the statistics of CCM value and the weight value. The number of clusters must be determined taking into account the distribution of color components in the color space and image domain. As we mentioned before, according to the Wandell 1, 20, human visual system shows the low sensitivity to the color value as the spatial color pattern variation increase. This imply that there need small number of clusters where the image is composed of the region that include the complex and full of variety color pattern.

The complexity of the color pattern in an image can be deduced by the CCM value. Because CCM value implies the local complexity about the each pixel, the average of the CCM values can be used for estimating the complexity of an entire image. Another importance fact is that the relation between the human visual sensitivity and the spatial color pattern could be approximated by a Gaussian function. We can deduce by combining these fact that the number of optimal cluster is related to the average of the color weight value.

To get the optimal cluster number depending on images, we use normalized weighting function that is given as

$$w_N(\varphi(i,j)) = \rho_N(\varphi(i,j), \sigma_N) \quad (16)$$

where $\rho_N(x,\sigma)$ is Gaussian kernel similar to the equation (7).

$$\rho_N(\varphi(i,j), \sigma_N) = k_N \cdot exp\left(-\frac{\varphi(i,j)^2}{2\sigma_N^2} \right) \quad (17)$$

k_N denotes the normalizing factor.

Finally we can get the K value using the equation like

$$K = M \cdot \frac{\iint_{x,y\in I} w_N(\varphi(x,y))dxdy}{N_I} \quad (18)$$

where N_I is the number of pixels in an image and M is the allowable maximum cluster number and related to the segmentation level.

3.6 CLUSTERING PROCESS

We briefly described the *K-means* clustering in the section II. We follows the clustering steps using the K value and weighted color vectors.

First of all, we define the objective function as like

$$J = \sum_{i=1}^{K} \sum_{C\in S_i} \Theta(C) \left\| C - \overline{C}_{S_i} \right\|^2 \quad (19)$$

This functions denotes the sum of the squared distances from all color points in a color space to the cluster center.

We choose K initial cluster centers near the center of all color point as like

$$\overline{C}_{S_i} = \overline{C} + \varepsilon_i \quad (20)$$

where $\overline{C}$ is the center of all color points and ε_i is the small random noise. This method shows uniform clustering result, although the initial cluster centers change its location every time, because the all initial centers will be located uniformly around the center of all color points.

After choosing initial centers, we iteratively minimize the object function by following the *K-means* clustering steps. Practically, 30~50 iteration is enough for the convergence.

4. EXPERIMENTAL RESULTS

We applied proposed algorithm to many natural color images. Because there is no objective performance measure for image segmentation, we show results of conventional method, which uses uniform weight value for the all color pixels in the image and uses same color space, and that of proposed algorithm.

Fig. 4 shows the experimental result for the ‘Flower Garden’ image. Fist of all, we calculated the CCM value for each pixel and assign weighting to the pixel. We used 5 by 5 mask centered at interesting pixel to get the CCM value. Fig. 4(b) shows the relative magnitude of color weight value in the image. Dark pixels have small weight value, while bright pixels have relatively large weight value. We can see that color points in the homogeneous region have more large weight value than the color points in the intricate region according to the CCM values. After calculating the weight values, we determine the number of clusters using proposed algorithm. The *K* value that we used is 22 for the ‘Flower Garden’ image. To compare the result, we use same number of cluster for both methods. Fig. 4(c) is the segmentation result of the conventional method that does not consider the spatial information at all and all color points are assumed to have same weighs. Fig. 4(d) is the result of proposed algorithm. In the result, we can observe that the proposed methods provides more accurate boundary in uniform color regions and shows comparable segmentation result in the intricate region. This effect is well shown in sky region and flower garden region in the image. Proposed algorithm allows that homogeneous region that human visual system shows high sensitivity are divided more accurately by allocating the more clusters. These effects are results from the color weight value. While the dark regions in the Fig. 4(b) are segmented more roughly than the conventional method, the bright regions are more large factors and segmented more accurately although its color variation is small. In fact, the rough segmentation result of the dark region in the Fig. 4(b) does not devaluate the proposed algorithm because human visual system has low color perception sensitivity in that region.

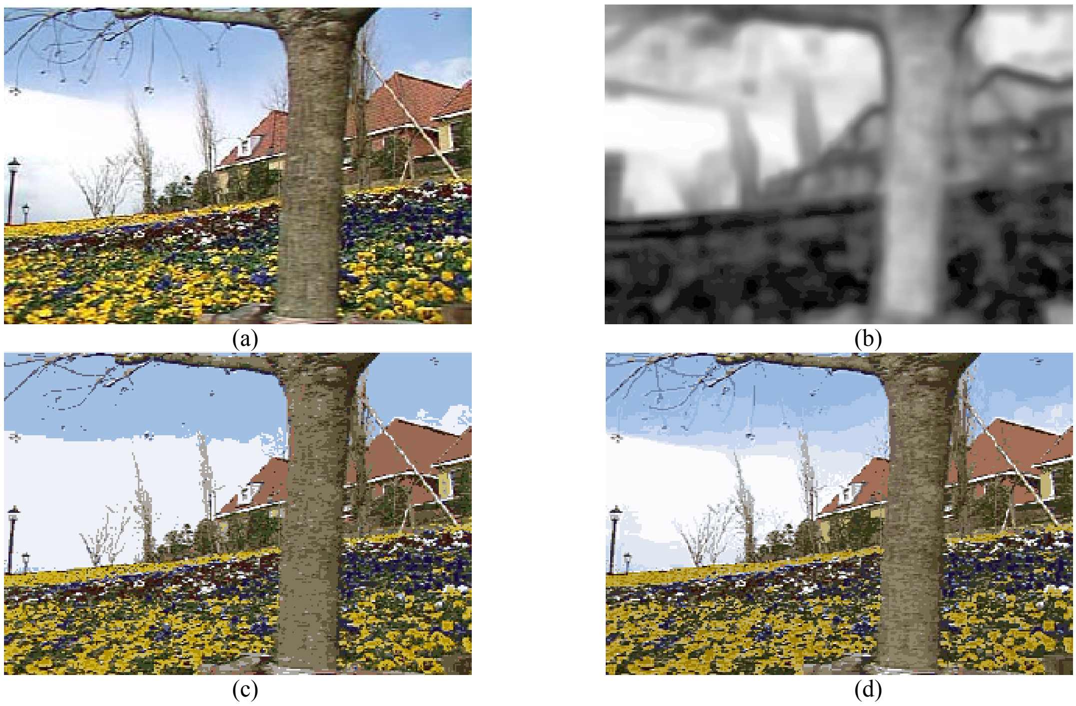
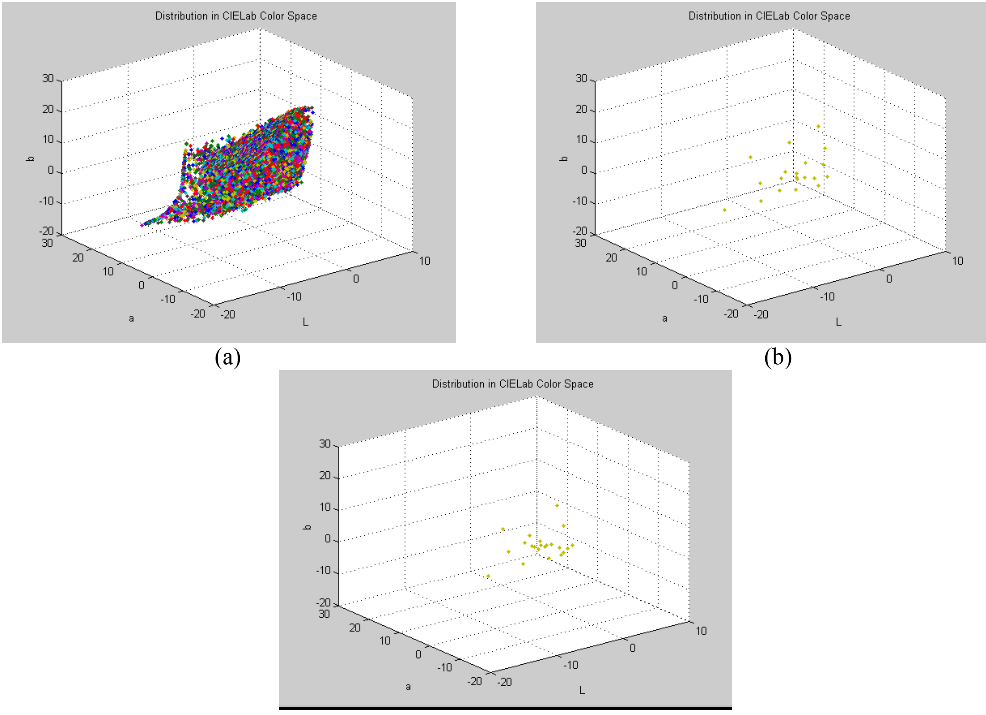


Fig. 4: Segmentation Result of ‘Flower Garden’ Image. (a) original input image, (b) relative color weight value, (c) segmentation result with uniform weight value, (d) segmentation result of proposed algorithm (with 22 clusters)

Fig. 5 shows the color distribution of the image shown in the Fig. 4 in the CIELab color space domain. Small points denote the position of the color position and their occupancy rate with its color value in the Fig. 5(a). Points in the Fig. 5(b)-(c) denotes the center positions of clusters of obtained from the conventional method and proposed method respectively. As we can see in the figure, although the number of clusters is same, the distributions of the cluster positions are greatly different between conventional method and proposed method. This cluster distribution induces different segmentation result of proposed algorithm Conventional algorithm groups the pixel according to the status of the color points distribution and finally the positions of the clusters are located uniformly. But, because the behavior of the proposed algorithm is governed by not only the status of the color points distribution but also weight values that they have, the final locations of the clusters are not uniform. Instead, the center positions are gathered around some point, that is the most sensitive color points to human visual system.



(a) (b)

(c)

Fig. 5: Color Distribution of 'Flower Garden' Image in CIELab Color Space. (a) color distribution of input image, (b) color distribution of segmented image using conventional method, (c) color distribution of segmented image using proposed algorithm.

Fig. 6 also shows some segmentation results and their cluster distribution in CIELab color space. We can see that the clusters of the proposed algorithm are not uniformly distributed but gathered some points. In the conventional scheme, the color point that is occupied by small number of pixel is lost its color value in the final stage. But if the color point has large weight, that means its color is sensitive to human visual system, then proposed algorithm preserves its color and don't loss the significant color region. Also, although many points are gathered in the some ranges in the color space, if the weights values of those points are low, then there locates small number of clusters.

This phenomenon is surely appeared in the result of the 'Golf' image. There are two large groups of point of the input image in the color space. But the most clusters are included in only one clusters and small number of clusters are allocated in the other group. That is the main advantage of proposed algorithm. Proposed algorithm provides the more accurate region boundaries corresponding to the human visual system and preserves the significant details that human visual system perceives vividly and removes unimportant details.

5. CONCLUSION

In this paper, we propose a novel color image segmentation algorithm in consideration of human visual sensitivity for color pattern variations. We define the CCM (Color Complexity Measure) by calculating the absolute deviation with Gaussian weighting within the local mask to account for the fact that human visual system has different color perception sensitivity according to the spatial color pattern variation. Then, we assign weight value to each color vector using the CCM values. Weighted color vectors are used in *K-Means* algorithm and the shape and the center position of each cluster is formed according to the color distribution in the image. We adaptively determine optimal K value, which is the number of cluster, by using the statistics of the color complexity measure that implies the complexity of the color image. The experimental results show that proposed algorithm provides the more accurate region boundaries corresponding to the human visual system and preserves the significant details that human visual system perceives vividly and removes unimportant details with optimal *K* value.

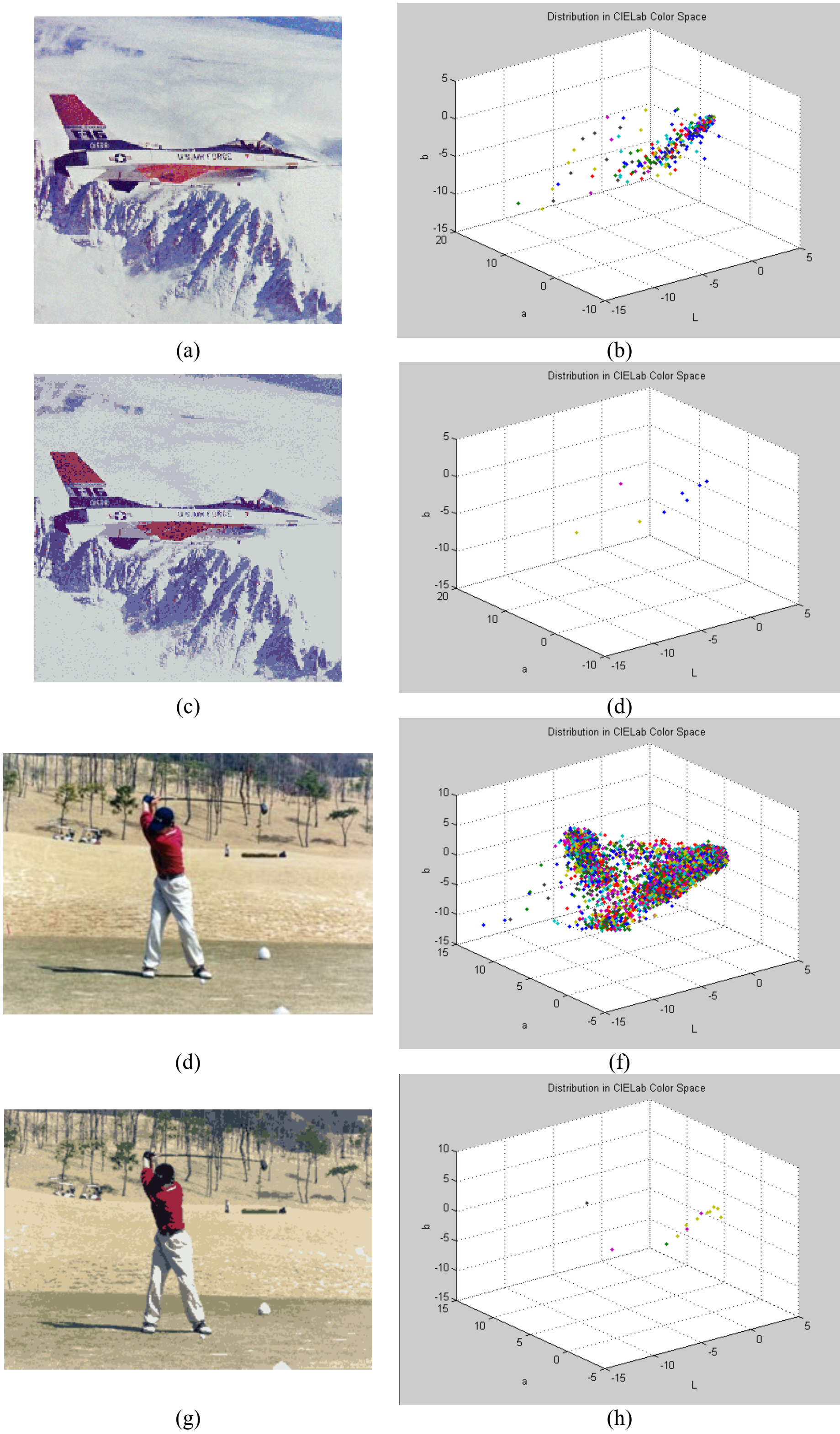


Fig. 6: Segmentation Result and Its Color Distributions in CIELab Color Space. (a) ‘Plane’ input image, (b) color distribution of (a), (c) segmentation result of ‘Plane’ image (with 8 clusters), (d) color distribution of (c), (e) ‘Golf’ input image, (f) color distribution of (e), (g) segmentation result of ‘Golf’ image (with 13 clusters), (h) color distribution of (g).

REFERENCES

1. B.A. Wandell, "Color Appearance: the Effects of Illumination and Spatial Patterns", Proc. Nat. Acad. Sci., USA, Vol. 90, page(s) : 1494-1501, 1993.
2. D. Comaniciu, P. Meer, "Robust Analysis of Feature Spaces: Color Image Segmentation", Proc. of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Page(s): 750 –755, 1997.
3. D. MacAdam, "Color measurement", Springer-Verlag, 1981.
4. J.L. Schnapf, T.W. Kraft, D.A. Baylor, "Spectral Sensitivity of Human Cone Photoreceptors", Nature, Vol. 325, Page(s): 439-441, 1987.
5. K.J. Yoon, I.S. Kweon, C.Y. Kim, Y.S. Seo, "Moving Object Segmentation Based on Human Visual Sensitivity", IEEE International Workshop on Biologically Motivated Computer Vision, Pape(s): 62-72, 2000.
6. K.M. Kim, C.S. Lee, E,J. Lee, Y.H. Ha, "Color Image Quantization using Weighted Distortion Measure of HVS Color Activity", Proc. of International Conference on Image Processing, Vol. 3, Page(s): 1035 –1039, 1996.
7. L. Lucchese, S.K. Mitra, "An Algorithm for Unsupervised Color Image Segmentation", IEEE Second Workshop on Multimedia Signal Processing, Page(s): 33 –38, 1998.
8. M. Mirmehdi, M. Petrou, "Segmentation of Color Textures**",** IEEE Transactions on Analysis and Machine Intelligence,
   Vol. 22 2, Page(s): 142 –159, Feb. 2000.
9. N. Chaddha, Wee-Chiew Tan, T.H.Y. Meng, "Color Quantization of Images Based on Human Vision Perception", Proc. of IEEE International Conference on Acoustics, Speech, and Signal Processing, Vol. 5, Page(s): V/89 -V/92, 1994.
10. N. Kehtarnavaz, J. Monaco, J. Nimtschek, A. Weeks, "Color Image Segmentation Using Multiscale Clustering", Proc. of IEEE Southwest Symposium on Image Analysis and Interpretation, Page(s): 142-147, 1998.
11. N. Ikonomakis, K.N. Plataniotis, M. Zervakis, A.M. Venetsanopoulos, "Region Growing and Region Merging Image Segmentation**",** Proc. of the 13th Conference on Digital Signal Processing, Vol. 1, 1997
12. S.E. Palmer, "Vision Science-Photons to Phenomenology", MIT Press, 1999.
13. W. Woelker, "Image Segmentation Based on an Adaptive 3D-Analysis of the CIE-L*a*b* Color Space", SPIE Visual Communications and Image Processing, Vol.2727 Part 3/3, March, 1996.
14. S. Toninaga, "Color Classification of Natural Color Image", Color Res. Appl., Vol. 17, Page(s): 230-239, 1992.
15. T. Gonzalez, "Pattern Recognition Principles", Addison-Wesley Publishing, 1974.
16. T. Uchiyama, Michael A. Arbib, "Color Image Segmentation Using Competitive Learning", IEEE Transactions on Pattern Analysis and Machine Intelligent, vol. 16, No. 12, Page(s): 1197-1206, December 1994.
17. T.N. Pappas, "An Adaptive Clustering Algorithm for Image Segmentation", IEEE Transactions on Signal Processing, Volume: 40 4, Page(s): 901 –914, April 1992.
18. W. Skarbek, A. Koschan, "Color Image Segmentation – A Survey", Technical Report 94-32, Technical University Berlin, October 1994.
19. X. Zhang, D.A. Silverstein, J.E. Farrell, B.A. Wandell, "Color Image Quality Metric S-CIELAB and its Application on Halftone Texture Visibility", Proc. of IEEE Compcon, Page(s): 44 –48, 1997.
20. X. Zhang, B.A. Wandell, "A spatial extension of CIELAB for digital color image reproduction", In Society for Information Display Symposium, 1996.
21. Y. Deng, B.S. Manjunath, H. Shin, "Color Image Segmentation", Proc. of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Vol. 2, 1999.