COLOR IMAGE SEGMENTATION USING MULTI-SCALE CLUSTERING

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ABSTRACT

The use of clustering in color image segmentation poses two distinct problems: (a) equal distances throughout a color space may not be perceived equally by the human visual system, and (b) the number of color clusters must be predetermined. This paper describes a color clustering method that resolves these problems. The first problem is addressed by operating in the nonlinear, geodesic chromaticity space where color shifts are nearly uniform. The second problem is remedied by utilizing a newly developed multi-scale clustering algorithm. This algorithm determines the prominent numbers of color clusters via an objective measure named lifetime. The obtained segmentation results indicate that this color segmentation approach identifies the prominent color structures or objects in a color image.

I. INTRODUCTION

The problem of color segmentation is defined as the grouping of pixels in a color image that have similar colors as perceived by the human visual system. In many object recognition or tracking applications color segmentation plays a major role when color provides a distinguishing feature of the object of interest. Although the human eye is capable of distinguishing thousands of different colors, color devices only produce a small subset of these colors. This suggests that the processing of subtle color differences is not essential for computer recognition or tracking purposes.

Many techniques have been proposed to perform color segmentation [1] [6] [9]. A popular technique is based on clustering pixels in a color space. For example, Weeks and Hague [10] have used the K-means clustering algorithm to group pixels having similar colors in the HSI color space.

Two shortcomings are noted when clustering is used for color segmentation. First, clustering algorithms treat the distance between two points the same regardless of where the points are located in a color space. As a result, color points are grouped without considering the fact that the human visual system responds differently to different color points, i.e. equal distances in color space may not be perceived equally by the human eye and hence should not be treated the same. Second, the number of clusters or color segments usually is specified by the user. In other words, the number of classes for clustering algorithms is assumed known. This paper presents the use of a newly developed clustering algorithm, named multi-scale clustering (MSC) [3] [8], in an appropriately chosen color space to overcome the above shortcomings.

Section 2 provides a discussion of a color space appropriate for any clustering algorithm. In Section 3 the developed color segmentation approach is presented. The color segmentation results are then shown in Section 4. Finally, the conclusions are stated in Section 5.

II. APPROPRIATE COLOR SPACE FOR CLUSTERING

A color image is normally specified in terms of its RGB components. In practice, these components are transformed into other color spaces for various reasons. A list of different color spaces appears in [2]. Two such color models that provide a better match to the human visual perception than the RGB model are the HSI and YIQ models. The HSI model is used in color enhancement applications and the YIQ model in the NTSC color television.

It has been shown that colors that lie within MacAdam ellipses [7] are visually indistinguishable. Any color lying on the perimeter of a MacAdam ellipse is just noticeably different (JND) as compared to the center of that ellipse. Unfortunately, the size and shape of these ellipses vary considerably in the color models used in image processing, including the HSI and YIQ models. In other words, the same distances in different parts of the color space denote different amounts of perceived color shifts. Consequently, it is not appropriate to do the clustering in the above color spaces. Attempts have been made to define a space in which the size, orientation, and eccentricity of MacAdam ellipses become the same. The so called uniform chromaticity scale (UCS) model is the best linear transformation model that has been devised for this purpose. However, this model still does not provide equal distances throughout its color space.

Here we have used a non-linear transformation to operate in a color space called geodesic chromaticity [7] which has been shown to provide almost equally perceived color shifts throughout the space. The equations for this non-linear transformation are given by [7]:

$$p = 3751a^2 - 10a^4 - 520c^2 + 13295c^3 + 32327ac - 25492a^2c - 41672ac^2 + 10a^3c - 5227a^{1/2} + 2952a^{1/4}$$

$$q = 404d - 185d^2 + 52d^3 + 69b(1-d^2) - 3b^2d + 30bd^3$$

where

$$a = \frac{10x}{2.4x + 34y + 1},\quad b = \frac{10x}{4.2y - x + 1}$$
$$c = \frac{10y}{2.4x + 34y + 1},\quad d = \frac{10y}{4.2y - x + 1}$$

$$x = \frac{X}{X+Y+Z},\quad y = \frac{Y}{X+Y+Z}$$

and XYZ are the tristimulus CIE color coordinates derived from RGB tristimulus values via the following transformation matrix [2]:

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.490 & 0.310 & 0.200 \\ 0.177 & 0.813 & 0.011. \\ 0.000 & 0.010 & 0.990 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

A nearest neighbor approach is adopted to map color points from the p-q geodesic space back to x-y chromaticity space. Figure 1 illustrates the color differences in the x-y and p-q spaces. As apparent from these figures, the p-q space provides a more appropriate color space for clustering.

III. COLOR SEGMENTATION APPROACH

A. Overview of Multi-Scale Clustering (MSC) Algorithm

In general, most clustering algorithms require the number of clusters to be known or given. Our devised clustering algorithm, MSC, addresses this issue by providing an objective measure to find an appropriate number of clusters. That is, it segments a color image into distinct color regions without requiring the user to specify the number of colors. An overview of this algorithm is provided in this section, refer to [3] [8] for more details.

Consider a set of n color points $\mathbf{x}_k$'s, $k = 1,2,\ldots n$, of dimension r. A scale-space representation of these points can be realized by convolving them with a Gaussian kernel $\phi_\sigma(\mathbf{x})$ of a scale size σ,

$$\phi_\sigma(\mathbf{x}) = -\frac{1}{\sigma^r\sqrt{(2\pi)^r}}\exp\left\{-\frac{1}{2}\sum_{j=1}^{r}\left(\frac{x_j}{\sigma}\right)^2\right\}$$

to generate the following function:

$$\psi_\sigma(\mathbf{x}) = \sum_{k=1}^{n}\phi(\mathbf{x} - \mathbf{x}_k)$$

$\psi_\sigma(\mathbf{x})$ can be viewed as a potential field function for a scale size σ.

Let $c(\sigma)$ be the number of clusters for the scale size σ. Cluster prototypes or representatives, $\mathbf{v}_i$'s, $i = 1,2,\ldots k$, are considered to be the local minima of $\psi_\sigma(\mathbf{x})$, and are obtained by setting the gradient $\nabla\psi_\sigma(\mathbf{x})$ to zero and requiring the Hessian matrix $\nabla^2\psi_\sigma(\mathbf{x})$ to be semi-positive.

Note that the number of clusters and the location of prototypes are governed by the scale size σ. The developed MSC algorithm consists of two parts: (i) an inter-cluster representation of data based on a structural criterion called lifetime, and (ii) an intra-cluster representation of data based on another structural criterion called drift speed. These concepts originate from the scale-space theory [5]. Here we have employed the first part of the MSC algorithm to find an appropriate number of color clusters. The locations of the prototypes are determined by minimizing the trace of the within-cluster scatter matrix.

The term lifetime in the MSC algorithm is defined as follows:

$$\tau(c) = \sigma_{\max}(c) - \sigma_{\min}(c)$$

where $\sigma_{\max}$ and $\sigma_{\min}$ denote the maximum and minimum scale sizes, respectively, when the number of clusters is c.

The approach adopted in the MSC algorithm requires the examination of different scale sizes; the larger the scale, the lower the resolution and consequently the fewer the number of clusters. In a c versus σ plot, the long, plateau-like segments denote the ranges over which the number of clusters remain the same or survive for relatively long durations. From a structural standpoint, they represent long lasting or persistent groupings of points. Based on this lifetime measure, a histogram or density function can be derived to reflect the frequencies with which different numbers of clusters occur. This histogram is then used to identify the prominent numbers of clusters.

B. Pre and Post Processing

Considering that the computational complexity of the MSC clustering is $O(n^2r^3)$, where n is the number of color points and r the dimensionality of the points, much computation time is saved by a preprocessing procedure that allows one color point to represent a small color neighborhood containing many color points. Such a representative point is weighted by the number of points it represents. This procedure is reasonable considering that the human eye is relatively insensitive to small chrominance variations. The above data reduction is achieved via ART2 clustering [4]. The radius for ART2 is selected based on the desired reduction in computation time. The MSC algorithm is then applied to the representative color points to generate a lifetime histogram.

In addition to preprocessing, a post-processing procedure is devised to select the prominent numbers of clusters that do not incur too much color generalization, i.e. many colors represented by only one prototype. This procedure consists of two steps: first non-prominent numbers of clusters are separated by arranging the lifetimes in descending order and finding the largest relative drop in lifetime. This can be thought of as detecting the edge between two lifetime regions. Second, among the identified prominent numbers of clusters, the one generating the smallest within-cluster scatter is chosen. In this manner, it is ensured that the selected prominent number of clusters does not lead to large clusters consisting of many color points.

IV. SEGMENTATION RESULTS

Figure 2 shows a 256x256 color image (the original color images are viewable at http://ee.tamu.edu/~dsplab /colorseg.html). The corresponding color points in the non-linear, geodesic space are shown in Figure 3. As mentioned previously, since the clustering of these points requires many hours of processing, a representative set of color points were generated by using the centers of JND regions. These centers were then weighted by the number of color points they represented. For a processing time of less than an hour, it was required to have a radius of 10 JND's. Figure 4 shows the representative points after the preprocessing procedure. In general, since the number of clusters is small as compared to the number of color points even after preprocessing, the clustering outcome is relatively unaffected by a change in JND radius. This is due to both the small cluster to point ratio and the weighting applied to representative points.

The outputs of the MSC algorithm applied to the representative color points are shown in Figures 5a and 5b. Figure 5a shows the c versus σ plot. Figure 5b illustrates the corresponding lifetime histogram. By arranging the lifetimes in descending order and finding the largest relative drop, the prominent cluster numbers $c = 2,3,4,7$ were identified. As can be seen from Figure 5a, these numbers denote the groupings with relatively long lifetimes. Among these prominent numbers, the grouping corresponding to $c = 7$ provided the least amount of within-cluster scatter. This was the number of color clusters used to create the segmented color image illustrated in Figure 6. Each prototype $\mathbf{v}_i$ is indicated by an "O" in Figure 4. The segmentation results for two other color images are shown in Figures 7 and 8. Two clusters were obtained for the image in Figure 7 and five for the image in Figure 8.

V. CONCLUSIONS

This paper has provided a color segmentation method for grouping similar color points in a color image. It has shown that it is necessary to operate in a color space that appropriately models the response of the human visual system. In addition, it has introduced a multi-scale clustering algorithm capable of identifying prominent color areas or objects without requiring the user to specify the number of color clusters. It should be noted that the developed segmentation approach is general purpose in the sense that it can be used to segment the luminance (grey level) as well as the chrominance (color) component.

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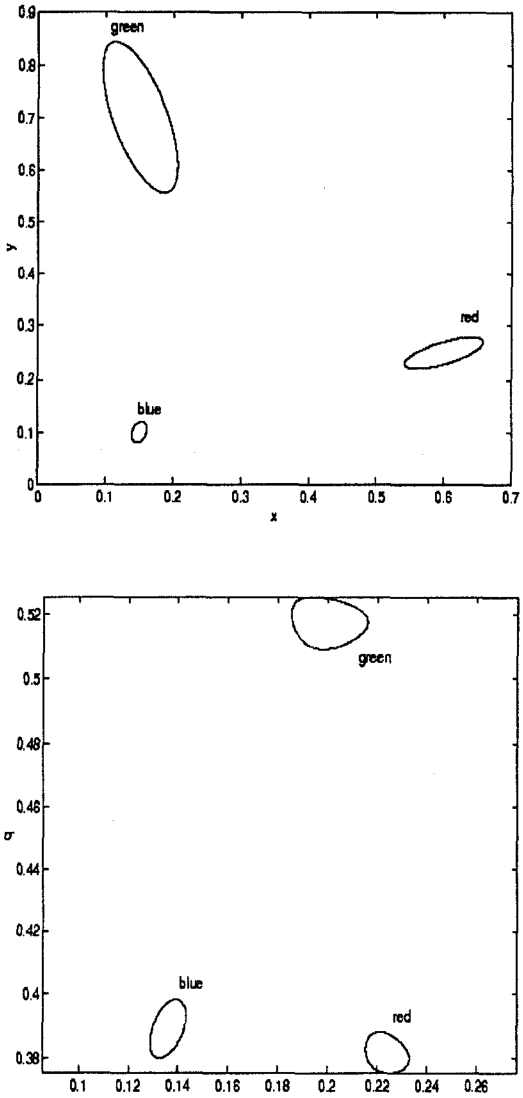

Figure 1-MacAdam Ellipses (15X enlarged) in (a) x-y and (b) p-q spaces

Figure 2- Hats image

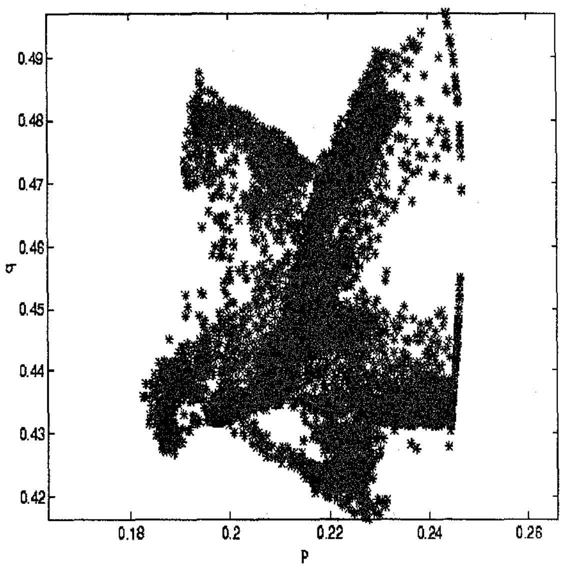

Figure 3 - Hats image color points in p-q space

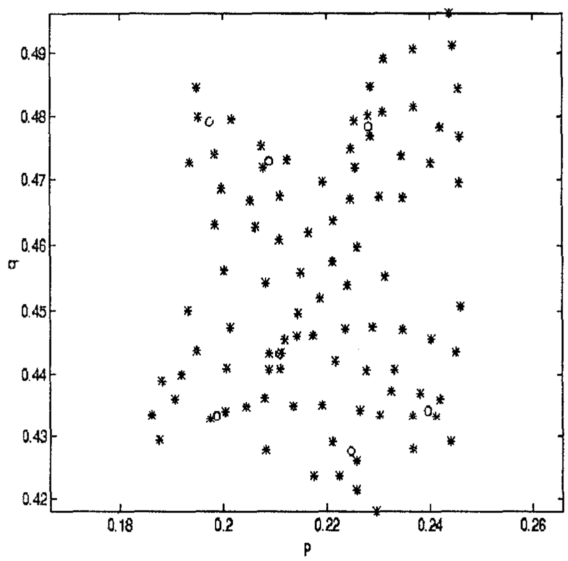

Figure 4 - Hats image representative color point in p-q space

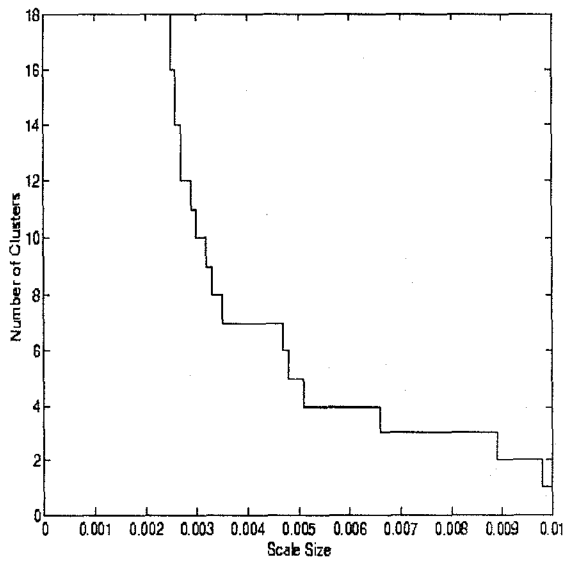

Figure 5a - Plot shows reduction in number of clusters as scale size increases

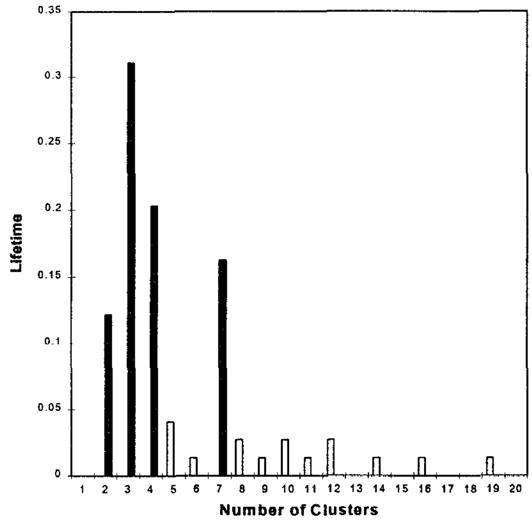

Figure 5b - Lifetime histogram

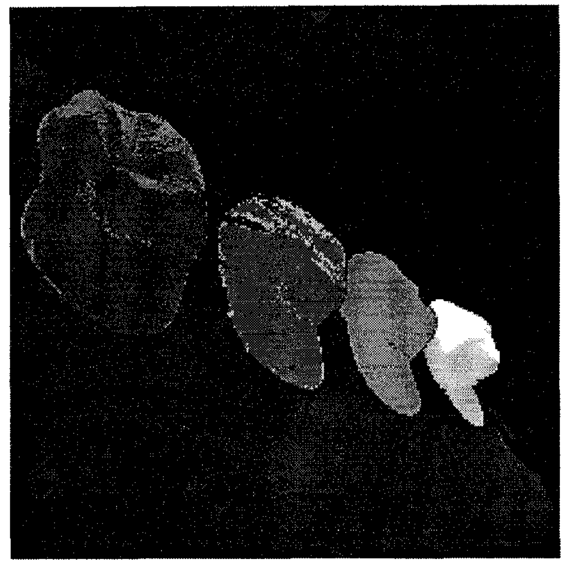

Figure 6 - Segmented hats image

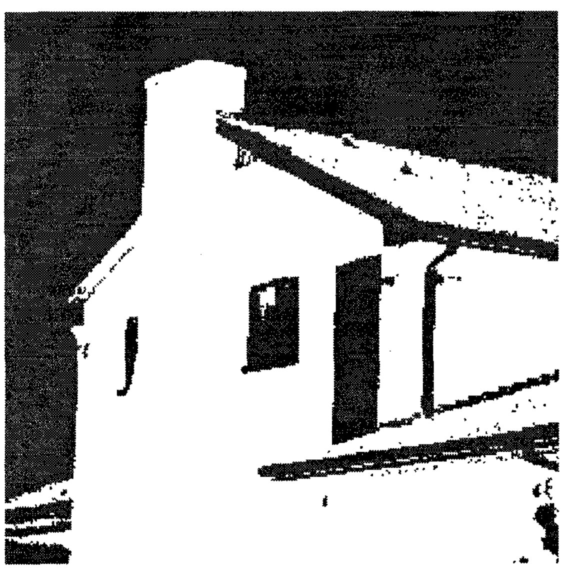

Figure 7 - Segmented house image

Figure 8 - Segmented parrot image