Collection, Analysis and Representation of Memory Color Information

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Abstract. Memory color plays an important role in the perceptual process. The aim of this research is to collect, analyze and represent memory color data for certain natural scenes objects: sky, grass and tree leaves. To emphasize reliable data collection, we consider several sources: (a) psychophysical experiment; (b) multispectral image; (c) standard image database and (d) random image collection. Moreover, we consider different daylight conditions and locations. We perform an in-depth analysis of the collected information in the CIE-xy chromaticity space and present the natural scene objects as a memory color ellipse or polygon. Finally, we demonstrate a potential use of the collected information for natural image segmentation and enhancement.

Keywords: Memory Color · Natural Scene Objects

1 Introduction

Memory colors are those colors which are recalled in association with familiar objects in long-term memory Bartleson [1960]. They have influence on the color appearance of objects, and hence play an important role on comparison and decision process. The naturalness of the images in the visuo-cognitive processing depends on the closeness of match between the representation of the image and memory Janssen [2001]. Natural objects like sky, grass etc. has the naturalness property and good candidate of objects containing memory color. These objects should be considered within the context of the entire image. Moreover, since memory colors are those that people often see in life, remember them and can tell when they look right, these objects must have very small gamut. Therefore, it is necessary to define a certain range of values for these objects. This research is motivated by such observations and hence contributes to collect reliable memory color information of certain natural scene objects and represent them in a standard form.

Heretofore, the concept of memory color has been widely studied by the scientific communities from different perspectives Bartleson [1960]; Pérez Carpinell et al. [1998]; Vurro et al. [2013]; Xue et al. [2014]. In image

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processing, it has been successfully adopted in numerous tasks Boust et al. [2006]; Xue et al. [2014], e.g., image quality evaluation, matching, segmentation and enhancement. For image enhancement, an expert first segments it into regions of interest. A set of these regions correspond to the natural objects. Then s/he changes the colors of these objects such that they match with the color that s/he recalls from memory. Likewise, naive observers use memory colors to judge an image for preference. It is found that, an image is preferred if the colors of the scene objects match with the colors that are stored in memory Boust et al. [2006]. Memory colors have been used for image enhancement through automatic color constancy. Most digital cameras apply color constancy (white balancing) algorithms to estimate the illumination, which ensures that color casts are compensated and colors (other than the neutrals) appear as correct or pleasing Rahtu et al. [2009]. A dataset was collected for such study Rahtu et al. [2009], which is not publicly available. Moreover, it was collected by maintaining several constrains. Therefore, more interests are grown towards conducting similar research with a dataset obtained from restricted as well as publicly available images. This eventually motivates us to collect memory color data that combines information from different sources and conditions.

In this research, our aim is to: (a) collect reliable memory color data for certain natural scenes objects; (b) analyze the data in a widespread color space and (c) provide a standard representation of the memory color. To this aim, first we collect memory color data from several sources, such as: psychophysical experiments, images from internet and personal collection, standard image dataset and multispectral image. Next, we analyze the data in the CIE xy-chromaticity space by observing the color variations of each object. Finally, we represent the objects as an ellipse or polygon in the color space.

A practical use of memory color is image segmentation and enhancement Xiao-Ning Zhang et al. [2010]; Xue et al. [2014]. We observe that, this can be accomplished by exploiting our analyzed data. Therefore, although it is not our primary interest, yet in this paper we demonstrate such an application to clarify the use of our data. Our segmentation procedure consists of simply verifying the pixels color location w.r.t. the memory color ellipse or polygon. We perform image enhancement with a directional shift of the input color of memory objects towards the preferable region.

In the rest of this paper we discuss data collection strategies in Section 2. Then, we present our analysis and observations in Section 3. We present the data representation method in Section 4. Next, we demonstrate an application in Section 5. Finally, we draw conclusions in Section 6.

2 Memory Color Data Collection

We collect memory color data for three natural objects: sky, grass and tree leaves. Our data collection procedure consists of two main strategies: (1) psychophysical experiment, similar to Bartleson [1960]; Pérez Carpinell et al. [1998] and (2) image based data collection.

2.1 Psychophysical Experiment

The aim of psychophysical experiment is to find out what would be the response of an observer when he/she is asked to choose a particular color corresponding to a certain natural scene object. In general, such experiments are conducted in a control environment and the observer does not have any contextual information, i.e., surrounding objects or a reference object.

Similar to Bartleson [1960], we use the Munsell color chart. The color chart is placed in the light cabinet under different light sources. In order to stabilize the light source, we switch ON the light booth for 2 hours before the experiments. At the beginning, the observer is asked to look at the walls of the cabinet for a certain period of time, so that s/he can adapt with the light source. The geometry used here is 0/45.

We consider 18 observers from different backgrounds, i.e., from different countries, male and female, with/without prior knowledge of color. We ask the following questions: (a) "what is the possible color of an object (sky, grass and tree leaves)" and (b) "what is the most preferable color for that object?". The preferred color is considered as "favorite color". The observers are not allowed to take a reference color. We measure the reflectance spectra for the selected color chips using *Perkin-Elmer Lambda 18 UV/VIS* spectrophotometer (specular excluded), between the wavelength 380 nm - 780 nm in step of 1 nm. From the measured spectra, we calculate the tristimulus values for further analysis.

2.2 Image Based Data Collection

In this strategy, an observer can select the memory color (image pixel) regardless of any controlled environment as well as considering the surrounding objects present in the image. A digital image is displayed to an observer. The task here is to select at least 3 pixels for certain natural object. Moreover, they select at least 1 pixel as preferred ("favorite") color.

We consider images from three different sources: (a) multispectral images; (b) standard image database and (b) random images from internet/personal collection. Table 1 provides a list of the number of images and selected data points for each source and object category.

Table 1. Number of images and selected data points for each memory color objects

	Sky		**Grass**		**Tree leaves**	
	images	points	images	points	images	points
Psychological	n/a	48	n/a	44	n/a	60
Spectral	13	384	15	428	20	828
Digital image(internet)	155	307	79	155	75	150
Digital image (standard)	188	200	183	551	110	224
Total data	356	939	277	1178	205	1262
Total after clean up	-	922	-	1138	-	1243

Multispectral Images: We collect 26 spectral reflectance images. These images are in the following wavelength ranges with different spatial resolution: (a) 420 nm to 721 nm at the interval of 7 nm; (b) 400 nm to 720 nm at the interval of 10 nm and (c) 450 nm to 800 nm at the interval of 10 nm. Several images consist of a mixture of rural scenes from the Minho region of Portugal, containing trees leaves, grass, earth and urban scenes. These images were used in the study by Foster et al. Foster et al. [2004]. Other images are obtained from the image collection of the Spectral Color Research Group in the University of Eastern Finland.

Due to several limitations, it was not possible to ensure that the collected spectral images are captured in different daylight conditions. Therefore, we use the SPDs of daylight simulators in order to simulate the effect of different day times. We consider four day light CIE standard illuminants: D50, D55, D65 and D75, which typically represent: Horizon light, Mid-morning/Midafternoon, Noon daylight and North sky daylight.

Standard image database: We emphasize to collect memory color data from the images of a renowned, color research oriented and publicly available database. Such an image database[1] Gehler et al. [2008] was created at Microsoft Research Cambridge for color constancy based research. It consists of 568 images, from which we consider 481 images of outdoor natural scenes. Additionally, we label the images as either mid-day or morning/afternoon images.

Random images: We collect 309 natural objects (sky, grass and tree leaves) specific images from internet and personal collection. The aim of this collection is ensure that the images are from different daylight conditions, places and times. Moreover, such images are taken by arbitrary unknown imaging sensors. We label these images based on different times of a day.

3 Data Analysis and Observations

First, We transform the memory color data from each source into the CIE xy-chromaticity space. Next, we identify and use particular thresholds to remove outliers through the data cleanup process. For each object category, we analyze: (a) variations of chromaticity coordinates for different data sources and (b) directions of shift for different daylight conditions. Finally, we store these data as training data for potential applications. Table 2 provides a list of minimum and maximum coordinates found from each data source and for each object.

psychophysical experiments: Fig. 1 illustrates the memory colors obtained from psychophysical experiments, where green indicates "favorite color". We observe that, the sky color in the chromaticity space justifies the identified region of sky color in the image based data collection. The grass color region in the chromaticity space is not in good agreement with the identified region of grass in other data sources. More specifically, they are within the range of 0.26 to 0.38

[1] http://files.is.tue.mpg.de/pgehler/projects/color/index.html

Table 2. Analysis of different datasets for memory color objects

	Min x	Max x	Min y	Max y
Sky				
Psychophysical	0.20	0.32	0.25	0.35
Spectral	0.24	0.32	0.26	0.35
Image (random)	0.21	0.31	0.21	0.34
Image (standard)	0.27	0.35	0.28	0.36
Grass				
Psychophysical	0.26	0.38	0.37	0.56
Spectral	0.30	0.40	0.35	0.47
Image (random)	0.36	0.41	0.47	0.54
Image (standard)	0.34	0.42	0.40	0.54
Tree Leaves				
Psychophysical	0.27	0.36	0.42	0.56
Spectral	0.24	0.41	0.26	0.51
Image (random)	0.35	0.44	0.43	0.56
Image (standard)	0.33	0.43	0.38	0.54

in x-coordinate whereas the range is between 0.30 to 0.42 for other datasets. The tree color shows good correlation with other source of images. Moreover, we notice that the favorite colors chosen by different observers are scattered within the region.

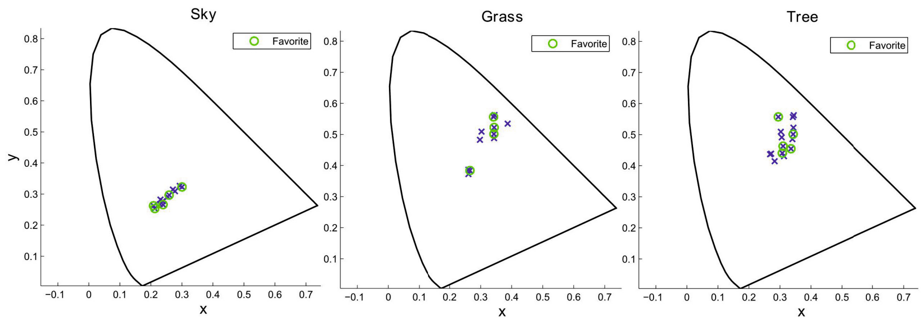

Fig. 1. Illustrations of results from psychophysical experiments. Plots show the CIE-xy coordinates of the natural objects: (from left) of sky, grass and tree leaves.

Spectral Images: Fig. 2 presents the memory color data obtained from the spectral images. Moreover, it illustrates the changes of colors as a function of different illuminations. We see that, due to simulations with different daylight, the memory colors of each object spans wider range in the CIE-xy diagram.

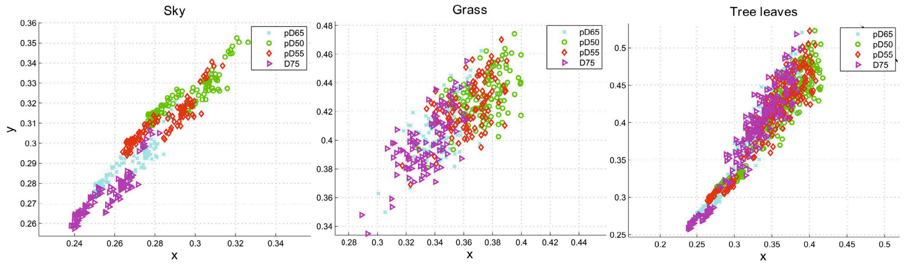

Fig. 2. Illustration of memory colors obtained from spectral images in the CIE-xy chromaticity space. From left, Sky, grass and tree leaf in: D50 (green), D55 (red), D65 (cyan) and D75 (pink).

Standard image database: Fig. 3 illustrates the memory colors obtained from the images of this category. From the analysis of variations, in Fig. 2 and Fig. 3, we found that the sky color regions in the chromaticity space justify the identified region from spectral image. Similar analysis on other objects reveals that, although grass and leaves colors have overlapping with colors data from different sources, yet there are some regions which mismatch.

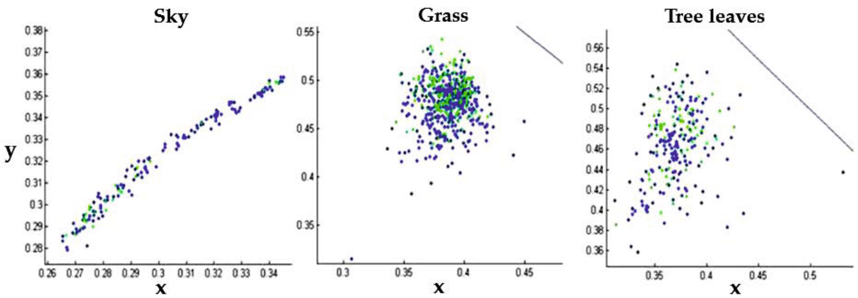

Fig. 3. Illustration of memory colors in the CIE-xy chromaticity space, obtained from standard image database Gehler et al. [2008]. In the plots, blue color indicates mid-day and green color indicates objects memory color in morning/afternoon.

Random image collection: Fig. 4 shows the memory color of objects from the random image collection. This analysis revealed that sky color at the mid-day shift diagonally from the yellow color region. This is because of the dominance of yellow color in the morning / afternoon. Grass and tree-leaves colors show very little amount of shift. Grass colors shift diagonally downwards and from tree-leaves colors no conclusion is possible to make. We can use this shifting directional information during enhancement.

Next, we analyze the data jointly from different sources. We observe that the combined data consists of few outliers. Based on observations, we define thresholds for each memory object to clean up the data. We determine these

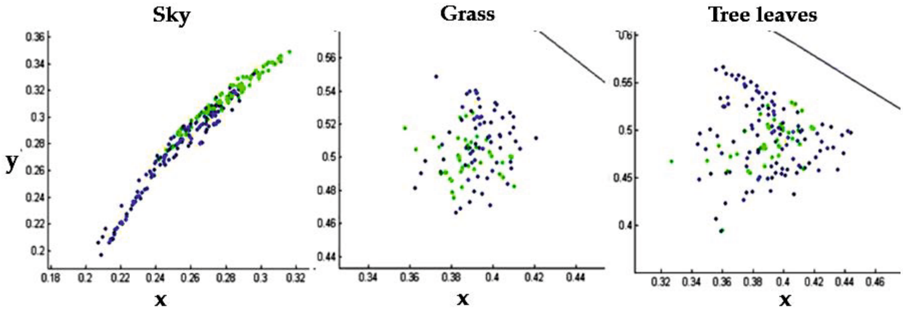

Fig. 4. Illustration of memory colors in the CIE-xy chromaticity space, obtained from randomly collected images. In the plots, blue color indicates mid-day and green color indicates objects memory color in morning/afternoon.

thresholds empirically by examining the Euclidean distances between each data point and the mean of all data. First, we remove the 5% - 10% most distant points from the entire data. Then, as the threshold values, see Table 3, we keep the minimum and maximum coordinates of the remaining data.

Table 3. Thresholds (chromaticity values) for memory color objects

	Min x	**Max x**	**Min y**	**Max y**
Sky	0.21	0.345	0.205	0.356
Grass	0.30	0.42	0.35	0.56
Tree leaves	0.24	0.435	0.262	0.562

In the chromaticity space, because of the changes in daylight situations the same object color may shift in any direction from a particular point. To accurately locate such shifts in color, it is necessary to identify the direction of changes. For this reason, based on the data collected from multispectral images, we calculate and study the angle of changes in different daylight conditions. Table 4 gives the analysis of the angular changes under different illuminations.

Table 4. Intra variation of Angles of colors in different illumination (The unit is in degree between two corresponding colors).

	Sky				**Grass**				**Tree Leaves**			
	Max	**Min**	**Avg**	**SD**	**Max**	**Min**	**Avg**	**SD**	**Max**	**Min**	**Avg**	**SD**
D65	48.17	46.00	47.36	0.56	52.25	46.99	49.77	1.08	53.18	46.19	49.44	1.66
D50	48.66	46.02	47.61	0.66	51.61	46.23	49.04	1.12	52.39	45.71	48.95	1.39
D55	48.54	46.08	47.58	0.61	51.90	46.57	49.37	1.10	52.71	45.95	49.19	1.47
D75	47.84	45.81	47.06	0.53	52.42	47.22	49.99	1.07	53.59	46.14	49.53	1.84

4 Memory Color Representations

In order to exploit the collected data for practical tasks, it is necessary to establish a meaningful form to represent them. Following existing work Xiao-Ning Zhang et al. [2010], we use the notion of ellipse and polygon to represent memory color data. Particularly, the ellipse and polygon are used for all memory colors, whereas, only the polygon is used to represent the favorite color. Total numbers of favorite points are around 10% of the total number of considered data points. Fig. 5 illustrates the obtained ellipses and polygons for the memory color data obtained in Section 2.

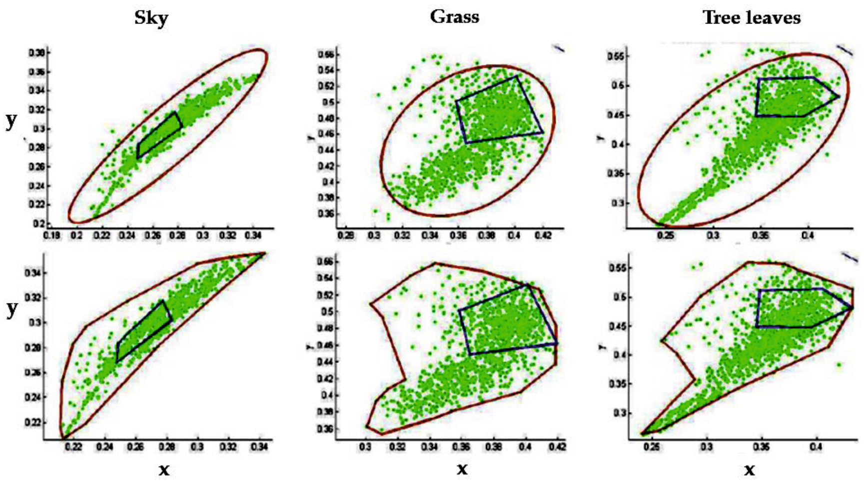

Fig. 5. Illustrations of Memory color ellipses (first row) and polygons (second row) for the entire data collected for different natural objects. The favorite color polygons are shown w.r.t. both ellipses and polygons.

First, we define memory color region in the CIE xy-chromaticity space using an ellipse. From the xy-coordinates, an ellipse is defined using least squares criterion as:

$$ax^2 + bxy + cy^2 + dx + ey = f \tag{1}$$

We observe that, an ellipse fitted with Eq. (1) tends to exclude many data points which belong to the memory color of certain objects. Moreover, it often encompasses unwanted regions. To handle such cases we manually correct the semi-major axis, semi-minor axis and the center of ellipse. The correction is done with the principle of minimizing false rejection and false selection. The first row of Fig. 5 illustrates the ellipses after correction. We see that they cover most of the regions while excluding few color points.

Experimentally (see Fig. 7(a)) we observed that, memory color ellipse, even after manual correction, may lead to segmentation fault due to false consideration of some unwanted region. In order to eliminate this problem, we propose the use of polygon rather than ellipse. The polygons are defined based on manual observation in the chromaticity space. The second row of Fig. 5 illustrates the polygons. Fig. 7(a) shows that, such polygons can successfully handle false selection and rejection.

We define favorite color polygon from the favorite memory color data. In Fig. 5, it is the most interior and smaller polygon. We observe that favorite color polygon is well suited inside the memory ellipse and polygon. Similar to Xiao-Ning Zhang et al. [2010], we will use the it for image enhancement.

5 Application: Image Segmentation and Enhancement

For image enhancement, first we employ a well-known color constancy algorithm called gray-world algorithm Gehler et al. [2008]. Next, we convert the white balanced image from RGB space to xyY space. After that, we apply segmentation based on the defined ellipse/polygon in order to obtain the region of interest (ROI). Any pixel is added to the ROI if it belongs to the ellipse/polygon. Finally, we shift the chromaticity coordinates of the segmented pixels based on its relative distance and subtended angle to the center of favorite color polygon. The distance according to which the data should be shifted depends on two parameters: the distance and the angle of the point in relation to the center of the rectangle Xiao-Ning Zhang et al. [2010].

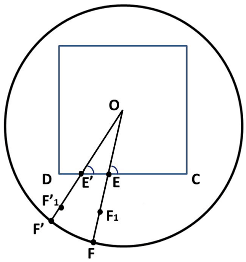

Fig. 6. Color shifting distance in the enhancement process

Fig. 6 illustrates the color shifting method. Point F is the candidate to shift towards the memory color rectangle. According to the rule: $OE : EF = EF^1 : F^1F$, the colors which are further away from the center should be enhanced more than the closer ones. Let us observe points $F^{'}$ and F. Even though the distance from the center to the colors are same, $F^{'}$ is closer to the DC boundary, and therefore should be enhanced less than F. To satisfy this rule, we must consider the angle from the rectangle boundary to the color point. The pixels within the memory rectangle should remain the same. If d is the distance from the center of the rectangle to the color F (let $d = OF$), then the distance from the center to the enhanced point $F^1(d^1 = OF^1)$ should be:

$$d^1 = \frac{h}{sin(\theta)}\left(2 - \frac{h}{d\,sin(\theta)}\right) \tag{2}$$

where, h is the distance from the center to the middle of the rectangle edge (i.e., O to DC). Finally, we convert shifted pixels from xyY to RGB space.

Fig. 7(a) illustrates the results of segmentation using ellipse/polygon. In the segmented image, the colored portions are the regions where enhancement will be applied. We observe undesirable result in middle column as the pixels belong to the cloud are segmented as sky. This indicates that, segmentation with ellipse produces incorrect segmentation (false selection). On the other hand, based on the result in the last column, we see that memory color polygon performs better.

(a)

(b)

Fig. 7. (a) Result of segmentation: (left) original image, (middle) segmented image generated by memory ellipse, (right) segmented image generated by memory polygon. (b) Results of enhancement of images with sky. Left column shows the original image and right column shows the enhanced image.

Fig. 7(b) illustrates the results of image enhancement. Note that, the proposed method only enhances a particular segment of the image that consist of certain natural object. We observe that, such an enhancement increases the contrast between the memory color objects and other objects of the image. Therefore, it is necessary to perform global enhancement to preserve the coherency of colors, which we consider as a potential future work. Additionally, we observe that: (a) performance of enhancement depends on the accuracy of segmentation and (b) amount of enhancement depends on the area as well as location of polygon in the chromaticity space.

6 Conclusions

The fundamental contribution of this research is to perform acquisition and analysis of memory color information for several objects commonly appears in natural scenes. Therefore, we consider different data sources and devices to collect memory color information. We study the collected data and provide in-depth analysis to ensure reliability and better understanding. We represent object specific data as an ellipse or polygon. As a potential use, we demonstrate applications in image segmentation and enhancement. Results show that, the collected data is reliable and hence can be used for different image processing tasks which concern about the natural scenes objects. In future, this fundamental research can be enhanced by providing different forms of representation of the collected memory color data, e.g., probabilistic representation of the decision boundary of memory color regions in the color spaces. Moreover, we can investigate different color spaces and evaluate them. For the application, we can focus on developing more robust methods and compare them with existing methods.

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