Computational Color: Representation, Constancy and Psychophysics

Javier Vazquez-Corral and Maria Vanrell

Computer Vision Center, Departament de Ciencies de la Computacio,
Universitat Autonoma de Barcelona, Edifici O, Campus UAB,
08193 Bellaterra (Cerdanyola del Valles), Catalunya
E-mail:javier.vazquez@cvc.uab.cat

Abstract

Computational Color is a multidisciplinar research field. In this paper we will focus on its applications to Computer Vision. Color in Computer Vision has been used in different tasks: Segmentation [4], Object Recognition [12], Saliency [11], Induction [14], Naming [1], Constancy [10]... The aim of this paper is to review about some of these topics and the authors' contributions to them. In particular we will discuss three different open problems: Color Representation, Color Constancy and Psychophysical evaluation.

Keywords: Computational Color, Color and Texture analysis, Color Constancy, Psychophysics

1 Introduction

Color has been widely studied as a multidisciplinar topic for a long time. Artists, Biologists, Physics, Physiologists even Philosophers have tried to understand and to explain color from different points of view. This role of color has had an important repercussion in the study of computational models for it. In this paper we will focus on three different problems (Color Representation, Color Constancy and Psychophysical evaluation) where we have been working during the last years. We will explain the problems and a tangential explanation of our solution to them. Then, this paper is organized as follows. First, we will explain the Color Representation problem. Later on we will move to the Constancy, and eventually we will arrive to its Psychophysical evaluation. Finally we will sum up some conclusions.

2 Color Representation

Several color spaces had been defined in color science [20], each one with a certain intention. Some of them, as RGB or CMY, trying to improve the image acquisition, visualization and results in printing devices. Others, the uniform spaces, such as, CIELAB or CIELUV, to represent perceptual similarity considering an Euclidean distance.

In computer vision, a usual way to work in color has been to extend gray-level methods to be applied on the RGB channels separately.

However, current spaces does not always preserve the features perceived in the color image to the channel representation. Two different situations can occur.

- There can be a high correlation between the three channels.

- The principal features of the color image are not represented in the channels individually, because these features are emerging from a combination of the channels (see Figure 1)

Therefore, our hypothesis is based on the fact that these situations can usually happen in color-texture images. Current spaces, therefore, are not able to correctly extract the texture information in the channels.

For this reason, in this work we propose a new color space that adapt to the image context. The main goal of our space is to facilitate the extraction of information such as blobs (where we will concentrate) in order to further represent the color-texture structure of the image.

To this end, we first extract the ridges of the color histogram of the image $r_1, \cdots, r_n$ [18]. These ridges select the essential the color information of the image. We can simplify the ridges by their main representative color point, then $r_i = (R_i, G_i, B_i)$. Then we select the three color ridges that form the biggest gamut among them

$$(r_1, r_2, r_3) = max_{i,j,k_{,i \neq j, j \neq k \neq k}} Area(r_i, r_j, r_k) \quad (1)$$

We select this three ridges in order to maximize the information. Later on, we compute a center point p where the three ridges behave as orthogonal as possible. This means

$$p = arg \min(v_1 \cdot v_2 + v_1 \cdot v_3 + v_2 \cdot v_3) \quad (2)$$

where

$$v_1 = p - r_1, v_2 = p - r_2, v_3 = p - r_3 \quad (3)$$

From now on, the point p will be de center of the space. Finally, by using a Gram-Schmidt normalization we convert v_1, v_2, v_3 in an orthogonal space. In Figure 2 we can see the original image and the three channels found.

3 Color Constancy

The color we perceive from an object depends on three different aspects: the reflectance of the object, the sensors of the capturing device and the illumination of the scene. Illumination, then, can substantially change the perception of an image and can disturb in many computer vision tasks such as tracking or object recognition. Then, to find an image representation independent from the illumination is useful and is the research goal in Color constancy. However, this problem is overdetermined, and, consequently, it has been tackled from different points of view.

This illuminant independency can be reached in two different ways. The first one is to create an image representation where the illuminant has been cancelled [5],[9]. This is usually called Color Normalization. The second one is based on the idea of discount the illuminant. It means, try to estimate the color of the illuminant in order to convert the image in a canonical one with the original colors of the scene. This is Color constancy.

Color constancy has usually been tackled using low-level assumptions: Image statistics, illuminant and sensors constraints, etc. Image statistics are the basis for methods as Grey-World [3] , White-Patch [13], Shades of Grey [7], Grey-Edge[16]. These statistical methods are non-calibrated. On the other hand, illuminant and sensor restrictions are applied to C-Rule [8], that is, is a calibrated method.

There are other approaches, as the Bayesian Color Constancy methods. These methods are based on the Bayes' Rule. For example, Color-by-Correlation [6] or Bayesian Color Constancy [2]. And, quite related to the Bayesian Color Constancy are the Voting methods [15].

On the other hand, there are a few number of methods using High-Level hypothesis. In fact, this idea is just starting to be checked, for example in [17] where Van de Weijer based is selection in image annotation.

To deal with the color constancy ill-posed problem we are working on a new high-level method that suggest the use of Semantic Categories to solve the Color constancy Problem. The main hypothesis underlying here is that illuminants allow-

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

Figure 1: RGB channels of image (a), where (b) is the red channel, (c) the green channel, and (d) the blue channel

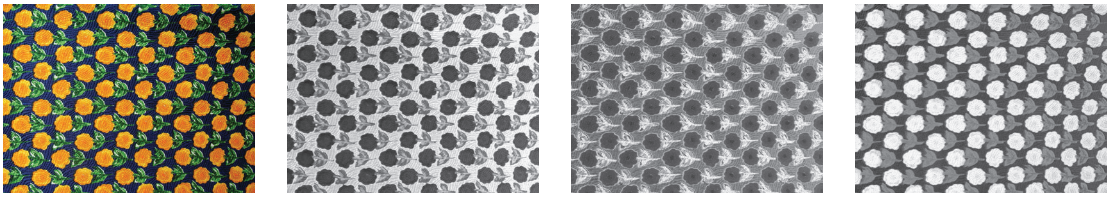

Figure 2: Examples of the results in the new color space: Original image (left) and channels found

ing a high association degree between image colors and semantic categories are the most plausible. We have tested this method by using the Categories of the Focals from Color Names extracted from [1]. Our results are achieving the current state-of-the-art in color constancy. Some results are shown in Figure 3 and they are sumed up in Table 1. This results have been computed in the same Real World Dataset used in [16], learning with the 33% of scenarios. The error measure used is the angular error defined as

$$e_{ang} = \arccos\left(\frac{p_w \hat{p}_w}{\|p_w\|\|\hat{p}_w\|}\right) \tag{4}$$

where p_w is the actual white point of the scene illuminant, and $\hat{p_w}$ is the estimation of the white point given by the method.

4 Psychophysical evaluation

Computing an error measure in Computational Color Constancy is a controversial topic. It is quite

Method	RMS
Our method	14.60°
Grey-Edge	14.73°
Max-RGB	16.28°
no-correction	20.54°

Table 1: Angular error results on the 150 image subset of the Real World Image Dataset

extended the angular error measure, that, as it has explained before, is, the angle between the physical solution of the image and the solution given by the method. Formally,

$$e_{ang} = \arccos\left(\frac{p_w \hat{p}_w}{\|p_w\|\|\hat{p}_w\|}\right) \tag{5}$$

where p_w is the actual white point of the scene illuminant, and $\hat{p_w}$ is the estimation of the white point given by the method.

Anyway, we have shown that this measure does not always agree with the observers choice when asking them to select the most natural image. In

Figure 3: Examples of the method: Original image (left), corrected image (center-left), classified values (center-right), semantic interpretation of the solution(right)

fact, in less than the 50% of the cases, the observers select the image with minimal angular error. we proved this hypothesis in [19]. Regarding this problem, we have define a new measure, the perceptual angular error distance able to cope with the human preferences. this measure is defined as follows

$$e_{ang_{perc}} = \arccos\left(\frac{p_{w_{perc}}\hat{p}_w}{||p_{w_{perc}}||\,||\hat{p}_w||}\right) \quad (6)$$

where $p_{w_{perc}}$ is the psychophysical natural illuminant selected by the observers, and $\hat{p_w}$ is the estimation of the white point given by the method.

All these results come from the experiment performed in [19]. Here, we mimic the explanation of this experiment. We used a set of 83 images from a new image dataset built for this experiment. The camera calibration allows us to obtain the CIE1931 XYZ values for each pixel and consequently, we converted 83 images from CIE XYZ space to CIE sRGB. Following this, we replaced the original illuminant by D65 using the chromaticity values of the grey sphere that was present in all image scenes.

Once the original illumination was digitally removed, 5 new pictures were created by re-illuminating the scene with 5 different illuminants, totaling 415 images. Afterwards, three color constancy algorithms were applied on these newly created images (the selected algorithms are Grey-World [3], Shades-of-Grey [7] and MaxName (our new algorithm). Consequently, we obtain one solution per test image and per algorithm, totaling 1245 different solutions. These solutions were converted back to CIE XYZ to be displayed on a calibrated CRT monitor (Viewsonic P227f) using a visual stimulus generator (Cambridge Research Systems ViSaGe). The experiment was conducted in a dark room.

The experiment was conducted on 10 nave observers recruited among university students and staff (none of the observers had previously seen the picture database). All observers were tested for normal color vision using the Ishihara and the Farnsworth Dichotomous Test (D-15). Pairs of pictures (each obtained using one of two different color constancy algorithms) were presented one on top of the other on a grey background (31 Cd/m2). The order and position of the picture pairs was random. Each picture subtended 10.5 x 5.5 degrees to the observer and was viewed from 146 cm. This brings us to 1245 pairs of observations per observer.

For each presentation, observers were asked to select the picture that seemed most natural, and to make the selection by pressing a button on an IR button box. The set up (six buttons) also allowed observers to register how convinced they were of their choice (e.g. strongly convinced, convinced, and marginally convinced). There was no time limit but observers took an average of 2.5 seconds to respond to each choice. The total experiment lasted 90 minutes approximately (divided in three sessions of 30 minutes each)

5 Conclusion

In this paper we have explained the work we have done during the last years. This work can be roughly split in three different topics. Firstly, we have created a color space which adapts to the image content. This space extracts the different features of the image in different channels, therefore, it can improve the color-texture description of the image. Secondly, we have formulated a Color Constancy method from a new point of view: the use of categories to correct the illuminant. This method achieves current state-of-the-art results in Color Constancy by introducing high-level prior knowledge. Finally, we have shown that the usual error measure in Color Constancy does not correlate with the human preferences. For this reason we have defined a new error measure to better cope with the human preferences.

Current research lines are focusing on the extension of the categories used in the Color Constancy method, and the application of the proposed color space to object segmentation and saliency.

6 Acknowledgments

This work has been partially supported by projects TIN2007-64577 and Consolider-Ingenio 2010 CSD2007-00018 of Spanish MEC (Ministery of Science)

References

[1] R. Benavente, M. Vanrell, and R. Baldrich. Parametric fuzzy sets for automatic colour naming. *Journal of the Optical Society of America A*, 25(10):2582–2593, 2008.

[2] D. H. Brainard and W. T Freeman. Bayesian color constancy. *Journal of the Optical Society of America A*, 14:1393–1411, 1997.

[3] G. Buchsbaum. A spatial processor model for object colour perception. *J. Franklin Inst*, 310:126, 1980.

[4] H.D. Cheng, X.H. Jiang, Y. Sun, and J. Wang. Color image segmentation:advances and prospects. *Pattern Recognition*, 34(6):2259–2281, 2001.

[5] G. Finlayson and M. Drew. White-point preserving color correction. In *G.D. Finlayson and M.S. Drew, White-point preserving color correction, Proc. IST/SID 5th Color Imaging Conference, pp. 258-261, 1997.*, 1997.

[6] G.D. Finlayson, S.D. Hordley, and P.M. Hubel. Color by correlation: A simple, unifying framework for color constancy. 23(11):1209–1221, November 2001.

[7] G.D. Finlayson and E. Trezzi. Shades of gray and colour constancy. In *Color Imaging Conference*, pages 37–41, 2004.

[8] D.A. Forsyth. A novel algorithm for color constancy. *International Journal of Computer Vision*, 1990.

[9] T. Gevers and A. W. M. Smeulders. Color based object recognition. *Pattern Recognition*, 32:453–464, 1999.

[10] S. D. Hordley. Scene illuminant estimation: past, present, and future,. *Color Research and Application*, 31(4):303–314, 2006.

[11] L. Itti, C. Koch, and E. Niebur. A model of saliency-based visual attention for rapid scene analysis. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 20(11):1254–1259, Nov 1998.

[12] F. Shahbaz Khan, J. Van de Weijer, and M. Vanrell. Top-down color attention for object recognition. In *Proceedings of the ICCV, Kyoto, Japan*, 2009.

[13] E. H. Land and J. J. McCann. Lightness and retinex theory. *J. Opt. Soc. Am.*, 61(1):1–11, 1971.

[14] X Otazu, M Vanrell, and C.A Párraga. Mutiresolution wavelet framework models brigthness induction effects, Feb 2008.

[15] G. Sapiro. Color and illuminant voting. *PAMI*, 21(11):1210–1215, November 1999.

[16] J. van de Weijer, Th. Gevers, and A. Gijsenij. Edge-based color constancy. *IEEE Transactions on Image Processing*, 16(9):2207–2214, 2007.

[17] J. van de Weijer, C. Schmid, and J. Verbeek. Using high-level visual information for color constancy. In *International Conference on Computer Vision*, oct 2007.

[18] E. Vazquez, J. van de Weijer, and R. Baldrich. Image Segmentation in the Presence of Shadows and Highlights. In *Proceedings of the 10th European Conference on Computer Vision: Part IV*, pages 1–14. Springer-Verlag Berlin, Heidelberg, 2008.

[19] J Vazquez-Corral, C.A Párraga, M Vanrell, and R Baldrich. Color constancy algorithms: Psychophysical evaluation on a new dataset, May-June 2009.

[20] G. Wyszecki and W.S. Stiles. *Color science: concepts and methods, quantitative data and formulae*. John Wiley & Sons, 2nd edition, 1982.