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Color names as a constraint for Computer Vision problems

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Abstract: Computer Vision problems are usually ill-posed. Constraining the gamut of possible solutions is then a necessary step. Many constraints for different problems have been developed during years. In this paper, we present a different way of constraining some of these problems: the use of colour names. In particular, we will focus on segmentation, representation and constancy.

Introduction: Computer Vision science faces off different kinds of problems. Nevertheless, most of them have the same drawback: they are ill-posed. This means that, in order to solve them, we shall use different constraints. Obviously in color images, restrictions on the color of the scenes are frequently used.

There are different colour constraints. The most used and well-known one is Gamut mapping. Gamut mapping consists on finding a canonic set of plausible solutions, and selecting the results which fall completely inside this set(gamut). Other typical constraints are based,for example in statistics over the colour tensor or the edges from an image. However, these constraints are just based on statistics in the image, and they do not insert any kind of high-level information.

In this paper, we present some results in different computational colour problems using colour names as a constraint. Colour names were firstly studied by Berlin and Kay in his seminal work [2]. In this work they claimed that developed languages own eleven basic colour categories; eight chromatic: red, green, blue, yellow, orange, purple, pink and brown, and three achromatic: black, grey and white. Several computational models for model these colour categories have been published. For example, Lammens [10], Seaborn-et-al [13] and Van de Weijer-et al- [16] have proposed different methods. The colour naming model we use in this paper is the one proposed by Benavente-et al- [1]. This paper is based on a fuzzy set paradigm, where data was obtained psychophysically. Moreover, this model is based on returning the membership of a colour in the different colour categories. For example, in the case of cyan, the model returns approximately 0.5 in blue and green and zero or almost zero in the other 9 categories.

The paper is organized as follows. In the next section, we will explain the use of colour names for image segmentation. Later on, we will discuss the ability of colour names to allow us to develop a colour space based on the image content. Beyond this section, we will discuss the capability of colour names to deal with colour constancy. Finally, we will sum up the conclusions and we will sketch some ideas for further work.

Colour segmentation: The direct application of a colour naming model is image segmentation. This application is done by just selecting in each pixel the colour name with higher membership value for that pixel. Mathematically, Let $I : R^2 \rightarrow R^3$ and image. Then, for a pixel $p \in Dom(I)$, the segmented image IS will be

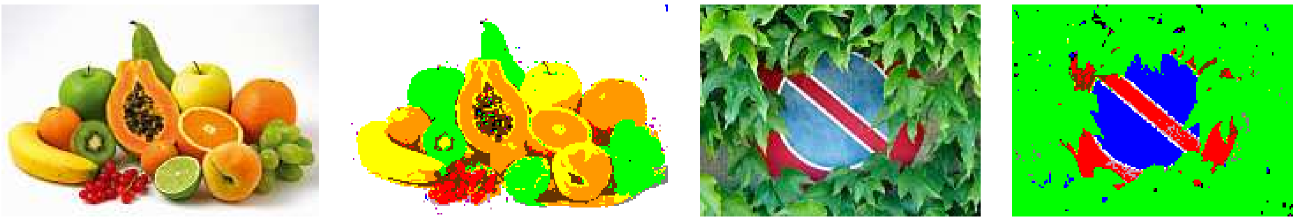
$$IS(p) = max_{C \in CN} \mu_C(I(P)) \qquad (1)$$

where, CN is the set of colour names, C is a colour name, and $\mu_C(x)$ gives the membership that x belongs to colour name C.

In figure 1 we show some segmented images. Moreover, figure 1.(d) is an example of image segmented for further processing, in this example, for traffic signs detection.

Colour Representation: Several colour spaces with different purposes had been defined in colour science [18]. Some of them, as RGB or CMYK, trying to improve acquisition, visualization and reproduction of images 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 colour has been to extend grey-level methods to be applied on the RGB



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

Fig. 1 (a)Original image (b) Segmented image (c) Original image (d) Segmented image

channels separately.

However, current spaces do not always preserve the features perceived in the colour 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 colour image are not represented in the channels individually, because these features are emerging from a combination of the channels (see Figure 2)

Therefore, our hypothesis is based on the fact that these situations can usually happen in colour-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 colour space that adapts to the image context. The main goal of our space is to facilitate the extraction of information such as blobs (where we will focuss) in order to further represent the colour-texture structure of the image.

To this end, we first extract the ridges of the colour histogram of the image $r_1, \cdots, r_n$ as done in[17]. These ridges select the essential colour information of the image. We can simplify the ridges by their main representative colour point, that is $r_i = (R_i, G_i, B_i)$. Then we select three colour ridges r_1, r_2, r_3. The criteria used to select these ridges can be modified:ridges forming the biggest gamut among them, ridges of three particular colours chosen by the user. Later on, we compute a center point p where the three ridges behave as orthogonal as possible. This means

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

where

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

From now on, the point p will be the 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 3 we can see an example of an image and the three channels found.

Colour Constancy: The colour we perceive from an object depends on three different components: 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, finding an illuminant-independent image representation can be useful and it is the research goal in Colour 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 colour normalization. The second one is based on the idea of discounting the illuminant. This is Colour constancy.

Colour constancy has usually been tackled using low-level assumptions: image statistics, illuminant and sensors constraints, etc. Image statistics are the basis for methods as

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

Fig. 2 RGB channels of image (a), where (b) is the red channel, (c) the green channel, and (d) the blue channel

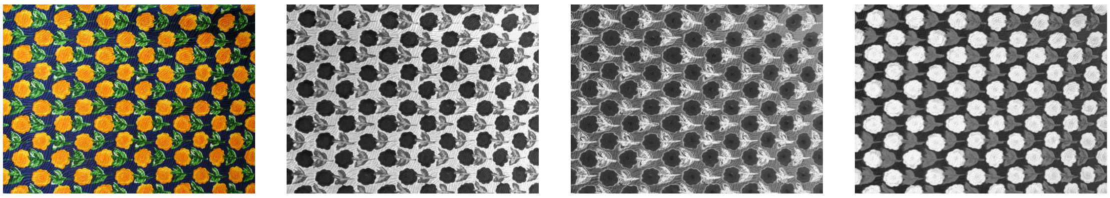


Fig. 3 Examples of the results in the new colour space: Original image (left) and channels found

grey-world [4] , white-patch [11], shades of grey [7], grey-edge[14]. These statistical methods are non-calibrated. On the other hand, illuminant and sensor restrictions are applied to C-Rule [8], in order to constraint the set of plausible solutions.

There are other approaches, as the Bayesian Constancy methods which are based on the Bayes' Rule. For example, colour-by-correlation [6] or bayesian colour constancy [3]. And, quite related to the bayesian constancy are the voting methods [12].

On the other hand, there are just a few number of methods that use high-level hypothesis. In fact, this idea is just starting to be checked, for example in [15] where Van de Weijer based its selection in image annotation.

To deal with the colour constancy ill-posed problem we are working on a new high-level method that uses semantic categories to solve the colour constancy problem. The main hypothesis underlying here is that illuminants allowing a high association degree between image colours and semantic categories are the most plausible. We have tested this method by using the categories of the focals from colour names extracted from [1]. Our results are achieving the current state-of-the-art in colour constancy. Some results are shown in Figure 4 and they are sumed up in Table 1. These results have been computed in the same real world dataset used in [14], 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.

Conclusions: In this paper we have shown the capability of colour names to constraint different computer vision problems. In particular, we have developed solutions for segmentation, colour representation and colour constancy. In each case we have used colour names from different points of view. Firstly, we have directly used the results reported by the colour naming model to segment images. In this research line, the inclusion of different categories,

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

Fig. 4 Examples of the method: Original image (left), corrected image (center-left), classified values (center-right), semantic interpretation of the solution(right)

such as grass, sand and others or some statistical assumptions might improve the results obtained. Secondly, we have created a colour space which adapts to the image content. This space extracts the different features of the image in different channels, therefore, it can improve the colour-texture description of the image. Moreover, we use colour names in order to know the colour of the channels, or, even, to a priori select the colours wanted in the image. Finally, we have formulated a colour constancy method from a new point of view: the use of categories to correct the illuminant. In particular, the categories used are the focals of the colour names This method achieves current state-of-the-art results in colour constancy by introducing high-level prior knowledge.

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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] B. Berlin and P. Kay. *Basic Color Terms: Their Universality and Evolution*. University of California Press, Berkeley, CA, 1969.

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

[4] G. Buchsbaum. A spatial processor model for object colour perception. *J. Franklin Inst*, 310:1–26, 1980.

[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. *IEEE Trans. Pattern Anal. Mach. Intell.*, 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] J. M. G. Lammens. *A computational model of color perception and color naming*. PhD thesis, Buffalo, NY, USA, 1995.

[11] E. H. Land and J. J. McCann. Lightness and retinex theory. *Journal of the Optical Society of America.*, 61(1):1–11, 1971.

[12] G. Sapiro. Color and illuminant voting. *IEEE Trans. Pattern Anal. Mach. Intell.*, 21(11):1210–1215, November 1999.

[13] M. Seaborn, L. Hepplewhite, and T. John Stonham. Fuzzy colour category map for the measurement of colour similarity and dissimilarity. *Pattern Recognition*, 38(2):165–177, 2005.

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

[15] 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.

[16] J. van de Weijer, C. Schmid, J. Verbeek, and D. Larlus. Learning color names for real-world applications. *Trans. Img. Proc.*, 18(7):1512–1523, 2009.

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

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