BLUR ROBUST AND COLOR CONSTANT IMAGE DESCRIPTION

Joost van de Weijer *, *Cordelia Schmid*

LEAR TEAM
GRAVIR-INRIA
655, avenue de l'Europe, 38330 Montbonnet, France
{joost.van-de-weijer, cordelia.schmid}@inrialpes.fr

ABSTRACT

An important class of color constant image descriptors is based on image derivatives. These derivative-based image descriptors have a major drawback: they are sensitive to changes of image blur. Image blur has various causes such as being out-of-focus, motion of the camera or the object, and inaccurate acquisition settings. Since image blur is a frequently occurring image degradation, it is desirable for object description to be robust to its variations. We propose a set of descriptors which are both robust with respect to blurring effects, and invariant to illuminant color changes. Experiments on retrieval tasks show that the newly proposed object descriptors outperform existing descriptors in the presence of blurring effects.

Index terms: Image color analysis, Image matching, Image representations, Object recognition.

1. INTRODUCTION

To successfully index objects, image representations should be robust to scene incidental events, such as viewpoint, shadow, shading and illuminant color variations. A change of the illuminant, e.g. from outdoor sunlight to indoor fluorescent lighting, can significantly influence the measured RGB values. The ability to reliably recognize the color of objects, despite of the changes in the illuminant color, is called color constancy [1]. An important set of color constant descriptors is based on color derivatives [2, 3, 4, 5]. In this article we will focus on these color constant derivative-based descriptors.

Ballard and Swain [6] have shown how to successfully use color information for object recognition. Their method, Color Indexing, recognizes objects by using color histograms. Funt and Finlayson [2] pointed out that this method lacks robustness with respect to changes of the illuminant's color. Based on a physical reflection model they deduced a set of color constant derivatives. These color constant derivatives are applied to construct color histograms which represent objects independent of the illuminant color. However, these descriptors are still dependent on the lighting geometry. Hence, changes due to object orientation or camera viewpoint alter the object's description. A solution to this problem was proposed by Gevers and Smeulders [3]. They introduced a derivative-based invariant which is both robust to variations of illuminant color and lighting geometry.

Apart from the previously discussed photometric variations, blur changes are another frequently encountered phenomenon. They can be caused, among others, by out-of-focus, relative motion between the camera and the object, and abberations in the optical system [7]. For zero order descriptions (e.g. normalized RGB) variations in blur have little influence. However, a change in blur will drastically change edge-based descriptions. Edge-based color methods measure two intertwined phenomena: the color change between two regions, and the edge sharpness of the transition between the regions. A change in blur will have little influence on the color change, but it will influence the edge sharpness of the transition. Therefore, representations based on derivatives have the undesirable effect that they vary under image blur.

We observed that the ratios of some image derivatives are robust to smoothing [8]. Here we exploit this observation to obtain blur robustness for the color constant ratios presented in [2, 3]. In doing so, we are able to describe images both invariant to physical variations and robust to acquisition parameters which influence the image blur.

2. SUMMARY OF EDGE-BASED COLOR CONSTANCY

The sensor responses, $C \in \{R, G, B\}$, of a camera with spectral sensitivities f^C, are given by:

$$C\left(\mathbf{x}\right) = m^b\left(\mathbf{x}\right)\int b\left(\lambda, \mathbf{x}\right) e\left(\lambda\right) f^C\left(\lambda\right) d\lambda, \tag{1}$$

where m^b is a geometric term representing changes due to lighting geometry, b the surface albedo, and $e\left(\lambda\right)$ the spectral distribution of the illuminant. If we assume delta functions, which is shown to acceptably approximate reality [9], the equation simplifies to

$$C\left(\mathbf{x}\right) = m^b\left(\mathbf{x}\right) b^C\left(\mathbf{x}\right) e^C, \tag{2}$$

*This work is supported by the Marie Curie Intra-European Fellowship Program of the Commission of the European Union.

where $b^C(\mathbf{x}) = b(\lambda^C, \mathbf{x})$, and $e^C = e(\lambda^C)$.

We first consider the lighting geometry to remain constant, which means that m^b is independent of $\mathbf{x}$. This is called a Mondrian, or flat world assumption. Funt and Finlayson [2] showed that the derivative of the logarithm of the sensor response is independent of the illuminant color, since

$$\frac{\partial}{\partial \mathbf{x}} \ln C(\mathbf{x}) = \frac{\partial}{\partial \mathbf{x}} \left(\ln b^C(\mathbf{x}) + \ln m^b + \ln e^C \right) = \frac{b^C_{\mathbf{x}}}{b^C} \quad (3)$$

is only dependent on the surface albedo. The subscript $\mathbf{x}$ is used to indicate spatial differentiation. For the three color channels this leads to three color ratios $\mathbf{p} = \{p_1, p_2, p_3\} = \{\frac{R_{\mathbf{x}}}{R}, \frac{G_{\mathbf{x}}}{G}, \frac{B_{\mathbf{x}}}{B}\}$.

Instead of a Mondrian world we now consider the 3D world case. Then $m^b(\mathbf{x})$ varies with $\mathbf{x}$, e.g. when the viewing direction or the object orientation is changed. The differently oriented planes will undergo varying changes of m^b, thereby changing the color ratios of Eq. 3. Gevers and Smeulders [3] proposed invariants which are both color constant and invariant for lighting geometry changes:

$$\frac{\partial}{\partial \mathbf{x}} \ln \frac{C(\mathbf{x})}{D(\mathbf{x})} = \frac{b^C_{\mathbf{x}}}{b^C} - \frac{b^D_{\mathbf{x}}}{b^D} = \frac{b^C_{\mathbf{x}} b^D - b^C b^D_{\mathbf{x}}}{b^C b^D}, \quad (4)$$

where $D \in \{R, G, B\}$ and $D \neq C$. For the three color channels this leads to two independent ratios $\mathbf{m} = \{m_1, m_2\} = \{\frac{R_{\mathbf{x}}G - G_{\mathbf{x}}R}{RG}, \frac{G_{\mathbf{x}}B - B_{\mathbf{x}}G}{GB}\}$.

3. BLUR ROBUST AND COLOR CONSTANT IMAGE DESCRIPTION

Image degradation due to blur can have multiple causes [7]. Relative motion of the camera with respect to the object and varying acquisition parameters such as aperture and shutter time result in blurring effects. First we will investigate the undesired influence of blur on the color constant ratios discussed above. Next, we propose a method to reduce the sensibility of color ratios to image blur.

The ratios are computed by derivation with a Gaussian derivative at scale σ_d. As a consequence the ratios have a certain scale, e.g. $p_1^{\sigma_d} = R^{\sigma_d}_{\mathbf{x}} / R^{\sigma_d}$. We model blur by a convolution with a Gaussian kernel with σ_b. Then blurring will have a similar effect as computing the ratio at a different scale $\sigma = \sqrt{\sigma_d^2 + \sigma_b^2}$, since

$$p_1^{\sigma} = \frac{(R \otimes G^{\sigma_b}) \otimes \frac{\partial}{\partial \mathbf{x}} G^{\sigma_d}}{R \otimes G^{\sigma_b} \otimes G^{\sigma_d}} = \frac{R \otimes \frac{\partial}{\partial \mathbf{x}} G^{\sqrt{\sigma_b^2 + \sigma_d^2}}}{R \otimes G^{\sqrt{\sigma_b^2 + \sigma_d^2}}}, \quad (5)$$

and hence robustness with respect to blur is equal to robustness with respect to changing the scale of the ratios.

We will now analyse the influence of scale on the ratios. We assume that an edge can be modelled by a step edge $R(x) = \alpha u(x) + \beta$. Then,

$$p_1^{\sigma} = \frac{\frac{\partial}{\partial \mathbf{x}} (\alpha u(x) + \beta) \otimes G^{\sigma}}{(\alpha u(x) + \beta) \otimes G^{\sigma}} = \frac{\alpha \delta(x) \otimes G^{\sigma}}{(\alpha u(x) + \beta) \otimes G^{\sigma}}, \quad (6)$$

where we used the fact that the derivative of the step edge is the delta function δ. Let us now consider the ratio response exactly at the edge, $x = 0$. Here the denominator remains constant, and

$$p_1^{\sigma} = \frac{\alpha}{\beta + \frac{1}{2}\alpha} G^{\sigma}(0) = \frac{\alpha}{\beta + \frac{1}{2}\alpha} \frac{1}{\sigma\sqrt{2\pi}}. \quad (7)$$

This response is clearly not independent of the scale, which proves that color ratios vary with blur.

To obtain robustness with respect to blur we propose the following color angles $\boldsymbol{\varphi}_p = \{\varphi_p^1, \varphi_p^2\}$:

$$\varphi_p^1 = \arctan\left(\frac{p_1}{p_2}\right), \varphi_p^2 = \arctan\left(\frac{p_2}{p_3}\right). \quad (8)$$

The dependence on blur is diminished by the division of the color ratios. Consider the edge of the green channel to be modelled by $G(x) = \lambda u(x) + \gamma$, then,

$$\varphi_p^1 = \arctan\left(\frac{\alpha\left(\gamma + \frac{1}{2}\lambda\right)}{\left(\beta + \frac{1}{2}\alpha\right)\lambda}\right) \quad (9)$$

which is independent of the scale σ, and therefore robust to variation of blur. Moreover, φ_p^1 is invariant for illuminant color changes since both p_1 and p_2 are.

A similar derivation of dependence to blur can be given for the color constant and lighting geometry invariant ratios m_1 and m_2. To obtain robustness with respect to blur we propose the following color angle:

$$\varphi_m = \arctan\left(\frac{m_1}{m_2}\right). \quad (10)$$

When using the color angles proposed in Eq. 8 and Eq. 10 one should take the reliability into account [10]. Application of error analysis to any of the color angles yields the following results:

$$\left(\partial \arctan\left(\frac{a}{b}\right)\right)^2 = \frac{(\partial\epsilon)^2}{\sqrt{a^2 + b^2}}, \quad (11)$$

where $\partial a = \partial b = \partial \varepsilon$. This equation informs us that color angles, for which $\sqrt{a^2 + b^2}$ is low, are less reliable. This fact will be exploited to construct reliable histograms.

4. RESULTS

We apply the proposed image descriptions to an image retrieval task. The task is designed to test the descriptions with respect to blur and illuminant color variations. The performance is assessed by the rank results of the correct matches, where the rank indicates after how many images the correct image was retrieved. We also provide the normalized average rank which is defined for a single query as

$$\mathrm{NAR} = \frac{1}{N N_R} \left(\sum_{i=1}^{N_R} R_i - \frac{N_R(N_R + 1)}{2} \right) \quad (12)$$

Fig. 1. *Examples of object images from the Simon Fraser data set (637×468 pixels). First line: images of two objects and their smoothed versions used to test robustness with respect to Gaussian blur. Second line: four instantiations of a single object under 4 different illuminants and with varying object orientation. These are used to test the image description with respect to illuminant color and illuminant geometry changes.*

where N is the number of images in the database, N_R the number of relevant images to the query, R_i is the rank at which the ith relevant image is retrieved. A NAR of zero indicates perfect results, and a NAR$=\ 0.5$ is equal to random retrieval. We will give the average NAR results over all queries, indicated by ANAR.

Histograms of the color ratios and the newly proposed color angles are constructed to represent the image. We have used 16 bins in each color dimension (there are 3 dimensions for $\mathbf{p}$, two dimensions for $\boldsymbol{\varphi}_p$ and $\mathbf{m}$, and one dimension for φ_m). To robustify the construction of the histograms of the color angles we use Eq. 11. E.g., for φ_m we update the histogram with $\sqrt{m_1^2 + m_2^2}$. The retrieval is based on the Euclidean distance between the histograms and the derivatives are computed with Gaussian derivative filters with a standard deviation of $\sigma = 2$. The first two experiments are performed on a set of 20 colorful object, all taken under 10 different light sources with varying object orientations [11], of which examples are given in Fig. 1.

Robustness to Gaussian blur. First we test the image descriptions with respect to changes in blur. To this end, we take a single image of all twenty objects taken under the same illuminant. Next, Gaussian smoothing with standard deviation of $\sigma = 2$ is applied to the images, which leads only to a slight visual change on the images (see Fig. 1). We used the non-smoothed image as a query to find its smoothed counterpart in the set of twenty smoothed images. The retrieval results of this experiment are given in Table 1. The unreliability of the color ratios $\mathbf{p}$ and $\mathbf{m}$ under blur is apparent: only for a few of the queries the relevant image was found with rank 1. The two color angles, which were designed to be robust with respect to blur, obtain good results. For $\boldsymbol{\varphi}_p$ only for a single image the relevant image was *not* the first image to be retrieved. In conclusion, color angles provide a more reliable image description under image blur.

rank	1	2	> 2	ANAR
$\mathbf{p}$	5	0	15	0.218
$\boldsymbol{\varphi}_p$	19	1	0	0.003
$\mathbf{m}$	1	3	16	0.258
φ_m	15	3	2	0.023

Table 1. Rank and ANAR for robustness to blur experiment.

Robustness to illuminant color. Here we test the image descriptions with respect to robustness to illuminant color variations. For each of the twenty objects we pick one single image as a query. For each query there exist 10 relevant images of the same object taken under different light sources and in various object orientations. The results are summarized in Table 2. These images were all taken at a similar distance and hence the edges are equally sharp in most images. Therefore robustness with respect to blur is not required and the two color ratios, $\mathbf{p}$ and $\mathbf{m}$, obtain good results. The added robustness with respect to blur for color angles results in lower discriminative power, however for $\boldsymbol{\varphi}_p$ the drop in performance is minimal. For the 16 bin representation of φ_m the performance drop due to loss of discriminative power is bigger.

Robustness to real-world blurring effects. For this experiment we have collected a set of 20 pairs of images [1]. Each pair consists of two images of the same scene, however the images vary in blur. The blur is caused by changing the acquisition parameters such as shutter time, and aperture, and

[1] We acknowledge Matthijs Douze for the image acquisition. The data is available on http://lear.inrialpes.fr/people/vandeweijer/data/

Fig. 2. *Examples database: (a),(b) motion blur, (c) change in focus from foreground to background, and (d) out-of-focus blur.*

rank	$1-10$	$11-20$	>20	ANAR
$\mathbf{p}$	180	5	15	0.010
$\boldsymbol{\varphi}_p$	169	17	14	0.012
$\mathbf{m}$	155	22	23	0.024
φ_m	115	23	65	0.049

Table 2. Rank and ANAR for the robustness to color constancy experiment.

rank	1	2	>2	ANAR
$\mathbf{p}$	7	2	11	0.365
$\boldsymbol{\varphi}_p$	16	3	1	0.018
$\mathbf{m}$	6	2	12	0.303
φ_m	13	1	6	0.053

Table 3. Rank and ANAR for the robustness to real-world blurring experiment.

due to relative movement between the camera and the object (see Fig. 2). Table 3 provides the results. The variations in blur cause the color ratios, $\mathbf{p}$ and $\mathbf{m}$, to perform badly. Although the real-world blurring effects are often not modelled by a Gaussian [7], the proposed blur-robust color angles obtain good results: for $\boldsymbol{\varphi}_p$ only a single image is not retrieved within the first two images.

5. CONCLUSIONS

In this paper we have proposed a set of new image descriptions which are invariant with respect to the illuminant color and are robust to image blur. Retrieval results on data with real-world blur show that existing image representations fail for these cases, whereas the proposed color angles obtain exellent results.

6. REFERENCES

[1] D.A. Forsyth, “A novel algorithm for color constancy,” *International Journal of Computer Vision*, vol. 5, no. 1, pp. 5–36, 1990.

[2] B.V. Funt and G.D. Finlayson, “Color constant color indexing,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 17, pp. 522–529, May 1995.

[3] Th. Gevers and A. Smeulders, “Color based object recognition,” *Pattern Recognition*, vol. 32, pp. 453–464, Mar. 1999.

[4] J.M. Geusebroek, R. van den Boomgaard, A.W.M. Smeulders, and H. Geerts, “Color invariance,” *IEEE Trans. Pattern Analysis Machine Intell.*, vol. 23, no. 12, pp. 1338–1350, 2001.

[5] J. van de Weijer and Th. Gevers, “Color constancy based on the grey-edge hypothesis,” in *ICIP’05*, Genua, Italy, 2005.

[6] M.J. Swain and D.H. Ballard, “Color indexing,” *International journal of computer vision*, vol. 7, no. 1, pp. 11–32, 1991.

[7] R.L. Lagendijk and J. Biemond, “Basic methods for image restoration and identification,” in *The Image and Video Processing Handbook*, A. Bovik, Ed., pp. 125–139. Academic Press, 1999.

[8] J. van de Weijer and C. Schmid, “Coloring local feature extraction,” in *Proc. of the European Conference on Computer Vision*, Graz, Austria, 2006, vol. 2, pp. 334–348.

[9] G.D. Finlayson, M.S. Drew, and B.V. Funt, “Color constancy: Generalized diagonal transforms suffice.,” *Journal of the Optical Society of America A.*, vol. 11, pp. 3011–3022, 1994.

[10] Th. Gevers and H.M.G. Stokman, “Classification of color edges in video into shadow-geometry, highlight, or material transitions,” *IEEE Trans. on Multimedia*, vol. 5, no. 2, pp. 237–243, 2003.

[11] K. Barnard, L. Martin, B.V. Funt, and A. Coath, “A data set for colour research,” *Color Research and Application*, vol. 27, no. 3, pp. 147–151, 2002.