An Illumination Independent Descriptor using Moment Invariants

Bing Li[1], De Xu[1], Weihua Xiong[2]
[1] Institute of Computer Science & Engineering, Beijing Jiaotong University, Beijing 100044, China
[2] OmniVision Technologies, Santa Clara, CA 95054, USA

Abstract

Color-based object indexing and matching is attractive since color is an efficient visual cue for characterizing an object. However, different illuminations will bring in color deformation of objects so as to degrade the performance of recognition. In order to circumvent this confounding influence, we present an effective color invariant descriptor that is considerably insensitive to the variations of light conditions, object geometric transformation, and image blur level. The descriptor is a feature vector consisting of several two dimensional normalized moment invariants of color pixels' distribution with different orders in a new color coordinate. The new color coordinate is introduced on the diagonal-offset model. The experiments on real image databases in terms of recognition rate show that our method is robust and performs very well under various situations.

Keywords

Color constancy, illumination independent, image description, moment invariants

Introduction

Color has proven to be simple, straightforward information for object matching. Swain and Ballard [1] developed an indexing scheme that recognizes the object using color histogram intersections. Although this method is insensitive to geometric transformation, the performance will degrade when light conditions change, because color information from any imaging device depends on not only the characteristics of the object but also the spectral power distribution of the light incident on it.

A number of techniques for representing color invariant descriptors have been reported in the literatures [2-5]. Funt and Finlayson presented an algorithm, named color constancy color indexing (CCCI), by matching histogram of color ratios between neighboring pixels[2]. Gevers and Smeulders [3] extend CCCI technique to account for the effect of both illumination color and shading. Adjeroh and Lee [4] proposed another color ratio based feature by integrating the variation between any pixel and its neighbors. Although these methods have been shown to be superior to Swain's method in the presence of illumination change, they work along the image edges while ignoring the wealthy information from the original image itself, so they are too sensitive to image quality. For darker regions, the derivatives are easily affected by noises; for those blurred or uniform regions, the derivatives are close to 0. To address this problem, Healey et al [5] gave out an object recognition algorithm using high-order color distribution information. But this approach did not consider the change in color intensity due to light direction.

In this paper, to remove the confounding effect due to various illumination conditions, changing object geometry and different image blur levels, we propose a novel descriptor in a new color coordinate system introduced on the diagonal-offset model. The proposed descriptor is a feature vector that includes several two dimensional normalized moment variants with different orders, each summarizing the shape of color distribution of the image. Experiments using two real image databases show that our scheme is robust and works very well under various situations.

Central Chromaticity Space

According to the Lambertian reflectance model, the image $f=(R,G,B)^T$ can be computed as follows:

$$f(X)=\sigma\int_{\omega} e(\lambda)s(X,\lambda)c(\lambda)d\lambda \tag{1}$$

where X is the spatial coordinate, λ is wavelength and ω represents the visible spectrum. $e(\lambda)$ is spectral power distribution of light source, $s(X,\lambda)$ is the surface reflectance, and $c(\lambda)$ is the camera sensitivity function. σ is the shading factor depending on the angular between the normal of surface patch and illumination direction. Because the Lambertian model is much more ideal, Shafer proposed to add a "diffuse" light term to this model [6]. The diffuse light has a lower intensity and is coming from all directions in an equal amount:

$$f(X)=\sigma\int_{\omega} e(\lambda)s(X,\lambda)c(\lambda)d\lambda+\int_{\omega}\alpha(\lambda)c(\lambda)d\lambda \tag{2}$$

where $\alpha(\lambda)$ is the term that models the diffuse light.

The aim of many color constancy applications is to transform all colors of the input image f_1, taken under a light source e_1, to colors as they would appear as f_2 under a reference light e_2. This transformation can be in the form of a diagonal model or Von Kries model [6].

$$f_1=D^{1,2}f_2 \tag{3}$$

where $D^{1,2}$ is a diagonal matrix. In the $(R,G,B)^T$ color space, the transformation can be written as:

$$\begin{pmatrix}R_1\\G_1\\B_1\end{pmatrix}=\begin{pmatrix}\alpha&0&0\\0&\beta&0\\0&0&\gamma\end{pmatrix}\begin{pmatrix}R_2\\G_2\\B_2\end{pmatrix} \tag{4}$$

Finlayson et al. further proposed a diagonal-offset model by adding an offset term [7]. In this model, the illumination color changes can be considered as comprising scaling as well as an offset for each color band. It has advantages over the commonly used one in which it takes diffuse lighting into account, so it is more general.

$$\begin{pmatrix} R_1 \\ G_1 \\ B_1 \end{pmatrix} = \begin{pmatrix} \alpha & 0 & 0 \\ 0 & \beta & 0 \\ 0 & 0 & \gamma \end{pmatrix} \begin{pmatrix} R_2 \\ G_2 \\ B_2 \end{pmatrix} + \begin{pmatrix} o_1 \\ o_2 \\ o_3 \end{pmatrix} \tag{5}$$

From this diagonal-offset model, we define a new color coordinate system, named Central Color Coordinate System, or CCS, as follows:

$$[r\ g] = [\frac{R-\overline{R}}{B-\overline{B}}\ \ \frac{G-\overline{G}}{B-\overline{B}}] \tag{6}$$

$[\overline{R}\ \ \overline{G}\ \ \overline{B}]$ are the average pixel value of the whole image in R,G,B channel separately. Therefore, the offset term in the diagonal-offset model can be obviously removed. And the color change conforms to the diagonal transformation model.

$$\begin{pmatrix} \dfrac{R_1-\overline{R}_1}{B_1-\overline{B}_1} \\[2ex] \dfrac{G_1-\overline{G}_1}{B_1-\overline{B}_1} \end{pmatrix} = \begin{pmatrix} \alpha' & 0 \\ 0 & \beta' \end{pmatrix} \begin{pmatrix} \dfrac{R_2-\overline{R}_2}{B_2-\overline{B}_2} \\[2ex] \dfrac{G_2-\overline{G}_2}{B_2-\overline{B}_2} \end{pmatrix} \tag{7}$$

where $\alpha' = \dfrac{\alpha}{\gamma}$ *and* $\beta' = \dfrac{\beta}{\gamma}$

Illuminant Independent Descriptor

The $u+v$ order of image f in this new central color coordinate system, M_{uv}, is defined as follows:

$$M_{uv} = \iint r^u g^v \rho(r,g)\,drdg \tag{8}$$

The density function $\rho(r,g)$ is joint probability distribution in the CCS of image *f*.

$$\rho(r,g) = \frac{Num(r,g)}{pixNum} \tag{9}$$

The $pixNum$ is image size of f, while the $Num(r,g)$ represented the total number of pixels with value of $(r,g)^T$ in the image.

The moment is invariant under translation. According to the Eq. (7)-(9), the relationship between $(M_{uv})_1$, the chromatic moment under illumination e_1, and $(M_{uv})_2$, the chromatic moment under reference light e_2, can be obtained as:

$$\begin{aligned} (M_{uv})_1 &= \iint (\alpha' r_2)^u (\beta' g_2)^v \rho(r_2,g_2) \begin{vmatrix} \alpha' & 0 \\ 0 & \beta' \end{vmatrix} drdg \\ &= (\alpha')^{u+1} (\beta')^{v+1} (M_{uv})_2 \end{aligned} \tag{10}$$

where $\begin{vmatrix} \alpha' & 0 \\ 0 & \beta' \end{vmatrix}$ is Jacobi Determinant. To eliminate the scale factors describing the light color change, α', β', the normalized moment invariant is defined as:

$$\eta_{uv} = \frac{(M_{00})^{\frac{u+v+2}{2}}}{(M_{02})^{\frac{u+1}{2}} (M_{20})^{\frac{v+1}{2}}} M_{uv} \tag{11}$$

Now η_{uv} stays constant across a change of illumination.

The normalized moment invariant of different orders, *u*+*v*, describe distinct shape features of image color distributions. Therefore their combination can serve as a robust descriptor of the image. According to two important criteria given out in [8], 7 normalized moment invariants are used in this paper.

$$J = [\eta_{01}, \eta_{10}, \eta_{11}, \eta_{02}, \eta_{20}, \eta_{12}, \eta_{21}] \tag{12}$$

Experiments

To evaluate the performance of the proposed algorithms, object recognition experiments based on two images databases are conducted in terms of its robustness to three conditions: light source change, geometric affine transformation and image instability.

Object recognition is performed by means of k-nearest neighbor (KNN) classification, and performance is assessed with reference to recognition ratio (RR).

$$RR = \frac{Correct}{All} \times 100\% \tag{13}$$

Where All represents total number of the images used for object recognition. $Correct$ is total number of the images that are recognized correctly. The k in KNN means the first k matches in the increasing sorted of matching distance values. If k is set to be 1, the image from first rank is selected as matching scene; otherwise, the most numerously matched object will be selected. In this paper, we make k to be 1,3,5,7,9 respectively. We also compute the average RR over the performance of these five different k values.

The first data set is based on the 321 images of 30 scenes under 11 varying illuminations [10]. Some of the images are excluded because they are very dark and could bias the performance of the tested algorithm. The resulting data set consists of 172 images of 17 scenes. The example images of same white paper under 3 varying illumination, white, red and blue respectively, are shown in figure 1. Since the image data set is of medium size, the recognition ratio performance is estimated by means of a leave-one-out procedure [9]. Table 1 compares our method's performance to that of Histogram Matching method (HIST)[1].

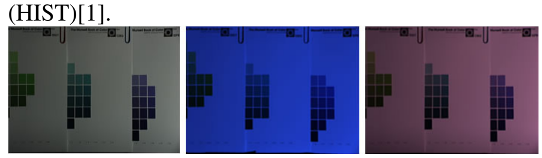

Figure 1 Three images of same scene under different illuminants

To simulate geometric affine transformation, each image pixel's location (x,y) is changed into (x,y'), where $y' = s \times x + y$. That is, the new vertical coordinate is acquired by shift $s \times x$ pixels along vertical direction while the horizontal coordinate is kept untouched. The scale factors are chosen from 5 different values {0.2, 0.4, 0.6, 0.8, 1}. To simulate images with different blur level, we smooth the image with Gaussian filter with various standard deviations chosen from {2, 4, 6, 8, 10}. Some of transformed and blurred images are shown in figure 2. When an affine transformation scale factor (or Gaussian filter standard deviation) is selected, the transformed 172 images (or blurred images) and original 172 images are put together, then the performance is evaluated on the database with 344(172*2) images, the results are shown in table 2-3. Figure 3 gives out how overall performance changes as affine transformation scale or blur lever varies. As both the figure and table show, our method provides a technique that remains stable and good performance under distinct conditions.

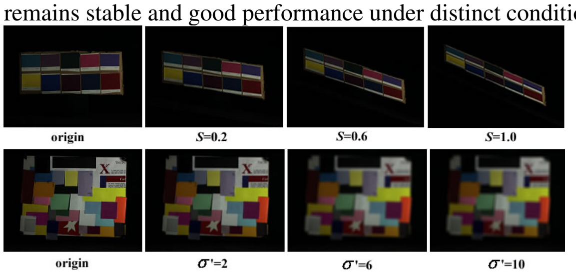

Figure 2 Top line: affine transformation examples with different s. Bottom line: examples using Gaussian blur with different σ'.

The second experiment is based on 220 images of 22 scenes lit by 11 various lights [10]. The affine transformed images and blurred images are created using the same procedure noted in first experiment. The leave-one-out procedure is also used again. Their results are shown in table 4-6 and figure 4

Conclusion

Object recognition is a fundamental task in computer vision and color can provide valuable clue for it. However, the color of objects will vary depending on the illumination incident on it. To address this problem, a new color independent descriptor is presented in this paper. The descriptor is defined as a feature vector consisting of 7 normalized two dimensional chromatic moment invariants in a new color coordinate system, which is based on diagonal-offset model. Our experiments show that the proposed algorithm provides good performance under the change of illumination, 3D object geometry and image blur level.

Acknowledgement

This work is supported by National High Technology Research and Development Program of China (2007AA01Z168) and Science Foundation of Beijing JiaoTong University (2007XM008).

References

[1] M. J. Swain and D. H. Ballard: "Color Indexing", International Journal of Computer Vision, 7, (1), pp. 11-32 (1991)

[2] B. V. Funt and G. D. Finlayson, "Color Constant Color Indexing", IEEE Trans. On Pattern Analysis and Machine Intelligence, 17, (5), pp. 522-529, (1995)

[3] T. Gevers, A. Smeulders, "Color based Object Recognition", Pattern Recognition, 32, pp. 453-464, (1999)

[4] D.A. Adjeroh; M.C. Lee, M.C. , "On ratio-based color indexing", IEEE Transactions on Imaging Processing, Vol. 10, Issue 10, pp. 36-48, (2001)

[5] G. Healey, D. Slater, "Global color constancy: recognition of objects by use of iullumination-invariant properties of color distribution", J. Opt. Soc. Am. A, Vol. 11, Issue 11 pp. 3003-3010, (1994)

[6] A. Gijsenij, T. Gevers and J. V. Weijer: " Color Constancy by Derivative-based Gamut Mapping", Photometric Analysis for Computer Vision (PACV'07) in conjunction with ICCV, Oct 2007, Rio de Janeiro, Brazil, pp.21-28, (2007)

[7] G. Finlayson, S. Hordley, and R. Xu. "Convex programming colour constancy with a diagonal -offset model". In Proc. Int. Conf. on Image Processing, pp.948–951, (2005)

[8] Mindru, F.; Moons, T.; Van Gool, L., "Recognizing color patterns irrespective of viewpoint and illumination" In Proc. CVPR, pp. 23-25, (1999)

[9] F. Mindru, T. Tuytelaars, L. V. Gool and T. Moons: "Moment invariants for recognition under changing viewpoint and illumination", Computer Vision and Image understanding, 2004, 94, (1), pp.3-27 (2004)

[10] K. Barnard, L. Martin B. V. Funt and A. Coath: "A data set for colour research", Color Research and Application, 27, (3), pp. 147-151 (2002)

Author Biography

Mr. Bing Li, is pursuing the PhD degree at the Beijing Jiaotong University, China. His research interests include computer vision, color constancy, and visual perception.

Mr. De Xu, is currently a professor in the Beijing Jiaotong University, China. His research interests include database system, computer vision, and multimedia processing.

	$k=1$	$k=3$	$k=5$	$k=7$	$k=9$	Mean
HIST	50.6%	54.7%	47.7%	41.9%	40.1%	47.0%
Our method	97.1%	89.0%	87.2%	86.6%	82.6%	88.5%

Table 1 Object Recognition Ratio of 172 images under the change of illumination change

Affine transformation scale		$k=1$	$k=3$	$k=5$	$k=7$	$k=9$	Mean
0.2	HIST	96.8%	54.7%	64.2%	64.2%	60.8%	68.1%
	Our method	100.0%	97.1%	97.1%	90.7%	89.5%	94.9%
0.4	HIST	96.5%	54.7%	64.2%	64.2%	60.8%	68.1%
	Our method	100.0%	97.1%	97.1%	90.7%	89.5%	94.9%
0.6	HIST	96.5%	54.4%	64.5%	64.2%	60.8%	68.1%
	Our method	100.0%	97.1%	97.1%	90.7%	89.5%	94.9%
0.8	HIST	96.8%	54.4%	64.2%	64.2%	61.3%	68.2%
	Our method	100.0%	97.1%	97.1%	90.7%	89.5%	94.9%
1	HIST	100.0%	50.6%	64.5%	65.7%	61.6%	68.5%
	Our method	100.0%	97.1%	97.1%	90.1%	89.0%	94.7%

Table 2 Object Recognition Ratio of 344 images (including 172 original images and 172 transformed images) under the change of affine transformation

Gaussian deviation Value		$k=1$	$k=3$	$k=5$	$k=7$	$k=9$	Mean
2	HIST	96.8%	54.7%	64.2%	64.2%	60.8%	68.1%
	Our method	99.7%	96.8%	94.8%	90.4%	90.1%	94.4%
4	HIST	96.5%	54.7%	64.2%	64.2%	60.8%	68.1%
	Our method	98.8%	95.9%	93.3%	90.4%	89.5%	93.6%
6	HIST	96.5%	54.4%	64.5%	64.2%	60.8%	68.1%
	Our method	98.5%	96.2%	93.9%	90.7%	90.4%	93.9%
8	HIST	96.8%	54.4%	64.2%	64.2%	61.3%	68.2%
	Our method	98.5%	96.2%	93.3%	91.0%	90.1%	93.8%
10	HIST	100.0%	50.6%	64.5%	65.7%	61.6%	68.5%
	Our method	98.5%	96.5%	93.6%	91.0%	90.1%	93.9%

Table 3 Object Recognition Ratio of 344 images(including 172 original images and 172 blurred images) under the change of image blur level

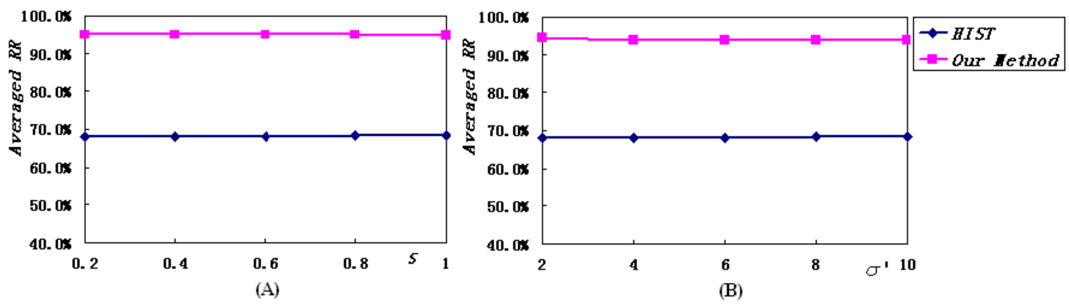

Figure 3 (a) The average object recognition ratio of 344 images (including 172 original images and 172 transformed images) as a function of affine transformation and (b) The average object recognition ratio of 344 images (including 172 original images and 172 blurred images) as a function of image blur level

Feature	$k=1$	$k=3$	$k=5$	$k=7$	$k=9$	Mean
HIST	27.7%	25.9%	24.1%	22.3%	22.3%	24.5%
Our method	85.5%	86.4%	84.5%	82.7%	80.5%	83.9%

Table 4 Object Recognition Ratio of 220 images under the change of illumination change

Affine transformation Scale		$k=1$	$k=3$	$k=5$	$k=7$	$k=9$	Mean
0.2	HIST	84.1%	33.2%	37.0%	43.2%	38.2%	47.1%
	Our method	99.8%	87.5%	92.7%	88.2%	89.3%	91.5%
0.4	HIST	84.3%	32.5%	37.0%	42.5%	38.0%	46.9%
	Our method	99.8%	87.7%	92.5%	88.2%	89.3%	91.5%
0.6	HIST	84.3%	32.5%	37.3%	42.5%	37.7%	46.9%
	Our method	100.0%	87.7%	92.3%	88.4%	89.3%	91.5%
0.8	HIST	83.9%	32.7%	37.5%	42.5%	38.2%	47.0%
	Our method	99.5%	87.0%	92.7%	88.0%	89.1%	91.3%
1	HIST	96.4%	27.7%	37.3%	44.1%	37.7%	48.6%
	Our method	100.0%	85.5%	92.3%	87.3%	89.5%	47.1%

Table 5 Object Recognition Ratio of 440 images (including 220 original images and 220 transformed images) under the change of affine transformation

Gaussian deviation Value		$k=1$	$k=3$	$k=5$	$k=7$	$k=9$	Mean
2	HIST	84.1%	33.2%	37.0%	43.2%	38.2%	47.1%
	Our method	99.7%	96.8%	94.8%	90.4%	90.1%	94.4%
4	HIST	84.3%	32.5%	37.0%	42.5%	38.0%	46.9%
	Our method	98.8%	95.9%	93.3%	90.4%	89.5%	93.6%
6	HIST	84.3%	32.5%	37.3%	42.5%	37.7%	46.9%
	Our method	98.5%	96.2%	93.9%	90.7%	90.4%	93.9%
8	HIST	83.9%	32.7%	37.5%	42.5%	38.2%	47.0%
	Our method	98.5%	96.2%	93.3%	91.0%	90.1%	93.8%
10	HIST	96.4%	27.7%	37.3%	44.1%	37.7%	48.6%
	Our method	98.5%	96.5%	93.6%	91.0%	90.1%	93.9%

Table 6 Object Recognition Ratio of 440 images (including 220 original images and 220 blurred images)under the change of image blur level

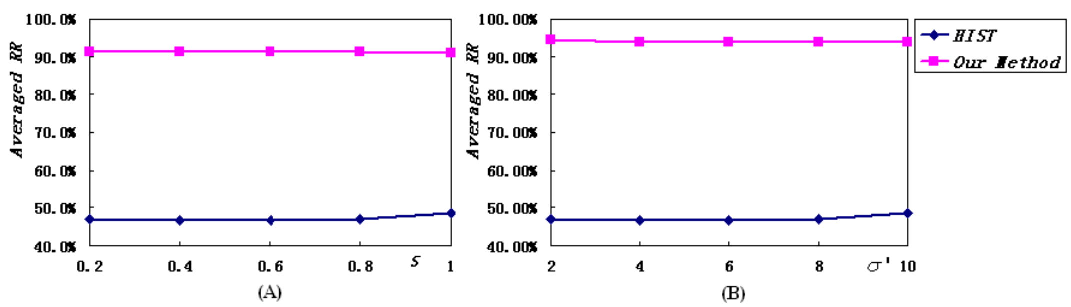

Figure 4 (a) The average object recognition ratio of 440 images (including 220 original images and 220 transformed images) as a function of affine transformation and (b) The average object recognition ratio of 440 images (including 220 original images and 220 blurred images) as a function of image blur level