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COLOR CONSTANT DESCRIPTORS COMBINING IMAGE DERIVATIVE STRUCTURES

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Abstract. Color constant image description is a fundamental problem in many computer vision applications. In this paper, the diagonal-offset model is adopted as reflectance model to get color constant image descriptors. This model makes the descriptors much more robust, and also fits the real world images very well. By introducing 3D moment invariants, this paper contributes to give an illumination independent descriptor generation framework. In detail, 0-, 1- and even higher order color constant descriptors can be generated from such framework. These descriptors can characterize n-order derivative image information. Furthermore, the combination thereof can characterize not only original image but also n-order edge image color information. The experiments on real image databases show that all these descriptors are robust to illumination variation and affine transformation, and perform very well for object recognition under various situations.

Keywords: Color invariants, color constant descriptor, moment invariants

1 INTRODUCTION

The image recorded by a camera depends on three factors: the physical content of the scene, the illumination incident on the scene, and the characteristics of the camera. Different illuminations can result in different colors of same object. Fortunately, humans have the ability of color constancy: they perceive the same color of an object despite large various illuminations. Color has proven to be simple, straightforward information in object matching. Consequently, the similar color constancy capability is also necessary for computer vision system for removing illumination effect to successfully index objects. There are two major solutions: The first one is estimating the illumination characteristics and directly mapping the image into that under a canonical illumination. Although a variety of illumination estimation methods [1, 2] as well as some combinational strategies [3] have been proposed in the past decades, their performances and generalities are not enough to be systematically applied in a large number of objects' recognition [4]. The second one is representing images by features which are independent of the light source, which is called color invariant or color constant descriptor, so they do not depend on the performance of color constancy algorithm. A number of techniques belonging to this category have been reported in [4–11].

Swain and Ballard [5] developed an indexing scheme that recognized the object using color histogram intersections. Although this method is insensitive to geometric transformation, the performance will degrade when light conditions change, as color information from any imaging device depends on not only the characteristics of the object but also on the spectral power distribution of the light incident on it. Funt and Finlayson[6] deduced a set of color constant derivatives based on physical reflection model. They presented a descriptor, named color constancy color indexing (CCCI), by matching histogram of color ratios between neighboring pixels [6]. Gevers and Smeulders [7] extended CCCI technique to account for the effect of both illumination color and shading. Adjeroh and Lee [8] proposed another color ratio based feature by integrating the variation between any pixel and its neighbors. J. van de Weijer et al. [9, 10] introduced ratio of image derivatives to the edge-based color constant descriptors. 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. The derivatives are easily affected by noises for those darker regions; and are close to 0 for those uniform regions. Beside derivative-based descriptors, G. D. Finlayson et al. [11] have proposed another descriptor in outdoor illumination for shadow removal; but this descriptor needs camera parameters, which is inconvenient for practical applications. The moment invariants are also introduced to get color invariants by L. V. Gool et al. [12]. However, they paid more attention to image color content, ignoring the contours and edges information in images. As we all know, both image color and edge color information are very important for most computer vision applications.

In this paper, 3D moment invariants are introduced into illumination independent image description. An illumination independent descriptor generation framework is given. 0-, 1- and even higher order descriptors can be generated from it. Different from derivative-based descriptors, we can characterize both original image color and n-order edge color by using the descriptors generated from the framework. All these descriptors are invariant to illumination and affine transformation. Furthermore, the 0-order descriptor is robust to image blurring change as well.

The rest of this paper is organized as follows. In Section 2, diagonal-offset model is described. Then we explain the details of color constant descriptors using 3D moment invariants in Section 3. The experimental results are presented in Section 4. Section 5 concludes this paper.

2 DIAGONAL-OFFSET MODEL

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

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

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 of three responses. Because the Lambertian model is much more ideal, Shafer proposed to add a "diffuse" light term to this model [13]. The diffuse light has a lower intensity and comes from all directions in an equal amount:

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

where $\alpha(\lambda)$ is the term that models the diffuse light. This equation can model the objects under daylight well, since daylight consists of both a point source (the sun) and diffuse light coming from the sky; so this model is much better for natural images and much more robust than Equation (1).

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 modeled by a diagonal model or von Kries Model [13].

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

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

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

However, this diagonal model is too strict. It cannot satisfy the situations under some conditions, for example saturated colors. To overcome these problems, Finlayson et al. [14] proposed a more robust diagonal-offset model by adding an offset term to the diagonal model.

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

Interestingly, the diagonal-offset model also takes diffuse lighting into account, which consists with Equation (2). The n-order derivative for $(R,G,B)^T$ can be computed as:

$$\begin{pmatrix} \partial^n R_1/\partial X^n \\ \partial^n G_1/\partial X^n \\ \partial^n B_1/\partial X^n \end{pmatrix} = \begin{pmatrix} \alpha & 0 & 0 \\ 0 & \beta & 0 \\ 0 & 0 & \gamma \end{pmatrix} \begin{pmatrix} \partial^n R_2/\partial X^n \\ \partial^n G_2/\partial X^n \\ \partial^n B_2/\partial X^n \end{pmatrix} + \begin{pmatrix} o_1 \\ o_2 \\ o_3 \end{pmatrix} \tag{6}$$

where $\frac{\partial^n}{\partial X^n}$ is n-order derivative for $(R,G,B)^T$. If $n > 0$, $(o_1, o_2, o_3)^T = (0,0,0)^T$. According to Equation (6), the same object's n-order derivative color change caused by illumination conforms to the affine transformation. Thus the illumination color changes can be considered as comprising scaling combined with an offset for each color band.

3 COLOR CONSTANT DESCRIPTORS USING 3D MOMENT INVARIANTS

From Equation (6), the two factors, offset and scale, must be normalized to remove illumination affect to color. In this section, introducing the 3D moment invariants, we propose a unified framework for color constant image description.

3.1 General Color Moments

In order to simplify description, we use $\partial^n f$ instead of $\frac{\partial^n f}{\partial X^n} = (\frac{\partial^n R}{\partial X^n}, \frac{\partial^n G}{\partial X^n}, \frac{\partial^n B}{\partial X^n})^T$ in the following sections. The $u+v+w$ order moment $\partial^n M_{uvw}$ of the n-order derivative image is defined as follows:

$$\partial^n M_{uvw} = \int \int \int_{\partial^n f} R^u G^v B^w \rho(R,G,B) \mathrm{d}R \, \mathrm{d}G \, \mathrm{d}B. \tag{7}$$

The density function $\rho(R,G,B)$ is defined as the percentage of each color value in $\partial^n f$.

$$\rho(R,G,B) = \frac{Num(R,G,B)}{pixNum} \tag{8}$$

The *pixNum* is image size of $\partial^n f$, while the $Num(R, G, B)$ represents the total number of pixels with value of $(R, G, B)^T$ in the $\partial^n f$. The centroid of the color distribution in $\partial^n f$ can be computed as:

$$\overline{R} = \frac{\partial^n M_{100}}{\partial^n M_{000}}, \quad \overline{G} = \frac{\partial^n M_{010}}{\partial^n M_{000}}, \quad \overline{B} = \frac{\partial^n M_{001}}{\partial^n M_{000}}. \tag{9}$$

In order to remove the offset $(o_1, o_2, o_3)^T$ in Equation (3), the central moment is defined as:

$$\partial^n \mu_{uvw} = \int\int\int_{\partial^n f} (R - \overline{R})^u (G - \overline{G})^v (B - \overline{B})^w \rho(R, G, B) \mathrm{d}R \, \mathrm{d}G \, \mathrm{d}B. \tag{10}$$

The central moment is invariants under translation. Obviously, $\partial^n \mu_{001} = \partial^n \mu_{010} = \partial^n \mu_{100} = 0$. According to the Equations (6) and (10), the relationship between $(\partial^n \mu_{uvw})_1$, the central moment in $\partial^n f_1$, and $(\partial^n \mu_{uvw})_2$, the central moment in $\partial^n f_2$, can be obtained as:

$$(\partial^n \mu_{uvw})_1 = \alpha^u \beta^v \gamma^w \begin{vmatrix} \alpha & 0 & 0 \\ 0 & \beta & 0 \\ 0 & 0 & \gamma \end{vmatrix} (\partial^n \mu_{uvw})_2 = \alpha^{u+1} \beta^{v+1} \gamma^{w+1} (\partial^n \mu_{uvw})_2. \tag{11}$$

From Equation (11), the scale factors α, β, γ can be normalized in Equation (12) to get moment invariants.

$$\partial^n \eta_{uvw} = \frac{(\partial^n \mu_{000})^{\frac{u+v+w+3}{3}}}{(\partial^n \mu_{300})^{\frac{u+1}{3}} (\partial^n \mu_{030})^{\frac{v+1}{3}} (\partial^n \mu_{003})^{\frac{w+1}{3}}} \partial^n \mu_{uvw} \tag{12}$$

In Equation (12), the $\partial^n \eta_{uvw}$ is invariant not only to the offset factor but also to the scale factor; so it is independent of illumination to use this moment invariant to characterize images.

3.2 Color Constant Descriptors Using Moment Invariants

Two important criteria are given to guide using $\partial^n \eta_{uvw}$ to construct a color constant image descriptor [12]:

1. Keep the moment order $u + v + w$ as low as possible. Because if $u + v + w$ is higher, the moment invariants are easier to be affected by noise. For the same reason, we also keep n not very large.
2. Include as many low-order moment invariants as possible. According to the two principles, 13 candidate moment invariants are used to construct the image description vector $\partial^n J$.

$$\begin{aligned} \partial^n J = {} & [\partial^n \eta_{002}, \partial^n \eta_{020}, \partial^n \eta_{200}, \partial^n \eta_{011}, \partial^n \eta_{101}, \partial^n \eta_{110}, \partial^n \eta_{111}, \\ & \partial^n \eta_{012}, \partial^n \eta_{021}, \partial^n \eta_{102}, \partial^n \eta_{120}, \partial^n \eta_{201}, \partial^n \eta_{210}] \end{aligned} \tag{13}$$

In this paper, we select all of them to construct description vector. With different n, this color constant descriptor framework can be decomposed as follows:

- $n = 0$, original image color constant descriptor J. In this situation, $(\partial^n R, \partial^n G, \partial^n B)^T = (R, G, B)^T$, the $\partial^n J$ degenerates as J, which just describes color content of original image.
- $n > 0$, edge image color constant descriptor $\partial^n J$. When $n = 1$,$(\partial R, \partial G, \partial B)^T$ is just the image edge color information. The ∂J can describe the image edge color. Even when $n > 1$, the higher order image edge color constant descriptor can be obtained. The proposed descriptor can characterize different order derivative images.
- Combinational color constant descriptor CJ. We combine the 0- and n-order moment invariant vectors to construct an integrated description vector as $CJ = [J, \partial J, \partial^2 J, \ldots]$. The combinational vector can describe not only original image but also the n-order edge image.

4 EXPERIMENTS

In the section, three descriptors $J, \partial J$ and $CJ = [J, \partial J]$ will be tested in various situations. To evaluate the performance of the proposed descriptors, object recognition experiment based on two image databases are conducted in terms of their robustness to two conditions: light source change and geometric affine transformation. Group (A) consists of 172 images of 17 scenes under 11 varying illuminations, which are picked out from the 321 images of 30 scenes [2] by removing some darker images. Group (B) consists of 220 images of 20 scenes under 11 varying illuminations [15] which have rotation and viewpoint changes. Both of them can be downloaded from [16, 17]. Figure 1 shows some example images of the two groups. Specially, the images in both groups will also be synthetically transformed to simulate affine transformation.

The experiment for the proposed color constant descriptors considers the performance under both synthetic transformation and real changes in illumination and viewpoint. Recognition of a pattern is performed by means of a k-nearest-neighbor (KNN) classification scheme based on feature vectors consisting of moment invariants, the performance is assessed with reference to recognition ratio (RR).k means the first k matches in the increasing sorted of matching distance values. If k is set to 1, the image from first rank is selected as matching object; otherwise, the most numerously matched object will be selected. In this paper, we make k to be 1, 3, 5, 7, respectively. We also compute the averaged RR over the performance of these four different k values.

4.1 Robustness to Illumination Change

Here we test the image descriptors with respect to robustness to illumination color variation. The performances of the proposed three descriptors are compared with

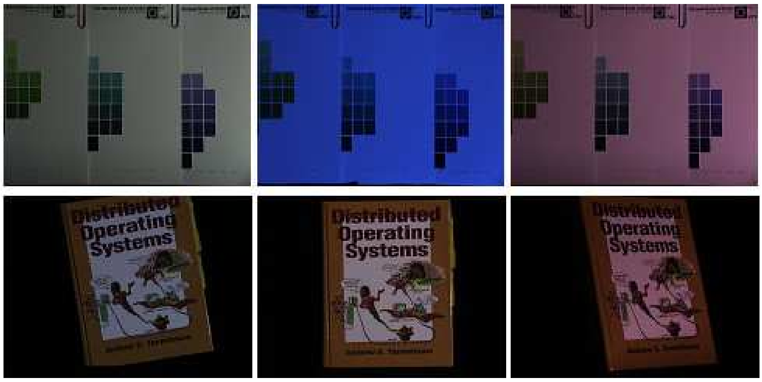

Fig. 1. Examples from the image data sets (637 × 468 pixles). First line: examples from group (A). Second line: examples from group (B).

other four kinds of different color constant descriptors [6, 7, 9], which are shown in Equations (14)–(17). Histograms of the four descriptors are constructed to represent an image. Each dimension of the 4 descriptors is divided into 16 bins. There are 3 dimensions for P, 2 dimensions for m and ϕ_p, 1 dimension for ϕ_m. The recognition performance is estimated by means of a leave-one-out procedure [12]. The Recognition Ratio (RR) of the proposed descriptors with different values of k is shown in Table 1.

$$P = \{p_1, p_2, p_3\} = \left\{\frac{R_X}{R}, \frac{G_X}{G}, \frac{B_X}{B}\right\} \tag{14}$$

$$m = \{m_1, m_2\} = \left\{\frac{R_X G - G_X R}{RG}, \frac{G_X B - B_X G}{BG}\right\} \tag{15}$$

$$\phi_p = \{\phi_p^1, \phi_p^2\} = \{\arctan(p_1/p_2), \arctan(p_2/p_3)\} \tag{16}$$

$$\phi_m = \{\arctan(m_1/m_2)\} \tag{17}$$

From the mean values of RR in Table 1 we can clearly see that, among these descriptors, CJ performs best in group (A). Only ϕ_p and m outperform J and ∂J; but the histogram dimensions of ϕ_p and m are much higher than J and ∂J. In group (B), all the three proposed descriptors outperform the other four descriptors, and the RR of the proposed descriptors are much higher than others. Consequently, the proposed descriptors show high performance and low dimension in both experiments.

4.2 Robustness to Affine Transformation

In this experiment, we will test the robustness to geometric affine transformation, which is usually encountered for real-world images. To simulate geometric affine

Set		Descriptor	$k = 1$	$k = 3$	$k = 5$	$k = 7$	Dimension	Mean
A	Existing	P	83.7 %	65.1 %	54.7 %	48.8 %	$16 \times 16 \times 16$	63.1 %
		ϕ_P	93.8 %	92.7 %	90.9 %	88.0 %	16×16	91.4 %
		m	93.2 %	91.3 %	90.2 %	87.9 %	16×16	90.6 %
		ϕ_m	83.1 %	73.3 %	72.1 %	70.3 %	16	74.7 %
	Proposed	J	94.2 %	91.3 %	85.5 %	80.8 %	13	87.9 %
		∂J	94.8 %	91.3 %	87.2 %	87.2 %	13	90.1 %
		CJ	95.9 %	92.4 %	89.5 %	90.1 %	26	92.0 %
B	Existing	P	82.3 %	74.5 %	73.6 %	71.4 %	$16 \times 16 \times 16$	75.5 %
		ϕ_P	71.8 %	56.4 %	50.0 %	45.9 %	16×16	56.0 %
		m	85.0 %	79.5 %	75.5 %	73.6 %	16×16	78.4 %
		ϕ_m	74.5 %	70.0 %	70.9 %	68.2 %	16	70.9 %
	Proposed	J	81.8 %	81.8 %	78.2 %	72.7 %	13	78.6 %
		∂J	91.4 %	86.4 %	85.0 %	84.1 %	13	86.7 %
		CJ	93.2 %	89.5 %	87.7 %	84.5 %	26	88.8 %

Table 1. Performance comparison of our proposed descriptors to other four descriptors in terms of robustness to illumination color

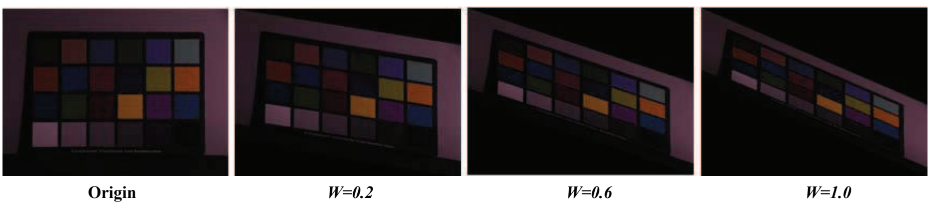

Fig. 2. Affine transformation examples with different w

transformation, each image pixel's location (x, y) is changed into (x, y'), where $y' = w \times x + y$; that is, the new vertical coordinate is acquired by shift $w \times x$ pixels along vertical direction while the horizontal coordinate is kept untouched. The scale factor w is chosen from 5 different values $0.2, 0.4, 0.6, 0.8, 1$. Some transformed example images are shown in Figure 2. For each scale factor, the transformed images compose the training set, while the original images are used as test ones. That is, we will use the transformed images to recognize the original ones based on the $J, \partial J$ and CJ descriptors. The changing performances of RR as the selection of different values of k are shown in Figures 3 and 4. From these two charts, we can draw a conclusion that RR performance of the each descriptor has nearly no obvious decrease with increase of w. The numeric details on affine transformation are shown in Table 2. The maximum change range of $J, \partial J$ and CJ is 2.4 %, 4.0 % and 3.5 %, respectively for image group (A) and 3.1 %, 1.4 % and 0.9 %, respectively for image group (B). So $J, \partial J$ and CJ are all robust to affine transformation.

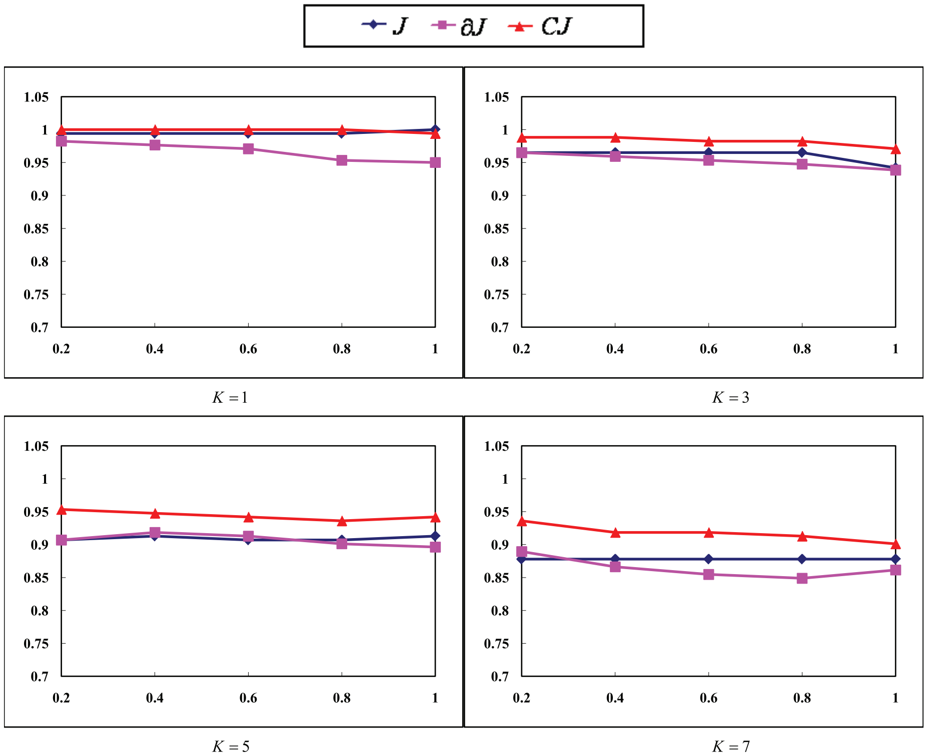

Fig. 3. The object recognition ratio of image group (A) as a function of affine transformation

5 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 them. To address this problem, a general color constant

Set	Descriptor	$k = 1(\%)$	$k = 3(\%)$	$k = 5(\%)$	$k = 7(\%)$	Max(%)
A	J	$[99.4, 100]$	$[94.1, 96.5]$	$[90.6, 91.3]$	$[87.8, 87.8]$	2.4
	∂J	$[95.0, 98.2]$	$[93.9, 96.5]$	$[89.6, 91.8]$	$[84.9, 88.9]$	4.0
	CJ	$[99.4, 100]$	$[97.1, 98.8]$	$[90.1, 93.6]$	$[85.5, 87.7]$	3.5
B	J	$[100, 100]$	$[91.3, 92.2]$	$[85.9, 89.0]$	$[82.3, 85.4]$	3.1
	∂J	$[98.6, 100]$	$[90.9, 92.2]$	$[85.9, 87.3]$	$[85.4, 86.8]$	1.4
	CJ	$[100, 100]$	$[93.6, 94.0]$	$[90.9, 91.8]$	$[90.0, 90.4]$	0.9

Table 2. Object recognition ratio change range. MAX means the maximal change among defined range

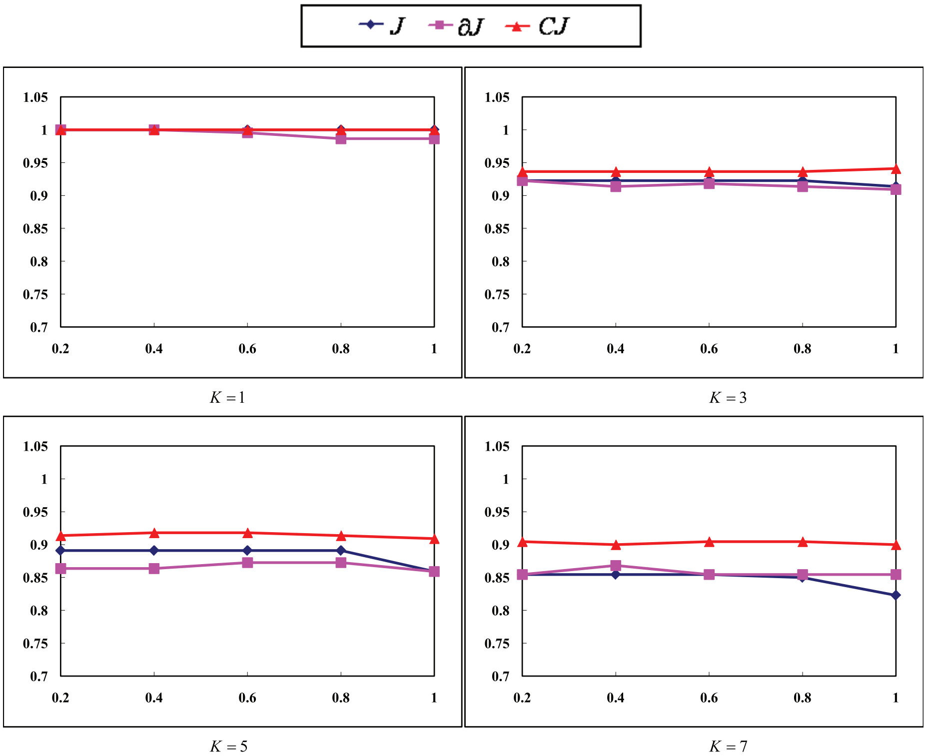

Fig. 4. The object recognition ratio of image group (B) as a function of affine transformation

description framework is given by introducing 3D moment invariants, from which 0-, 1- and even higher order descriptors can be obtained. All these descriptors can characterize different order derivative images. By testing on two different image sets, the proposed descriptors have shown the robustness to illumination color and affine transformation. In addition, the 0-order and the combinational descriptor are also robust to blur change. Furthermore, we can describe an image using not only one of these descriptors but also the combination of them.

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