Modified Color Ratio Gradients

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***Abstract*—Color ratio gradient is an efficient method used for color image retrieval and object recognition, which is shown to be illumination-independent and geometry-insensitive when tested on scenery images. However, color ratio gradient produces unsatisfied matching result while dealing with relatively uniform objects without rich color texture. In addition, performance of color ratio gradient degenerates while processing unsaturated color objects. In this paper, a modified color ratio gradient is presented, which addresses the two problems above. Experimental results using the proposed method in this paper exhibit more robust performance.**

Keywords—Color ratio gradient; uniform background; unsaturated-color object;

Topic area—2.a: Multimedia Databases(content recognition analysis)

I. Introduction

Using color histograms as a stable object representation for object recognition was first explored by Swain and Ballard [1, 2] which introduced *color indexing* technique to efficiently recognize objects by matching their color-space histograms. This method, however, did not address the issue of illumination variation. Funt and Finlayson [3] proposed a new measurement based on the ratio of color RGB triples in neighboring area to locate objects. Compared with Swain's way, such method is more robust to illumination variation. Other improved methods include illumination-independent color reflection ratios proposed by Nayar and Bolle [4]. Gevers [5] further developed the color ratio gradient to make it insensitive to the geometry and position of the object, shadows, illuminations, and other imaging conditions.

However, such color ratio gradients have two limitations: 1) when applied to locate the objects with relatively uniform textural surface like car license plates, the processing results based on common color ratio gradient histograms is dissatisfied; 2) there are only three channels being defined for color ratio gradient. When dealing with unsaturated color objects, this three-channel color ratio gradient fails to give an adequate description of objects.

In this paper, the color ratio gradient is redefined. A quasi-LOG operator is introduced in the algorithm. Moreover, instead of three-channel color ratio gradient, a four-channel color ratio gradient is proposed as the feature of a region for object recognition. With the modification, the algorithm becomes more robust and applicable.

This paper is organized as follows. Common color ratio gradient as a feature of object region is summarized in Section II followed by modified algorithm proposed by us in Section III. In Section IV, the proposed modified method is tested and compared with common algorithm. Conclusions are given in Section V.

II. Color Ratio Gradient Histgram

A. Color Ratio Gradient

Supposing that the sensor response is measured on an infinitesimal surface patch of an inhomogeneous dielectric object and the spectral power distribution of illumination is unknown, the body reflection term in dichromatic reflection model with narrow-band filtering is written as [5, 6],

$$C_k^{\vec{x}} = G_B(\vec{x},\vec{n},\vec{s}) \cdot E(\vec{x}, l_k) \cdot B(\vec{x}, l_k) \quad k = 1,2,\cdots N \tag{1}$$

where $G_B(\vec{x},\vec{n},\vec{s})$ is the geometric term dependent on the surface orientation $\vec{n}$ and illumination direction $\vec{s}$, $E(\vec{x}, l_k)$ is the illumination intensity at light wavelength l_k, and $B(\vec{x}, l_k)$ is the surface albedo at wavelength l_k.

Gevers[5] proposed the following color constant color ratio,

$$M(C_i^{\vec{p}_1}, C_j^{\vec{p}_2}, C_i^{\vec{p}_2}, C_j^{\vec{p}_1}) = \frac{C_i^{\vec{p}_1} C_j^{\vec{p}_2} - C_i^{\vec{p}_2} C_j^{\vec{p}_1}}{C_i^{\vec{p}_1} C_j^{\vec{p}_2} + C_i^{\vec{p}_2} C_j^{\vec{p}_1}} \quad i \neq j, \tag{2}$$

where $M \in [-1, 1]$. It denotes the color ratio between two adjacent positions at P_1 and P_2 under different wavelengths.

Note that in an infinitesimal area it may be assumed that $G_B(\vec{x}_{P1},\vec{n},\vec{s}) \approx G_B(\vec{x}_{P2},\vec{n},\vec{s})$, $E(\vec{x}_{P1}, l_2) \approx E(\vec{x}_{P2}, l_2)$, and $E(\vec{x}_{P1}, l_1) \approx E(\vec{x}_{P2}, l_1)$.

By substituting (1) into (2), we have,

$$M(C_1^{\vec{x}_1}, C_2^{\vec{x}_2}, C_1^{\vec{x}_2}, C_2^{\vec{x}_1}) = \frac{C_1^{\vec{x}_1} C_2^{\vec{x}_2} - C_1^{\vec{x}_2} C_2^{\vec{x}_1}}{C_1^{\vec{x}_2} C_2^{\vec{x}_1} + C_1^{\vec{x}_1} C_2^{\vec{x}_2}} = \frac{B(\vec{x}_1, l_1) \cdot B(\vec{x}_2, l_2) - B(\vec{x}_2, l_{1_1}) \cdot B(\vec{x}_1, l_2)}{B(\vec{x}_2, l_1) \cdot B(\vec{x}_1, l_2) + B(\vec{x}_1, l_1) \cdot B(\vec{x}_2, l_2)} \tag{3}$$

It is seen that color ratio is only determined by the ratio of surface albedo only [6].

The gradient of the color constant color ratio is written as,

$$\nabla M(C_1^{\vec{x}_1}, C_1^{\vec{x}_2}, C_2^{\vec{x}_1}, C_2^{\vec{x}_2}) = \left\{ M\left[C_1^{(x-1,y)}, C_1^{(x+1,y)}, C_2^{(x-1,y)}, C_2^{(x+1,y)}\right]^2 + M\left[C_1^{(x,y-1)}, C_1^{(x,y+1)}, C_2^{(x,y-1)}, C_2^{(x,y+1)}\right]^2 \right\} \tag{4}$$

where $(x-1, y)$, $(x+1, y)$, $(x, y-1)$, and $(x, y+1)$ are four adjacent positions of $\vec{x} = (x, y)$ as shown in Fig. 1.

On standard RGB color space, Gevers defined three-channel color ratios as,

$$\begin{cases} M_1(R^{x_1}, R^{x_2}, G^{x_1}, G^{x_2}) = \dfrac{R^{x_1} \cdot G^{x_2} - R^{x_2} \cdot G^{x_1}}{R^{x_2} \cdot G^{x_1} + R^{x_1} \cdot G^{x_2}} \\ M_1(R^{x_1}, R^{x_2}, B^{x_1}, B^{x_2}) = \dfrac{R^{x_1} \cdot B^{x_2} - R^{x_2} \cdot B^{x_1}}{R^{x_2} \cdot B^{x_1} + R^{x_1} \cdot B^{x_2}} \\ M_1(G^{x_1}, G^{x_2}, B^{x_1}, B^{x_2}) = \dfrac{G^{x_1} \cdot B^{x_2} - G^{x_2} \cdot B^{x_1}}{G^{x_2} \cdot B^{x_1} + G^{x_1} \cdot B^{x_2}} \end{cases} \tag{5}$$

Thus, by substituting (5) into (4), three-channel color ratio gradients on RGB space can be written as (6).

$$\nabla M_1(R^{\vec{x}_1}, R^{\vec{x}_2}, G^{\vec{x}_1}, G^{\vec{x}_2}) = \left(\left(\frac{R^{(x-1,y)} \cdot G^{(x+1,y)} - R^{(x+1,y)} \cdot G^{(x-1,y)}}{R^{(x+1,y)} \cdot G^{(x-1,y)} + R^{(x-1,y)} \cdot G^{(x+1,y)}} \right)^2 + \left(\frac{R^{(x,y-1)} \cdot G^{(x,y+1)} - R^{(x,y+1)} \cdot G^{(x,y-1)}}{R^{(x,y+1)} \cdot G^{(x,y-1)} + R^{(x,y-1)} \cdot G^{(x,y+1)}} \right)^2 \right)^{1/2} \tag{6}$$

$$\nabla M_2(R^{\vec{x}_1}, R^{\vec{x}_2}, B^{\vec{x}_1}, B^{\vec{x}_2}) = \left(\left(\frac{R^{(x-1,y)} \cdot B^{(x+1,y)} - R^{(x+1,y)} \cdot B^{(x-1,y)}}{R^{(x+1,y)} \cdot B^{(x-1,y)} + R^{(x-1,y)} \cdot B^{(x+1,y)}} \right)^2 + \left(\frac{R^{(x,y-1)} \cdot B^{(x,y+1)} - R^{(x,y+1)} \cdot B^{(x,y-1)}}{R^{(x,y+1)} \cdot B^{(x,y-1)} + R^{(x,y-1)} \cdot B^{(x,y+1)}} \right)^2 \right)^{1/2}$$

$$\nabla M_3(G^{\vec{x}_1}, G^{\vec{x}_2}, B^{\vec{x}_1}, B^{\vec{x}_2}) = \left(\left(\frac{G^{(x-1,y)} \cdot B^{(x+1,y)} - G^{(x+1,y)} \cdot B^{(x-1,y)}}{G^{(x+1,y)} \cdot B^{(x-1,y)} + G^{(x-1,y)} \cdot B^{(x+1,y)}} \right)^2 + \left(\frac{G^{(x,y-1)} \cdot B^{(x,y+1)} - G^{(x,y+1)} \cdot B^{(x,y-1)}}{G^{(x,y+1)} \cdot B^{(x,y-1)} + G^{(x,y-1)} \cdot B^{(x,y+1)}} \right)^2 \right)^{1/2}$$

	(x, y-1)	
(x-1, y)	(x, y)	(x+1, y)
	(x, y+1)	

Fig. 1 Quasi-Prewitt Operator in Gevers' method

B. Similarity Measure

Color ratio gradient based histogram is created and chosen as the measurement to compare the similarity between model image and target image. In order to make such matching invariant to the dimension of image, the created histogram is normalized by the number of pixels in the image. By such a way, the object matching problem is converted to a simple problem: how histogram of the model is similar to the histogram of target image?

A similarity function is needed to return a numerical measure of similarity between model image and target image. This paper uses histogram intersection [2] to obtain a numerical similarity measure. The advantage of using color histograms is the robustness to geometric changes of projected objects. Histogram is invariant to translation and rotation about the viewing axis and insensitive to view angle, scale, and occlusion[7].

Given a pair of histograms, $H(I)$ and $H(I')$, of image I and image I' respectively, each containing n bins, the histogram intersection between two histograms is shown in (7)

$$\tilde{H}(I) \cap \tilde{H}(I') = \frac{\sum_{j=1}^{n} \min\left(\tilde{H}_j(I), \tilde{H}_j(I')\right)}{\sum_{j=1}^{n} \tilde{H}_j(I)}. \tag{7}$$

Here, $\tilde{H}_j(I)$ and $\tilde{H}_j(I')$ are the values on the j^{th} bin of the histograms respectively. The denominator normalizes the histogram intersection to make the value of the histogram intersection fall into the range between 0 and 1.

III. MODIFIED ALGORITHM

As the algorithm proposed by Gevers and introduced in the previous section, in order to calculate the color ratio gradient at a pixel $P(x, y)$, its four neighboring pixels are involved (see Fig. 1.). Two aspects of modifications have been made on Gevers' algorithm.

		×		
	×	×	×	
×	×	P	×	×
	×	×	×	
		×		

Fig. 2 Cross ratio mask in modified algorithm

A. *Modification 1: Quasi-LOG Operator*

In Gevers' color ratio gradient algorithm, Quasi-Prewitt operator is applied (Fig.1). In such kind of mask, only directly related neighbors are involved into the color ratio gradient computation. If the objects have relatively uniform texture, such mask is too compact to present a histogram used to classify object. In our modified algorithm, the Quasi-LOG operator is applied (Fig. 2). Using Quasi-LOG operator, the color ratio gradient can be obtained in a bigger local area, which makes the algorithm more robust to the uniform texture. In our algorithm, the color ratio gradient is computed in a 5*5 mask window. The mask size should not be too large. Otherwise, it breaches the assumptions for obtaining (3).

B. *Modification 2: 4-Channels color ratio gradients*

In Gevers' color ratio gradient, there are only three-channel color ratios being defined, that are, between R and G components, between R and B components and between G and B components, as described in (6). These color ratio gradients, however, are degenerated when dealing with unsaturated-color objects. For example, considering a grey-level objects, the three components of RGB at any position on the objects have identical values, i.e.

$$R_1 = G_1 = B_1 = I_1 \tag{8}$$

and

$$R_2 = G_2 = B_2 = I_2 \tag{9}$$

where $I_1 \in \{0,1,2,\cdots,255\}$ and $I_2 \in \{0,1,2,\cdots,255\}$ are grey-level intensity at two pixels P_1 and P_2. Substitute (8) and (9) in (5), it is obvious that whatever values I_1 and I_2 take, the three color ratios appear to be zero. (Computationally, in the case of both the nominator and the denominator of (5) take zero value, we may avoid dividing-zero error by defining the quotient as zero.)

In order to make Gevers' method more robust when dealing with unsaturated-objects, besides Gevers' three-channel color ratio gradients, an additional channel is defined. That is intensity gradient to make the color ratio gradient really reflect the changes in both colors and intensities. The gradient of a given intensity function $I(x, y)$ is defined as the magnitude of the first derivatives of intensity function $I(x, y)$ in x-direction and y-direction,

$$\nabla I = \left(\left(\frac{\partial I}{\partial x} \right)^2 + \left(\frac{\partial I}{\partial y} \right)^2 \right)^{1/2} . \tag{10}$$

For consistency, the intensity gradient is defined similarly as the other three channels as described in (6) using discrete approximations as,

$$\nabla I = \left(\left(\frac{I^{(x+1,y)} - I^{(x-1,y)}}{255} \right)^2 + \left(\frac{I^{(x,y+1)} - I^{(x,y-1)}}{255} \right)^2 \right)^{1/2} . \tag{11}$$

Combining with Gevers' three-channel color ratio gradients described in (6), a four-channel color ratio gradient is defined, which is more robust when dealing with unsaturated-color objects as demonstrated in the next section.

IV. Experimental Results

To study the effects of modified algorithm, experiments are conducted on car license plate images. The experiments include three parts. The first part is to assess the performance of our new algorithm through measuring the self similarity (see below). The second part is to assess the performance through measuring the similarity of images from the same class having similar colors (e.g., number plates with yellow background color and black characters). The last part is to test the robustness of our new algorithm under the different illumination intensity. The details will be explained in the following.

A. *Self Similarity Measurement*

Self similarity means the similarity between part of object and the whole object itself. In a license plate, the color on any part of the background should not be much different. Hence, the self similarity of license plates should be very high.

In this experiment, 80 different car license plate images are tested. For each image, a part of image is cut out (see, for example, Fig.3.). Then, the image piece is compared with the original whole license plate image. The similarity is calculated using (7) based on the color ratio gradient histograms for the image piece and the whole image. The statistical results are listed in Table 1.

As shown in Table 1, our algorithm using the modified color ratio gradient histogram has a better description of real number plates than the Gevers' algorithm: any part of a license plate should be similar to the whole license plate itself in terms of color ratio gradient.

Fig. 3 One of the license plates and its part

TABLE 1. SELF SIMILARITY MEASUREMENTS USING GEVERS' ALGORITHM AND MODIFIED ALGORITHM

Methods	Gevers' Algorithm	Modified Algorithm
Average Similarity	53.38%	74.89%
Standard Deviation of Similarity	34.40%	9.03%

Fig. 4. Image piece and two license plate images of the same class

TABLE 2. SIMILARITY MEASUREMENTS IN THE SAME CLASS OF IMAGES

Methods	Gevers' Algorithm	Modified Algorithm
Average Similarity	36.34%	65.1%
Standard Deviation of Similarity	18.75%	8.84%

B. Similariry Measurements in the Same Class of Images

In this experiment, the car license plate images containing the same background color and foreground color are group into a class.

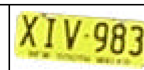
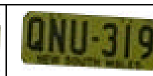
56 images in the same class are tested. The similar experimental procedure as in Section IV-A is adopted to calculate the similarity. As an illustration, one image piece and a few car license plate images from the same class are shown as in Fig. 4. It is expected that the degree of similarity between the image piece and any image in the same class should be high.

The experimental results are shown in Table 2. It is clearly shown that our modified method demonstrates better performance than the Gevers' methods again.

C. Illumination Independency

18 images containing the same background color and foreground color and taken under obviously different illumination situations are tested to verify the robustness of our new algorithm.

TABLE 3. ILLUMINATION INDEPENDENCY OF NEW ALGORITHM

			
Average Similarity	70.3%	76.1%	61.8%

The experimental results are displayed in Table 3. It can be seen that varying illumination does not affect much on the similarity measurement. This proves the illumination independency as claimed in Section III.

V. CONCLUSIONS

Gevers' color ratio gradient algorithm has limitation while applied on images with relatively simple and uniform background like car license plate images. In addition, performance of color ratio gradient degenerates while processing unsaturated-color objects. In this paper, a modified color ratio gradient algorithm is presented, which uses Quasi-LOG to replace the common Quasi-Prewitt operator, and a new four-channel color ratio gradient instead of three-channel gradient in Gevers' algorithm is defined. With the modification, our algorithm makes color ratio gradient more robust and applicable. The experimental results presented in this paper are encouraging.

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