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An Effective Image Retrieval Technique Based on salient features of image

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Abstract- In content-based image retrieval (CBIR), color and texture are the most intuitive image features and it is widely used. But the current color feature can describe the semantics of the whole image effectively, but does not reflect characteristics of the color salience objects in an image. For the purpose of giving paper proposes a new color feature description model is proposed at first. This model integrates the intensity, the color contrast and self-saliency, sparsity and centricity saliency to describe human color visual perception of the image. Then, the new color feature descriptor is calculated by weighting the significant bit-plane histograms with color perception map. Finally, similarity measure is presented for the new color feature. Then for more efficient retrieval again the retrieved images are then compared for texture .Now because of the texture of salience retrieved image more accurate images can be retrieved. Experiment results show that the proposed color feature and texture feature is more accurate and efficient in retrieving images with user-interested color objects. Here a typical query can be a region of interest provided by the user, such as outlining patch in satellite image. Compared with the other retrieval methods, the proposed technique improves the retrieval accuracy effectively.

Index Terms— Color Perception, Color Feature, Visual Saliency, Color Visual Perception, Image Retrieval, Texture Analysis, Gabor Wavelets.

1 INTRODUCTION

FIRSTLY, the color at present, with the rapid expansion of the digital images amount, users want to be able to find images quickly and accurately from a large number of digital images. For this purpose, content- based image retrieval (CBIR, Content-Based Image Retrieval) has become one of the hot research fields in image databases. Image features extraction and expression are the basis of content –based image retrieval technology. Image features include color, texture, shape and spatial relations, etc. color feature not only closely related to objects and scenes in an image, but also are less dependent on image size, orientation, and camera angle. Color feature has a high robustness. Common representation of color features include color histogram [1], color moment [2] and dominant color [3] etc. Among them, the color histogram feature extraction and similarity calculation is simple, and it is insensitive to the image scale and rotation. Therefore, the color histogram became the most widely used color features in images retrieval system. However, the traditional color histogram's problems are susceptible to noise interference, high feature dimensions, lack of color spatial distribution information. For these problems,[4]proposed a color block-histogram to fuse color spatial distribution information . This method divides the image into several blocks, and calculates the color histogram of each block. It is simple and can reflect some color spatial information. But it does not have the translation and rotation invariance. Reference presents the image significant bit-plane color histogram method to solve problems of susceptible to noise interference and high feature dimensions. But the significant bit-planes is global characteristic of an image that associated with the entire image, it lack color local spatial information and does not reflect the significant objects in image. Therefore, the current color feature effectively describes the semantics of the whole image, but does not reflect the human color salience objects in an image. According to visual physiology and visual psychology theories, the human visual perceptual system tends to show different sensitivity to different colors. So [6] presents color visual function to improve retrieval accuracy. But color visual function is also for the entire image, it can't inhibit the effects of background characteristics in retrieval accuracy effectively. In order to emphasis color characteristics and inhibit background in image. It will greatly improve the image retrieval accuracy.

This paper analyzes the process of human color visual perception model based on visual saliency. Integrated color perception model based on visual saliency. Integrated color perception map is calculated and weighted for static significant bit-plane histograms. New color feature to represent the image content. The proposed feature is not only insensitive to noise interference, image scale and rotation, but also describes the color spatial distribution information of salience objects. It closes to distribution information of the image and can improve the retrieval performance effectively.

Secondly, the saliency color information is obtained and then the texture pattern focuses on a multiresolution representation based on gabor filters. The use of gabor filters in extracting textured image features is motivated by various factors. The gabor representation has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency .These filters can be considered as orientation and scale tunable edge and line(bar) detectors and the statistics of these microfeatures in a given region are often used to characterize the underlying texture information. Gabor features have been used in several image analysis applications including texture classification and segmentation[1],[14], image recognition[13], image registration[15], and motion tracking[16].

The rest of the paper is organized as follows. A color visual perception model for image retrieval is introduced in section 2. In section 3, color visual perception calculation is presented in detail including features saliency calculation, normalization and synthesis. Section 4 and 5 give the new color feature descriptor and the similarity measurement respectively. Texture Feature extraction in section6 The experiment results and analysis are presented in section 7. Conclusions are drawn in section 8.

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2 COLOR VISUAL PERCEPTION MODEL

Visual psychology research shows that when people observe an image, not all of the ingredients of which have the same interest. Those who can produce a strong stimulation and stimulation of people look forward to the scene area prone to observer's attention. The classic is the Koch and Ullman's neurobiology structural framework on the basis of feature integration theory [7]. Based on this framework, some simulation models have been proposed to quantify the human visual perception characteristics. The most representative model is the Itti's visual saliency model[8]. Itti's model uses color, direction and intensity to measure visual saliency. It generates an integrated visual salience map[9]-[11] to represent the stimulation of an image to eyes in case of no available prior information exists. And then it quantifies the salience of each pixel of the image under the combination of various properties. The model is robust when dealing with noise, fuzzy, contrast and intensity [9],[11]. In color respect, it uses the color contrast of RG, BY channels in the RGB space to describe color perception characteristics. But the RG, BY channels cannot fully describe the color stimulation of the human eyes.
Previous research shows that the HSV color space has much

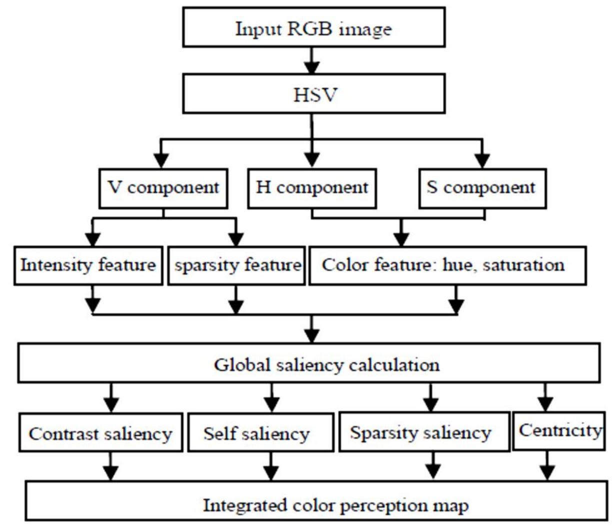

Figure 1. Color visual perception model.

better visual consistency than traditional RGB space. The intensity component of HSV space has nothing to do with the color information. Hue component and saturation component approach human observation. Based on human color vision theory, color visual saliency can be divided into contrast saliency and self-saliency. Self-saliency describes the internal advantage of features which can individually generate stimulation to the human eyes. Contrast saliency describes the difference between the object and back ground. Accordingly, the color features of image are also divided into contrast and self-saliency. Considering the following six factors [12], we propose a color visual perception model based on Itti's.

2.1 Intensity contrast

The change of image brightness makes the stronger contrast.

2.2Hue contrast

Different hues in different color ring of the image can stimulate human's eyes. Obviously, a big hue angle difference can form stronger color contrast. In hue ring, the biggest difference is 180^0.

2.3 Saturation contrast

Different saturation of an image forms contrast. Color saturation difference determines the contrast strength.

2.4 Warm color self-saliency

For the warm colors such as red, yellow and orange, etc., the human eyes can produce more stimulation than the other colors. These colors angles are less than 45^0.

2.5 Intensity and saturation self-saliency

High brightness and high saturation more easily attract the attention of eyes .

Intensity contrast, hue contrast and saturation contrast are called color contrast saliency. Warm color self-saliency, intensity and saturation self-saliency are called color self-saliency.

2.6 Sparsity and centricity

Taking into account the general case, a complex area in the image should be the attention focus. However, if the image is full of complex textures, a simple goal should be the attention focus. The area of the image center easily attracts human's attention. These are called sparsity and centricity.

The proposed color visual perception model is showed in Fig.1.This model calculates color features in terms of contrast and self-saliency, integrates the color, intensity, sparsity and centricity saliency to describe the human color visual perception in the image.

3. Color Visual Perception Calculation

3.1 Features saliency calculation

The intensity, hue and saturation features of image cannot be used to describe contrast saliency directly. In order to strengthen novel stimulus and weaken the ordinary stimulus, the pixel's global saliency can be described by calculating the mean difference of each pixel with other pixels in the entire image. For the novel stimulus, there are more pixels which have large difference. Thus, the average of difference is large. For the ordinary stimulus, there are more pixels which have small difference. So, the average of difference is small. The global color contrast saliency is calculated as follows:

$$DS_i(x,y) = \frac{\left[\sum_{u=1}^{M}\sum_{v=1}^{N}|F_i(x,y)-F_i(u,v)|\right]}{M.N} \quad \ldots(1)$$

$$S_i(x,y) = 1 - exp\left\{-\frac{DS_i(x,y)}{\overline{DS_i}}\right\} \text{ (i=1, 2,3) } \ldots.(2)$$

Where $F_i(x, y)$ $(i = 1, 2, 3)$ denote intensity, hue, saturation features of the (x, y) in the image. $DS_i(x, y)$ is the global feature difference, M and N respectively is the row number

And the column number of image. $\overline{DS_i}$ is the mean of global feature difference. $S_i(x,y)$ is the global color contrast saliency of feature $F_i(x,y)$.

Global color self-saliency is described by the following formula:

$$S_4(x,y) = AF_1(x,y)\cos(F_2)\,F_3(x,y); if\ \frac{\sqrt{2}}{2} \le \cos(F_2) \le 1 \ldots..(3)$$

$$= 0 \qquad otherwise \ \ldots\ldots.(3)$$

$$S_5(x,y) = A.F_1(x,y).F_3(x,y) \ldots\ldots(4)$$

Where A is the amplification factor, F1 and F3 normalize to [0,1].F2 normalizes to [0.2∏].Let sparsity saliency is S6(g), where g is the image intensity value . The specific formula is as follows:

$$S_6(g) = -\log\big(f(g).d(g)\big) \ldots\ldots.(5)$$

where f(g) is the frequency of intensity value g in image ,d(g) is calculated as follows :

$$d(g) = 1 - \frac{\sum_{j=1}^{M.N}|g-g_j|}{M.N\max(g)} \ldots\ldots..(6)$$

Where max(g) is maximum brightness of the image . If the difference of the gray value g between pixels in the image is larger, d(g) is smaller. Therefore, sparsity saliency is greater.

Centricity saliency is calculated as follows:

$$S_7 = centricity(x,y)$$

$$= 1 - \left(\frac{|x-\bar{x}|}{M} + \frac{|y-\bar{y}|}{N}\right) \ldots..(7)$$

Where $(\bar{x},\bar{y})$ is the image center coordinates.If pixel is close to the center position of the image, its centricity saliency is big.

3.2 Normalized and synthesis

Because the range of saliencies is different, saliencies values must be normalized to the same range. We regularize those saliency features by the normalization operator N(x)[8]. Seven saliency features are normalized by the normalization operator N(x) and combined into the final global integrated color vision perception map S(x,y). Linear weighting is used for different features. The specific formulas are as follows:

$$S(x,y) = \frac{1}{CNum}\sum_{i=1}^{Cnum} W_i\,.N\ \ (S_i)(x,y) \ldots\ldots(8)$$

$$\sum_{i=1}^{Cnum} W_i = CNum(W_i \ge 0{,}1{,}2 \ldots CNum)\ \ldots\ldots.(9)$$

Where C_{Num} is the number of the saliency feature categories (C_{Num}=7 in our approch), W_i is the weight of the feature and it meets the constraint formula (9).

4 Color Retrieval Feature Extraction

Taking into account the image subjected to noise attacks such as light, sharpen, blur, etc., its low bit-planes changed little. Therefore,[5] uses significant bit-planes to solve problems that the traditional color histogram feature dimension is too high, cannot effectively retrieve images with noise. So the color histogram feature dimension is too high, cannot effectively retrieve images with noise. So the color histograms based on significant bit-planes are used in the proposed new color feature. First, image's highest 5 bit-planes(these are significant bit-planes) are extracted in RGB space , total of 15 significant bit-planes. Significant bit planes integrated into new color value (in the range of 0 to 7). Through statistic frequency of each new color value, the

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significant bit-plane image color histogram is calculated. Then, weighting the significant bit-plane histograms with color visual perption map, the new color feature descriptor integrates the color spatial distribution, local correlation, frequency information and the object saliency to express the image's content. It is calculated as follows:

$$h_k(c) = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} s(x,y) \quad v_k(x,y) = c$$

$$h_k(c) = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} 0 \quad otherwise \quad \ldots..10$$

Where $h_k(c)(c=0,1,\ldots..7)$ denotes the frequency which colors c appears in significant bit-plane k.$V_k(x,y)$

Is the pixel (x,y) color value in significant bit-plane k. To make the new color feature does not change with scale, it needs to be normalized by formula (11).

$$H_k(c) = \frac{h_k(c)}{\sum_{c=0}^{7} h_k(c)} \quad \ldots\ldots(11)$$

5 The Similarity Measurement

A typical objective measure reflects similarity degree between the query example image and an image in database. The distance formula [5] between histograms is often used to represent similarity. Obviously, the small distance represents the similarity. There are many formulas which represent the similarity of histograms. For the new color feature descriptor, distance Dist.(Q,I) is used for similarity measure. The formula is as follows:

$$Dist(Q,I) = \sum_{k=0}^{7}\sum_{c=0}^{7} w_k \left|H_K^Q(c) - H_K^I(c)\right| \ldots.(12)$$

$$\sum_{k=3}^{7} w_k = 1 \quad \ldots(13)$$

Where Q is query example image, and an image in database is I. $H_K^Q(c)$ *and* $H_K^I(c)$ are the normalized new color features in significant bit-plane k of image Q and I respectively. w_k is the weight of bit-plane reflects the outlines information of objects in image, so the larger weight is assigned to the higher bit-plane. In our experiments, $w_k(K = 3,4\ldots..7)$ are assigned as 0.1, 0.1, 0.25, 0.25, and 0.3. We sums distances of bit-planes features to express new color feature distance. Image retrieval results are returned in accordance with the descending order of similarity.

6 Texture Feature Extraction

Now the color retrieved images from the database are again gone through the texture retrieval by using following technic

6.1 Gabor functions and wavelets

A two dimensional Gabor function g(x,y) and its Fourier transform G(u,v)can be written as:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right] + 2\pi jWx \quad \ldots\ldots(14)$$

$$G(u,v) = exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}\right]\right\} \quad \ldots\ldots\ldots(15)$$

$$where\ \sigma_u = \frac{1}{2\pi\sigma_x} and\ \sigma_y = 1/2\pi\sigma_y$$

Gabor functions form a complete but nonorthogonal basis set.Expanding a signal using this basis provides a localized frequency description.A class of self-similar functions, reffered to as Gabor wavelets in the following discussion, is now considered . Let g(x,y) be the mother Gabor wavlet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of g(x,y) though the generating function:

$$g_{mn}(x,y) = a^m g(x',y'), a > 1, \quad m,n = integer$$
$$x' = a^{-m}(xcos\theta + ysin\theta), and\ y' = a^{-m}(-xsin\theta + ycos\theta) \quad \ldots.(16)$$

Where $\theta = n\pi/k$ and k is the total nu,ber of orientations. The scale factor a^{-m} in (16) is meant to ensure that the energy is independent of m.

6.2 Gabor filter Dictionary Design

The non orthogonality of the Gabor wavelets implies that there is redundant information in the filtered images, and the following strategy is used to reduce this redundancy. Let u_l and u_h denote the lower and upper center frequencies of interest. Let K be the number of orientations and S be the number of scales in the multiresolution decomposition. Then design strategy is to ensure that the half-peak magnitude support of the filter responses in the frequency spectrum touch each other as shown in fig2. This results in the following formulas for computing the filter parameters σ_u and σ_v (and thus σ_x and σ_y).

$$a = (u_h/u_l)^{1/(s-1)}, \ldots\ldots.(17)$$

Where $W=U_h$ and m=0,1,…,S-1. In order to eliminate sensitivity of the filter response to absolute intesity values, the real(even) components of the 2D Gabor filters are biased by addding a constant to make them zero mean(This can also be done by setting G(0,0) in (15) to zero).

Fig 2. The contours indicate the half-peak magnitude of the filter responses in the gobar filter dictionary. The filter parameters used are U_h= 04, U_l= 0.05, K=6 and S=4.

6.3 Feature representation

Given an image I(x,y), its Gabor wavelet transform is then defined to be

$$W_{mn}(x,y) = \int I(x_1,y_1)g^*_{mn}(x-x_1,y-y_1)dx_1dy_1, \quad \ldots.(18).$$

Where * indicates the complex conjugate. It is assumed that the local texture regions are spatially homogeneous, and the mean μ_{mn} and the standard deviation σ_{mn} of the magnitude of the transform coefficients are used to represent the region for classification and retrieval purposes:

$$\mu_{mn} = \iint |W_{mn}(xy)|\, dxdy$$

and $\sigma_{mn} = \sqrt{\iint (|W_{mn}(x,y)| - \mu_{mn})^2\, dxdy}$.....(19)

A feature vector is now constructed using μ_{mn} and σ_{mn} as feature components. In the experiments, we use four scales S=4 and six orientations k=6, resulting in a feature vector
$\bar{f} = [\mu_{00}\sigma_{00}\mu_{01}\sigma_{01} \ldots \mu_{35}\sigma_{35}]$........(20)

6.3.1Distance measure:

Consider two image patterns I and j, and let $\bar{f}^{(i)}$ and $\bar{f}^{(j)}$ represent the corresponding feature vectors. Then the distance between the two patterns in the feature space is defined to be

$$d(i,j) = \sum_m \sum_n d_{mn}(i,j),$$

Where

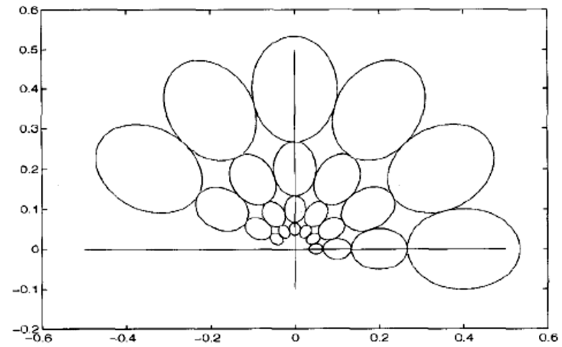
$$d_{mn}(i,j) = \left|\frac{\mu^{(i)}_{mn}-\mu^{(j)}_{mn}}{\alpha(\mu_{mn})}\right| + \left|\frac{\sigma^{(i)}_{mn}-\sigma^{(j)}_{mn}}{\alpha(\sigma_{mn})}\right| \ldots\ldots\ldots (21)$$

$\alpha(\mu_{mn})$ and $\alpha(\sigma_{mn})$ are the standard deviations of the respective features over the entire database, and are used to normalize the individual feature components.

6.4 Retrieval performance

D.1 Texture Database

The texture database used in the experiments consists of different texture classes. Each image is non-overlapping sub images, thus creating a database of different texture images. This pattern is then processed to compute the feature vector as in (20). The distance d(i,j), where I is the query pattern and j is a pattern from the database, is computed. The distances are then sorted in increasing order and the closest set of patterns are then retrieved. In the ideal case all the top 15 retrievals are from the same large image. The performance is



measured in terms of the average retrieval rate which is defined as the average percentage number of patterns belonging to the same image as the query pattern in the top 15 matches.

We observe that the use of σ_{mn} feature in addition to the mean improves the retrieval performance considerably. This perhaps explains the low classification rate of the Gabor filters reported in [17] where only the mean value was used. On the average 74.37% of the correct patterns are in the top 15 retrieved images. The performance increases to 92% if the top 100(about 6% of the entire database) retrievals are considered instead(ie., more than 13 of the correct patterns are present).

7 CONCULSION

This paper analyses the process of human color visual perception. The color visual perception model is presented based on visual saliency. It integrates the color, intensity, sparsity and centricity saliency to form a color perception map. A new color feature descriptor based on color visual perception is proposed. It can highlight the significant objects, inhibit background characteristics in image, and a texture then applied to the saliency color retrieved image which effectively improves retrieval precision ratio. The experiment results show that the proposed approach has a good performance and it is particularly applicable to retrieving the image with salience color objects such as in large images in internet to remove unwanted images, satellite patches for finding percentage of vegetation in world and also in knowing the presence of rear species of animals present in the surface of the earth and so on. Retrieval results can be closer to human color visual perception effectively.

fig(b)

8 EXPERIMENT RESULTS

fig(a)

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fig(c)

fig(3) (a)query image (b)images retrieved after color visual perception map. (c)images retrieved after applying texture retrieval by gabor filter to color retrieved.

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