Color image retrieval using edge and edge-spatial features

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A novel methodology to integrate edge feature and edge-spatial feature of an image is proposed. The edge feature is described by edge histogram of image, the edge-spatial feature is described by spatial distribution of pixels of identical edge value in the image. Experimental results show that the method can achieve better retrieval performance, especially for color natural images with more complex spatial layout.

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The need for efficient content based image retrieval (CBIR) has increased tremendously in many application areas. The accuracy of CBIR depends greatly on the description of low-level visual features[1−6]. How to efficiently describe the low-level visual features of image is still a challenging task. Mu *et al.*[2] introduced an algorithm with nonlinear weight factors in the summation process for fuzzy correlation of color histogram, in which nonlinear weights are assigned to some characteristic colors of interest. Comparing with color histogram, the researches[3,4] show that the effectiveness of a CBIR system increases when spatial relationship of colors is considered. Cinque *et al.*[3] introduced spatial-chromatic histogram (SCH), which describes the global spatial relationship of colors. Lim *et al.*[4] introduced geographical statistics (Geostat), which uses the looseness parameter from geostat to describe the global spatial relationship of colors, and the spatial measurement of geostat is size invariant. Huang *et al.*[5,6] introduced an edge descriptor and a neighbor edge directional difference feature (NEDDF) to describe color-spatial feature, respectively.

In this paper, a novel method to integrate edge and edge-spatial features (EESFs) of image is proposed. For every pixel in an image, its edge value is calculated and is used to generate edge histogram, then, the spatial distribution of pixels of identical edge value in the image is also calculated. The edge histogram and edge-spatial feature are integrated to retrieve image.

First, in order to get edge feature, the HSV (hue, saturation, value) color space is used[5]. The HSV color space has an intuitive coordinates system, in which hue is separated from saturation and bright. The hue value is the most important in the three components, and is denoted as h, and $h \in [0, 2\pi]$. Let $N(i,j)$ denote 3×3 neighborhood of a pixel at (i,j), Computing the average, maximum, and minimum values of hue values over $N(i,j)$, the average, maximum, and minimum values are denoted by Avg, Max, Min, respectively, and some parameters are defined as

$$D = \max\{\mathrm{Max} - \mathrm{Avg}, \mathrm{Avg} - \min\}.$$

For a pixel at (i,j), the membership function is defined as

$$\mu(i,j) = 1 - \frac{1}{2}\left(\frac{h - \mathrm{Avg}}{D}\right)^2.$$

The fuzzy entropy is defined as

$$H(i,j) = -\mu(i,j)\log(\mu(i,j)) \\ -(1-\mu(i,j))\log(1-\mu(i,j)).$$

Let $G(i,j)$ denote the average of fuzzy entropy of all pixels in $N(i,j)$. From Ref. [7], the entropy $G(i,j)$ over $N(i,j)$ can be viewed as a measure of edginess of pixel at (i,j).

Here, $0 <= G(i,j) <= 1$ for all $i = 0,1,\cdots,m$, $j = 0,1,\cdots,n$. $G(i,j)$ is then uniformly quantized into 20 entropy bins: $p(i,j) = 0,1,2,\cdots,19$.

For every pixel at location (i,j) $(i = 0,1,\cdots,m,\ j = 0,1,\cdots,n)$ of an image I, $p(i,j)$ can be calculated above. The value range of $p(i,j)$ is $P = \{0,1,2,\cdots,19\}$. The set $\{p(i,j)\ (i = 0,1,\cdots,m,\ j = 0,1,\cdots,n),\ p(i,j) \in P\}$ is also an image, and is denoted as I_{E}. This is the edge image of image I. The normalized histogram of I_{E} can be computed, which also is called edge histogram of image I

$$e(p) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\delta(p(i,j) - p), \quad \forall p \in P. \tag{1}$$

Second, edge-spatial feature must be obtained. For the image I, the image I_{E} can be obtained above. We shall describe how pixels of identical bin are distributed in the image I_{E}.

Let A_i be the set of pixels in bin i in the image I_{E}; $|A_i|$ be the count of pixels in bin i, $C_i = (x_i, y_i)$ be the centroid of bin i; $\sigma(i)$ be the standard deviation of bin i from C_i, where $i \in P = \{0,1,2,\cdots,19\}$; x_i, y_i, $\sigma(i)$ are defined as

$$x_i = \frac{1}{|A_i|}\sum_{(x,y)\in A_i} x, \quad y_i = \frac{1}{|A_i|}\sum_{(x,y)\in A_i} y, \tag{2}$$

$$\sigma(i) = \sqrt{\frac{\sum\limits_{(x,y)\in A_i}((x - x_i)^2 + (y - y_i)^2)}{|A_i|}}. \tag{3}$$

$\sigma(i)$ $(i = 0,1,2,\cdots,19)$ gives an idea of the pixels spread from the centroid, and describes how these pixels are spatially arranged. $(\sigma(0), \sigma(1), \cdots, \sigma(19))$ describes edge-spatial feature of image I.

Third, the edge feature and edge-spatial feature are combined as feature index for image I, which is $(e(0), \sigma(0), e(1), \sigma(1), \cdots, e(19), \sigma(19))$, where $e(i)$ and $\sigma(i)$ $(i \in P)$ are edge histogram and edge-spatial distribution of bin i of image I, respectively.

For two images, M and I, the similar metric is defined as

$$s(M, I) = \sum_{i=0}^{19} \min(e^M(i), e^I(i)) \frac{\min(\sigma^M(i), \sigma^I(i))}{\max(\sigma^M(i), \sigma^I(i))}. \quad (4)$$

The distance metric between images M and I is defined as

$$d(M, I) = \frac{1}{0.1 + s(M, I)}. \quad (5)$$

In the experiment, 900 24-bit JPEG color images of size 384×256 or 256×384 pixels are downloaded from three websites[8−10] and other websites as our image database. The images are divided into ten categories of different scenes (i.e., "bus", "flower", "persons", "horse", "elephant", "beach", "building", "flag", "fruit", "fungi"). There are 90 images in each category. To compare performance, three methods are used, which are SCH[3], NEDDF[6], and EESF proposed in this paper.

The performance of the retrieval results is measured by precision and recall:

precision=(number of relevant images retrieved)/(total number of images retrieved),

recall=(number of relevant image retrieved)/(total number of relevant image in database).

Relevant images are referred to images in the same category. The precision measures the hit-rate that the category of the retrieved images is the same as that of input reference image from the whole database. The recall measures the capability of finding the images with the same category from the whole category of images in the database. In evaluating the effectiveness of CBIR systems, the one which gives higher precision value at the same recall value is the more effective system.

Three categories in the ten categories are tested. The three categories are "bus", "flower", and "person". The average precision-recall results using the three categories as the reference query images by three methods are shown in Fig. 1.

From Figs. 1(a) and (b), it can be seen that the retrieval performance of NEDDF is better than that of EESF, the retrieval performance of EESF is better than that of SCH. From Fig. 1(c), it can be seen that the retrieval performance of EESF is stable and much higher than those of NEDDF and SCH. The categories of "bus" and "flower" have relatively regular characteristics, NEDDF is more effective for them. The category of "person" has complex spatial layout, EESF is more effective for it.

Let us compare with EESF, SCH[3] used color histogram and color-spatial feature to get feature index, i.e., $(h(0), \sigma(0), h(1), \sigma(1), \cdots, h(165), \sigma(165))$, where, $h(i)$ is color histogram, $\sigma(i)$ is the spatial distribution of pixels of identical color value in the image. EESF uses edge histogram and edge-spatial feature to get feature index, i.e., $(e(0), \sigma(0), e(1), \sigma(1), \cdots, e(19), \sigma(19))$. The edge value $p(i, j)$, is less sensitive to noise because of the use of

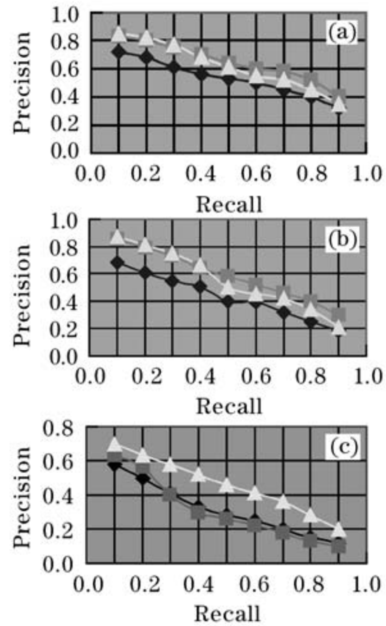

Fig. 1. Three average precision-recall curves using "bus" (a), "flower" (b) and "person" (c) categories as the reference query images. Diamonds: SCH; squares: NEDDF; triangles: EESF.

a dynamic membership function based on a local neighbor. It is also not sensitive to the direction of edges. So, edge histogram, $(e(0), e(1), \cdots, e(19))$, has better descriptive power than color histogram used in SCH. There are three sample natural color images: image1, image2, image3, which are shown in Fig. 2 and are selected from our image database. The sizes of image1 and 2 are all 384×256, that of image3 is 256×384. The contents of three image are "persons", "bus", and "persons", respectively. The color histograms of three images used in SCH are shown in Fig. 3. The edge histograms of three images given in this paper are shown in Fig. 4. From Fig. 3, the color histogram of image2 is more approximate to that of image1 than that of image3. The retrieval results of SCH using "image1" as the query image are "image1", "image2", "image3". From Fig. 4, the edge histogram of image3 approximates to that of image1, however, the

Fig. 2. Three sample images (in sequence: image1, image2, image3).

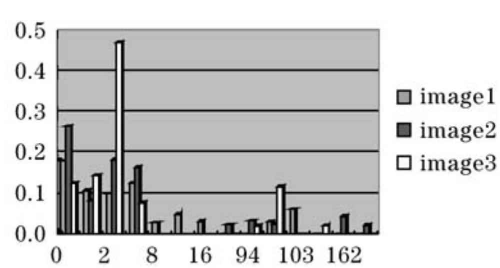

Fig. 3. Color histograms of three sample images.

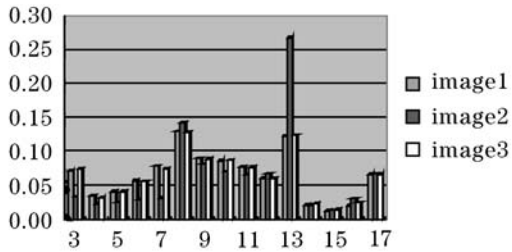

Fig. 4. Edge histograms of three images.

edge histogram of image2 is very different. The retrieval results of EESF using "image1" as the query image are "image1", "image3", and "image2", which are results that we expect.

In conclusion, a novel image retrieval method, EESF, is proposed. Compared with other related methods, EESF is less sensitive to noise because of the use of a dynamic membership function based on a local neighbor, and is more effective for images which have complex spatial layout. Experimental results have validated the effectiveness of this method.

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