

A Robust Similarity Measure Method in CBIR System

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Abstract

This paper presents a new similarity measure method on a combination of color and texture feature representations. In this method, the YIQ color space is chosen, because it can describe both color images and gray images and the transform from RGB to YIQ is linear and simple than other color space. In the proposed method, we firstly segment image using texture feature by combination of wavelet transform and texture co-occurrence matrix and then quantize color feature in YIQ color space for every segmentation partition. Based on image segmentation and color quantization, a new kind of similarity measure is proposed. Compared with the traditional image retrieval methods, the proposed method is very efficient for the image retrieval purpose.

1. Introduction

The exponential growth of image data has created a compelling need for innovative tools for managing, retrieving and visualizing images from large multimedia information data. The last few years many advanced techniques emerge in Content-Based Image Retrieval (CBIR) systems. The CBIR system is considered as the process of retrieving desired images from huge databases based on extracted features from the image themselves and matched images by some similarity measure algorithms. So, the visual features and the similarity measures are two important issues in CBIR systems. At present, often-used content-based image features are low-level features such as color, texture, shape, and so on [1-12]. Among these features, color is the effective feature to express visual information, which is invariant on complexity, and texture analysis is a major component of image processing and is fundamental to many applications such as remote sensing, quality inspection, medical imaging, etc

[1-6]. So, our study focuses on the combination of color and texture features. 2D Gabor Wavelet transform is used to extract texture feature and use the extraction gotten from the above to segment image. In addition, YIQ color space is chosen for color quantization. And we propose a new similarity measure based on image segmentation and color quantization. The rest of the paper is organized as follows. In Section 2, we introduce the image segmentation. The Section 3 is about the color representation. In Section 4, we propose a new similarity measure. Then the experimental results are provided in section 5, and in the last part we give the conclusions.

2. Image Segmentation

Image segmentation has been proposed for many years, and as a primary step in computer vision tasks, it nowadays plays a very important role in content-based image retrieval system. There exist many image segmentation techniques, including stochastic model based approaches, curve evolution, energy diffusion, region growing, graph partitioning, et al [1, 2].

Texture is a fundamental feature which provides significant information for scene interpretation and image segmentation [1, 3], so we describe a new image segmentation method using texture features extracted by wavelet transform and texture co-occurrence matrix. Generally, the image segmentation problem can be implemented by two steps: The first step is to extract the texture features of the random images, and the second step is to segment an image into homogeneous texture areas according to the texture features obtained above.

2.1. Texture feature analysis techniques

A variety of techniques have been used for measuring texture such as co-occurrence matrix,

texture spectrum, Gabor filter and so on [1-3]. Co-occurrence matrix is possible to measure the features like contrast, coarseness, directionality and regularity as used in a number of CBIR systems [2, 8]. Numbers of CBIR systems have explored different variations of wavelet transform to extract appropriate texture features. For enhancing the efficiency of our method, we use a combination of 2D Gabor wavelet transform and texture co-occurrence matrix for texture extraction.

2.1.1. Wavelet transform. 2D Gabor function $g(x,y)$ is below

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi j Wx\right) \quad (1)$$

and its Fourier transform $G(u,v)$ is

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

$$\text{where } \sigma = \frac{1}{2\pi\sigma_x}, \sigma = \frac{1}{2\pi\sigma_y}$$

A class of self-similar functions referred to as Gabor wavelets, is now considered. Let $g(x,y)$ be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of $g(x,y)$ through the generating function:

$$g_{mn}(x,y) = a^{-m} g(x',y') \quad a > 1, m, n \in Z \quad (3)$$

and

$$\begin{aligned} x' &= a^{-m} (x \cos \theta + y \sin \theta) \\ y' &= a^{-m} (y \cos \theta - x \sin \theta) \end{aligned}, \theta = \frac{n\pi}{k}, n \in [0, k]$$

k is the total number of orientations. The scale factor a^{-m} is meant to ensure that the energy is independent of m .

There exist two kinds of wavelet transforms: pyramid-structured wavelet transform (PWT) and tree-structured wavelet transform (TWT). We use the pyramid structure wavelet transform, with PWT the original image is first passed through the low-pass and high-pass filters to generate the low-low (LL), low-high (LH), high-low (HL) and high-high (HH) sub-images. The decompositions are repeated on the LL sub-image to obtain the four sub-images. The 1D and 2D partitions based on wavelet transform are represented in Fig. 1. (a) and (b).

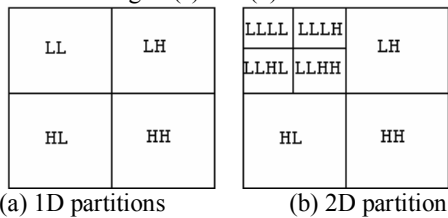


Fig. 1. The partitions of wavelet transform

2.1.2. Texture co-occurrence matrix. Texture co-occurrence matrix as one of texture analysis techniques has been proposed many years, and is also popular toady. The matrix is often used by 3 directions (horizontal, perpendicular and diagonal). The functions are below,

$$\begin{aligned} p(i,j,d,0^\circ) &= \#\{(k,l),(m,n) \in (l_r \times l_c) \mid k-m=0, |l-n|=d\} \\ p(i,j,d,45^\circ) &= \#\{(k,l),(m,n) \in (l_r \times l_c) \mid k-m=d, l-n=-d\} \\ p(i,j,d,90^\circ) &= \#\{(k,l),(m,n) \in (l_r \times l_c) \mid k-m=d, l-n=0\} \end{aligned} \quad (4)$$

$p(i,j)$ is the value of i -level and j -column in matrix, and $(k,l), (m,n)$ are the pixels in the original image, d is the distance between two pixels. In this method we choose the three-direction matrix.

2.1.3. The technique in this paper. The features using for segmentation are energy measure, mean, variance and gray-level co-occurrence matrix of the values of wavelet coefficients, and the formulations are as below:

$$\begin{aligned} E_i &= \frac{1}{M \times N} \sum_{x=1}^M \sum_{y=1}^N g_i^2(x,y) \\ m_i &= \frac{1}{M \times N} \sum_{x=1}^M \sum_{y=1}^N g_i(x,y) \\ \text{var} &= \sqrt{\left(\sum_{x=1}^M \sum_{y=1}^N [g_i(x,y) - m_i]^2\right)} \\ c_i &= \sum_{x=1}^M \sum_{y=1}^N [p(i,j)]^2 \end{aligned} \quad (5)$$

$g_i(x,y)$ is the transform value, $p(i,j)$ is the value of co-occurrence matrix, and M is the length and N is the width of the sub-image.

2.2. Image segmentation

Image segmentation methods can be divided into pixel-wise and block-wise methods [1]. Pixel-wise segmentation schemes evaluate the texture features in a neighborhood surrounding each pixel of the image. The advantage of pixel-wise segmentation is that this method can give the exactly boundary of the image. However, the computation load is heavier. As image retrieval system does not require exact boundary of the segmented regions, block-wise segmentation is often chosen since it is much faster. Before segmentation, the image is classified into blocks which have 16*16 pixels.

The segmentation process is also a process of combination, the algorithm describes as:

Step1 Firstly, make different block in different class, and the top-left block is in the first class.

Step2 Based on the wavelet transform, calculate the feature vectors of every block.

Step3 Using formulation (6) calculate the distances between the neighbors (include higher, lower, left and right), if the distance is less than the criterion (it is calculated by the 'var' feature vector), then classify the two blocks into the same class, else no.

$$D(i, j) = \sqrt{w_1(E_i - E_j)^2 + w_2(m_i - m_j)^2 + w_3(c_i - c_j)^2} \quad (6)$$

Step4 Calculate the feature vectors of every class, then go to step3.

Step5 When neighbors are not similar, the segmentation process is finish.

3. Color Representation

3.1. Color Space

The models of human perception of color differences are described in the form of color spaces, so the research on color image must be done in a given color space. RGB, CMY, HSV, YIQ [9] etc are the most frequently used color spaces.

In these color spaces, RGB and CMY color models are the original storage color models that are normally used on monitors and they correspond directly to the hardware. The R, G, B three acronyms stand for Red-Green-Blue in RGB color model and C, M, Y acronyms stand for Cyan-Magenta-Yellow in CMY color space. But for a human being, the two color spaces are not useful definitions.

HSV color space accords with human eye's color visual feature and HSV acronyms stand for hue-saturation-value. The transform from RGB to HSV is defined as below

$$H = \cos^{-1} \left\{ \frac{\frac{1}{2}[\{R-G\} + (R-B)]}{\sqrt{(R-G)^2 + (R-B)(G-B)}} \right\}$$

$$S = 1 - \frac{3}{R+G+B} [\min(R, G, B)] \quad (7)$$

$$V = \frac{1}{3}(R+G+B)$$

Based on the transform from RGB to HSV we can find that when $R=G=B$, the H has no definition.

YIQ color space is similar with the process of human proceeding, so it is often the first choice for researchers. Y, I and Q stand for luminance, red-cyan and green-magenta, respectively. The transform from RGB to YIQ is defined as below

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.275 & -0.321 \\ 0.212 & -0.523 & 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (8)$$

From the formulation above, note that Y has a range of [0, 255] (if red, green, and blue have a range of [0,255]), but I, and Q can be as well negative as

positive. YIQ color space can describe both color images and gray images and the transform from RGB to YIQ is linear and simple compared with HSV. So, consider the limitations of RGB (CMY) and HSV color spaces, and the advantages of YIQ color space, we chose the YIQ color space for using in this paper.

3.2. Color Quantization

Convert all our colors into a subset that is called quantization that can reduce the number of colors in images. A great number of arithmetic of color space quantization adopts fixed color quantization arithmetic. That is to say, all images use the same palette, so this quantization technique leads two adjacent colors belonging to different color bins. Therefore, errors will occur in image retrieval when we use the color quantization arithmetic. We can add quantization ranks to reduce this kind of errors. How to overcome the limitation is also a content of this paper.

We divide five degrees of dependence to every bin, the middle colors' dependent degree to this bin is 1, to the former and latter bin is 0. The most left colors' degree of dependence to this bin is 0.6 and to his former bin is 0.4. The most right colors' degree of dependence to this bin is 0.6 and to his latter bin is 0.4, the left colors' degree of dependence to his own bin is 0.8 and to former or latter bin is 0.2.

In this method, Y is quantized to 16 kinds of color bin. U and V are quantized to 4 kinds of color bin. The Fig.2 shows degree of dependence of Y quantization (Because Y has a range of [0,255], so the length of every bin is 16). While in I and Q quantization, the degree of dependence is Fig.3.

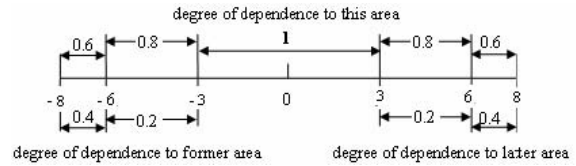


Fig.2. Degree of dependence in Y

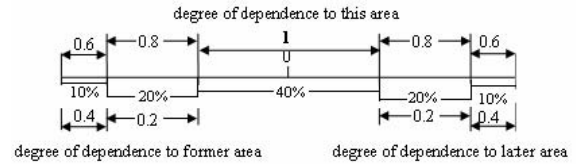


Fig.3. Degree of dependence in I and Q

4. Similarity Measure

Similarity measure is one of the most important parts in the image retrieval system. Once the feature

vectors are created, the matching process becomes the measuring a metric distance between the feature vectors in image retrieval system. Understanding the relationship among distance measures can help choosing a suitable one for a particular application.

4.1. Minkowski Distance

As one of the most popular distance measure, the formulation of Minkowski Distance is defined as below

$$d(X, Y) = \left(\sum_{i=1}^n |x_i - y_i|^r \right)^{1/r} \quad (9)$$

And when r is 1, the above formulation is the normal distance measure. And if r is 2, the formulation is Euclidean Distance measure.

4.2. Similarity measure in this paper

In our method, we propose a new similarity distance measurement using Euclidean Distance bases on image segmentation and color quantization, which have introduced in the former part.

4.2.1. The bins' value. In this part, we compute the value of every bin in the Y, Q quantization, using the formulation as below and I.

$$M_i = (\overline{M}_{i-1} * 0.4 + \overline{M}_{i_f} * 0.6) + (\overline{M}_{i-1} * 0.2 + \overline{M}_{i(f-m)} * 0.8) + \overline{M}_{i_m} + (\overline{M}_{i+1} * 0.2 + \overline{M}_{i(m-l)} * 0.8) + (\overline{M}_{i+1} * 0.4 + \overline{M}_{i_l} * 0.6) \quad (10)$$

M_i means how many pixels in the i th bin ($i=1 \dots 16$ in the example of Y. If in I and Q, $i=1 \dots 4$), \overline{M}_i is the i th bin's average pixel number, \overline{M}_{i_f} is the most left average pixel number and \overline{M}_{i_l} is the most right average pixel number, $\overline{M}_{i(f-m)}$ and $\overline{M}_{i(m-l)}$ are the left and right average pixel number.

4.2.2. The similarity between two segments in different images. In this part, how to compute the distance between two images and how to make the method efficient for our study are very important things, so we choose formulation (11) and (12).

The color distance between two segments:

$$D_c(X, Y) = w_Y * \sum_{i=1}^{16} \sqrt{(M_{X_i} - M_{Y_i})^2} + w_I * \sum_{i=1}^4 \sqrt{(M_{X_i} - M_{Y_i})^2} + w_Q * \sum_{i=1}^4 \sqrt{(M_{X_i} - M_{Y_i})^2} \quad (11)$$

$D_c(X, Y)$ is the color distance between image X and Y, w_Y, w_I, w_Q ($w_Y + w_I + w_Q = 1$) are there

color channels' weight, M_{X_i} and M_{Y_i} are the two images X and Y's the i th bin's value. In different images, the different values for w_Y, w_I, w_Q . In color images, $w_Y = 0.67$ and $w_I = w_Q = (1 - w_Y) / 2$, but in gray images, $w_Y = w_I = w_Q = 1/3$.

The texture distance between two segments

$$D_t(X, Y) = C_{X_i} - C_{Y_i} \quad (12)$$

C_{X_i} is the co-occurrence value of the segments.

And the color-texture distance between two segments is defined in formulation (13):

$$D(X, Y) = w_1 D_c(X, Y) + w_2 D_t(X, Y) \quad (13)$$

$w_1 + w_2 = 1$

4.2.3. The final similarity between two images.

This part use the image partitions getting from the image segmentation, we should know that the number of the partitions maybe not same between similar images, and the images have the same number maybe not similar, so we propose the formulation (14) that can give exactly similarity measurement between images. When compare two images having different numbers of classes, the k in equalize the small number.

The below formulation calculate the final similarity between two images.

$$D(X, Y)_F = \sum_{i=0}^{k-1} w_i * D(X, Y)_i + w_k D_t(x, y)_m \quad (14)$$

$\sum_{i=0}^k w_i = 1$

$D(X, Y)_F$ is the final distance between image X and Y, $D(X, Y)_i$ is the distance of the i th segment between image X and Y, w_i is the i th segment weight, $D_t(X, Y)_m$ is the distance of middle partitions in two different images. The main idea of this formulation is to reduce the error when the comparing images have different classes.

5. Experimental Results

To evaluate the effectiveness of the proposed method, the experiments are performed on an image database with 500 images whose sizes are 128×100, and we randomly select an image in the database as the query image. In ordinary CBIR systems, the image segmentation is also often used, but the feature, which is extracted by means of image segmentation, is not often used for the similarity measure. In our experiment, we mainly compare the proposed method using co-occurrence matrix with the traditional method no-using co-occurrence matrix in similarity measure.

The experimental results are shown in the Fig.4~ Fig.6. From the Fig.5 and Fig.6, we can find that the similarity measure method proposed in this paper can give good retrieval results, and is better than the traditional ones which not use texture feature.



Fig.4. The query image

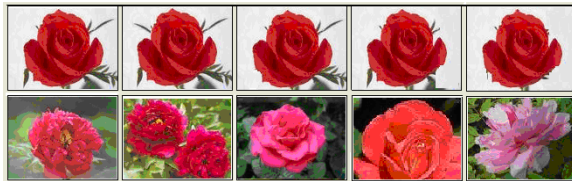


Fig.5. The retrieval results of the proposed method

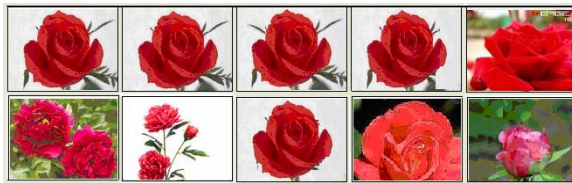


Fig.6. The retrieval results with no-using co-occurrence matrix in image segmentation

6. Conclusions

In this paper, we propose a novel similarity measure method using image segmentation and color quantization. We first give an image segmentation method using texture extraction by combination of wavelet transform and texture co-occurrence matrix, then, segment images by using the texture feature extracted above. We choose YIQ color space for color quantization, because it can describe both color images and gray images and the transform from RGB to YIQ is linear and simple than other color space. In addition, the proposed similarity measure method not only uses the color feature but also uses the texture co-occurrence matrix.

The experimental results show that the proposed similarity measure method is better than the traditional ones, which not use texture feature.

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