An Improved Algorithm of Image Retrieval Based on Combined BTC Color Moments and DT-CWT

Cai Huajie[1],* Zhao Yaxin[1], Xie Guangyi[1]

[1]Department of Information Engineering, Engineering University of Chinese Armed Police Force, Xi'an, Shaanxi, China710086

*Corresponding Author: CaiHuajie

Keywords: Image Retrieval, YIQ, BTC Color Moments, DT-CWT, Feature Fusion

Abstract. Feature extraction is the key technology in the process of image retrieval based on content. This paper puts forward an improved algorithm of image retrieval based on combined BTC color moments and DT-CWT. We firstly select the YIQ color space as the feature extracted space due to the strong correlation between each component of RGB color space. Combined with block coding thought, this paper encodes three component images in YIQ color space into a binary bitmap and calculates the BTC color moment to represent the image color feature.In order to overcome the shortcomings of traditional wavelet transform direction, we make use of DT-CWT to extract statistical characteristics of each sub-band as texture features. Finally, we carry out the weighted summation of similarity degree of the extracted color and texture features to constitute the basis of image retrieval.The experimental results show that the color and texture features extracted by the above-mentioned algorithm have more advantages in image retrieval, which has a higher average precision than the similar algorithms.

Selection of Color Spaces

Color space is the color model which represents the color information. The RGB color space is widely used. But the relationship between the color component is too strong; luminance and chrominance blending is too high; and color quantization effect is not so good.YIQ color space is three dimensional Cartesian coordinate space, which is hardware oriented and made by National Television System Committee (NTSC). In this space, Y is used to describe the brightness of the image information; I and Q describe the hue and saturation properties of the image. We choose YIQ color space as the feature extraction objects based on the following reasons:

(1) Each component has a good decorrelation in YIQ color space. It is an important attribute of image feature analysis, which is easy to deal with each component separately;

(2) When the image information is encoded by YIQ, the redundant information of the signal is very little, which is beneficial to the extraction of color and texture features;

(3) YIQ space and RGB space have a linear relationship,whichfacilitates the conversion;

(4) The color components are independent and can adapt to various illumination changes. The attribute can help us deal with the different light intensity image;

(5) The proportiondistribution of Y, I, Q color component in space matches he sensitivity of different color propertiesvery well. It is conducive to the image feature analysis and extraction.

Color Feature Extraction

Color moments can describe the distribution information of image pixels. BTC color moment learns the experience of Block Truncation Coding (BTC) used in lossy compression technology and extracts the color moments to represent the color feature. As the color information distribution mainly concentrated in the low order moments, we usually use only 9 dimensions. The extraction is rapid without the preprocessing and post-processing. The calculation of the BTC color moments is designed in the in YIQ components in this paper to reduce the redundancy encoding. Specific steps are as follows:

(1) We convert the image to YIQ color space and extract the Y, I, Q component image from it.

(2) We set m×mtemplate.Each template contains m×m pixels.This template is traversed three component images (M × N) to divide it into non overlapping sub-blocks.

(3) Set the Y component of the image as an example. For each sub-image, we calculate the mean value respectively and set the threshold T.

$$T_k = \frac{1}{m \times m} \sum_{i=1}^{m} \sum_{j=1}^{m} Y_k (i, j)$$

In the formulation, $k = \{1, 2, \ldots, (M / m) \times (N / m)\}$, $Y_k (i, j)$ represents the pixel value of (i, j) in the sub-image of k. We encode the pixel of sub-image according to the following formulation:

$$\mathrm{BY}_k (i, j) = \begin{cases} 1, Y_k (i, j) > \mathrm{T}_k \\ 0, Y_k (i, j) \le \mathrm{T}_k \end{cases}$$

(4) We calculate the two first-order moments (mean μ), two second order moment (standard deviation σ) and two third-order moment (s) of k sub block image according to the two kinds of pixels. The formulations are as follows:

$$Y_{u,k}^{1} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} \left(BY_k (i, j) \times Y_k (i, j)\right)}{\sum_{i=1}^{m}\sum_{j=1}^{m} BY_k (i, j)}$$

$$Y_{u,k}^{0} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} \left(\left(1 - BY_k (i, j)\right) \times Y_k (i, j)\right)}{m^2 - \sum_{i=1}^{m}\sum_{j=1}^{m} BY_k (i, j)}$$

$$Y_{\sigma,k}^{1} = \left[\frac{\sum_{i=1}^{m}\sum_{j=1}^{m} \left(BY_k (i, j) \times \left(Y_k (i, j) - Y_{u,k}^{1}\right)^2\right)}{\sum_{i=1}^{m}\sum_{j=1}^{m} BY_k (i, j)}\right]^{\frac{1}{2}}$$

$$Y_{\sigma,k}^{0} = \left[\frac{\sum_{i=1}^{m}\sum_{j=1}^{m} \left(\left(1 - BY_k (i, j)\right) \times \left(Y_k (i, j) - Y_{u,k}^{0}\right)^2\right)}{m^2 - \sum_{i=1}^{m}\sum_{j=1}^{m} BY_k (i, j)}\right]^{\frac{1}{2}}$$

$$Y_{s,k}^{1} = \left[\frac{\sum_{i=1}^{m}\sum_{j=1}^{m}\left(BY_k\left(i,j\right)\times\left(Y_k\left(i,j\right)-Y_{u,k}^{1}\right)^{3}\right)}{\sum_{i=1}^{m}\sum_{j=1}^{m}BY_k\left(i,j\right)} \right]^{\frac{1}{3}}$$

$$Y_{s,k}^{0} = \left[\frac{\sum_{i=1}^{m}\sum_{j=1}^{m}\left(\left(1-BY_k\left(i,j\right)\right)\times\left(Y_k\left(i,j\right)-Y_{u,k}^{1}\right)^{3}\right)}{m^{2}-\sum_{i=1}^{m}\sum_{j=1}^{m}BY_k\left(i,j\right)} \right]^{\frac{1}{3}}$$

(5) We calculate the mean value of the 6 color moments of all the sub-blocks.

$$Y = \left(Y_u^1, Y_u^0, Y_\sigma^1, Y_\sigma^0, Y_s^1, Y_s^0\right)$$

(6) Repeatthe processes of (3)-(5), and get the other two featurevectors of the component image, which is I and Q.

(7) Form the color characteristic vector of the image.

$$C = \left(Y_u^1, Y_u^0, Y_\sigma^1, Y_\sigma^0, Y_s^1, Y_s^0, I_u^1, I_u^0, I_\sigma^1, I_\sigma^0, I_s^1, I_s^0, Q_u^1, Q_u^0, Q_\sigma^1, Q_\sigma^0, Q_s^1, Q_s^0\right)$$

Texture Feature Extraction

Wavelet transform has the good characteristic of multi-resolution, which can separate the high frequency components of concentrated image texture information. It facilitates the process of extracting texture features and has been widely used in the field of image retrieval. However, the traditional 2D wavelet transform lacks the translation invariance, and each layer of the high frequency sub-band divided from the image decomposition after has only three directions: horizontal, vertical and diagonal. The slot with (±45 DEG)high frequency component has an inaccuratetexture description, which is not conducive to the feature extraction and analysis. Dual Tree complex wavelet Transform(DT-CWT) is a type of enhanced direction wavelet transform. When theDT-CWT processing of the image is done, each layer is decomposed into four low frequency components and twelve high frequency components. The twelve high-frequency components correspond to the real part and the imaginary part of the image of six different directions (±15 DEG, ±45 DEG, ±75 DEG). Compared to the traditional wavelet transform, dual tree complex wavelet transform getsmore directions of the high frequency, provides more abundant resources of texture and enhances the accuracy of image decomposition. Asthe extracted features can better describe the texture information of the image, it can improve the retrieval accuracy.

In order to avoid the effects on the sub-band coefficients of the decomposed image components, combining the independent characteristics of each color component in YIQ space, this paper puts forward dual tree complex wavelet transform in the YIQ three component imagesto extract the texture features. The texture features are represented by the mean (E) and variance (δ) of the coefficients of the sub-band after decomposition.

$$T = (E_1^Y, E_2^Y, \ldots, E_n^Y, \delta_1^Y, \delta_2^Y, \ldots, \delta_n^Y, E_1^I, E_2^I, \ldots, E_n^I, \delta_1^I, \delta_2^I, \ldots, \delta_n^I, E_1^Q, E_2^Q, \ldots, E_n^Q, \delta_1^Q, \delta_2^Q, \ldots, \delta_n^Q)$$

In the above formulation, $n_T = 12f$ f is the number of decomposition levels.

Feature Matching and Fusion

Feature matching is one of the most important image retrieval technologies based on content. This paper uses Euclidean distance to measure the similarity. We set a as the query image, B as database retrieval image.

The similarity measurement of BTC color moments is:

$$D_C(a, b) = \sqrt{\sum_{i=1}^{n_C} (C_{ia} - C_{ib})^2}$$

In the above formulation, C_{ia} and C_{ib} represent the color eigenvector of image a and image b respectively. n_C is the feature dimension.

The similarity measurement of dual-tree complex wavelet transform is:

$$D_T(a, b) = \sqrt{\sum_{i=1}^{n_T} (T_{ia} - T_{ib})^2}$$

In the above formulation, T_{ia} and T_{ib} represent the color eigenvector of image a and image b respectively. n_T is the feature dimension.

This paper uses weighted method of fusion of color and texture features. In order to avoid the different extraction methods of various characteristics, caused by the misalignment, the retrieval error, this paper uses Guassian model to normalize the distance.

The distance function of image a and image b is defined as follows:

$$D(a, b) = \omega_1 D_{CG}(a, b) + \omega_2 D_{TG}(a, b)$$

$D_{CG}(a, b)$ and $D_{TG}(a, b)$ are the distances of $D_C(a, b)$ $D_T(a, b)$ and after Gauss normalized; ω_1 and ω_2 are the weights of color feature and texture feature, which satisfy the equation of $\omega_1 + \omega_2 = 1$.

Experiment Results and Analysis

Experiment (1) compares the retrieval algorithm based on BTC color moments in different color spaces (YIQ and RGB). Figure 1 shows the comparison chart of three different kinds of images (animals, cars, flowers) which are the earliest12 pieces of imageswhen testing image retrievals. The first image of each sequence is the query image as well as the retrieval result image. We arrange the sequence of results images in accordance with the matching degree.

We can observe the images and get the following conclusion. The retrieval results of the same image in different color spaces perform different. The number of similar testing return results in YIQ color space is more than that in RGB color space by 1 to 3,which is moreconformtothehumaneyevisualcharacteristic.

In terms of texture feature extraction, we compare the retrieval performances of the two dimensionaldual tree complex wavelet transform and the traditional two-dimensional discrete wavelet transform (DWT). Each transformation is based on the component image of YIQ and RGB. The number of returned images of query results is 12. Table 1 gives the average precision of different decomposition levels based on two texture retrieval algorithms.

Table 1. Average precision of different decomposition levels based on different component images in DT-CWT and DWT

decomposition levels p	DT-CWT		DWT	
	component image based on YIQ	component image based on RGB	component image based on YIQ	component image based on RGB
1	69.21	62.85	59.83	56.5
2	78.94	67.7	66.62	61.44
3	74.16	70.43	69	67.34

From Table 1, we know thatthe average precision of DT-CWT is higher thanthat of DWTin the condition of the same decomposition levels and component images; the average precision based on YIQ component images is higher thanthe thing based on RGB component images in the condition of the same decomposition levels and wavelet transforms; the average precision reaches the highest point in the conditionthat the number of decomposition levels of DT-CWT based on YIQ component images is two. Reason analysis：1. DT-CWT can achieve more information about texture than DWT, which facilitates feature retrieval. 2. The correlation of component images in YIQ space is weaker than that in RGB space. 3. When we retrieve the images using the DT-CWT based on YIQ, more decomposition levels can lead to more redundant information, which is to the detriment offeature analysis.

We compare the average precision with other algorithms and get the curve comparison of three algorithms. The experimental results show that this algorithm is better than the other two algorithms.

Conclusion

This paper proposes an improved algorithm of image retrieval based oncolor and texture features. In order to avoid the impact of RGB color components between strong correlation, this paper puts forward the method using BTC color moment and DT-CWT to do feature extraction in YIQ color space to retrieve images. Experiments show that the algorithm has good advantages ofin the feature extraction, which caneffectively integrate image color and texture features to have a higher precision percent. But this paper ignores the impact of the weight of each feature in the characteristics fusion process and uses the fixed equal weights of all the features. The weight distribution will be discussed in the next step research.

References

[1] Ganesan P, V.Rajini. YIQ Color Space based Satellite Image Segmentation using Modified

FCM Clustering and Histogram Equalization[C].2014 International Coference on Advances in Electrical Engineering(ICAEE),2014.

[2] Selesnick I W,Baraniuk R G,Kingsbury N C.The Dual-tree Complex Wavelet Transform[J].IEEE Signal Processing Magazine,2005,22(6):123-151.

[3] Chen C C,Chu H T.Similarity measurement between images.Proc of the 29th Annual International Computer Software and Applications Conference(COMPSAC ’ 2005),2005,2:41-42.