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Content-Based Image Retrieval Using Combined Color and Texture Features Extracted by Multi-resolution Multi-direction Filtering

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Abstract

In this paper, we present a new texture image retrieval method which combines color and texture features extracted from images by a set of multi-resolution multi-direction (MRMD) filters. The MRMD filter set chosen is simple and can be separable to low and high frequency information, and provides efficient multi-resolution and multi-direction analysis. The color space used is HSV color space separable to hue, saturation, and value components, which are easily analyzed as showing characteristics similar to the human visual system. This experiment is conducted by comparing precision vs. recall of retrieval and feature vector dimensions. Images for experiments include Corel DB and VisTex DB; Corel_MR DB and VisTex_MR DB, which are transformed from the aforementioned two DBs to have multi-resolution images; and Corel_MD DB and VisTex_MD DB, transformed from the two DBs to have multi-direction images. According to the experimental results, the proposed method improves upon the existing methods in aspects of precision and recall of retrieval, and also reduces feature vector dimensions.

Keywords

Color and Texture Feature, Content-Based Image Retrieval, HSV Color Space, Multi-resolution Multi-direction Filtering

1. Introduction

Image data, as visual data, are essential means to provide major information to users. As such image data are massive, an effective image retrieval system is needed, which is able to provide accurate information to users. Current image retrieval technologies have been focused on content-based image retrieval which is able to define visual information objectively and process it automatically. Most of them have been developed to combine features of color, texture, shape, etc.

Color is used to identify objects effectively, and similarity between images is determined by the difference of colors in each pixel. Color features include the color histogram which has global color information from the image [1,2], the color correlogram which has spatial color information from the image [3,4], the CSD (color structure descriptor) which has localized color information from the color histogram, and the SCD (scalable color descriptor) which has scalable information from the color

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histogram using Haar transformation [5].

Texture, as a characteristic representing inherency of object surfaces, represents visual patterns of spatial dimension. Texture feature is one of the most fundamental features describing information of image content, so it can be effectively used to classify areas having similar color.

Texture feature mainly used in content-based image retrieval includes gray level co-occurrence matrix (GLCM) [6,7], the edge histogram descriptor (EHD) [5], Gabor transformation, wavelet transformation [8-11], the picture information measure (PIM) [12], the block difference of inverse probabilities (BDIP), and block variance of local correlation coefficients (BVLC) [13].

The GLCM is the statistical texture feature considered spatial relations. The EHD, as a MPEG-7 descriptor, represents local edge distribution from an image. Gabor transformation and wavelet transformation use multi-resolution texture features. The PIM and the BDIP have entropy characteristics. The BVLC is the texture feature using correlations.

As important components of visual recognition together with color and texture, shape features include area-based feature extraction methods, such as the Zernike moment [14] and the moment invariants [15,16], and contour-based feature extraction methods, such as the Fourier descriptor [17] and the chain code [18].

Recently, retrieval methods of combining features of color, texture, shape, etc., have been actively studied. Chun et al. [19] used color features of color autocorrelogram and texture features of BDIP-BVLC in wavelet domain. Agarwal et al. [20] used texture and shape features based on discrete wavelet transformation (DWT) and EHD of MPEG-7. Anandh et al. [21] used color, texture and shape features of color autocorrelogram, Gabor wavelets and wavelet transformation, respectively.

The main requirements of the content-based image retrieval system include that it must have robust feature values which are not influenced easily by transformation of rotations, translations, or sizes of objects, and that it does not have large dimensions of feature vector for efficient storage and management.

To satisfy such requirements, this paper proposes a set of MRMD filters and presents a combination of methods for extracting color and texture features, thereby increasing retrieval accuracy by using the filter set. Moreover, unlike the existing experiments which predominantly used images of homogeneous texture patterns, the experiment described in this paper uses images that contain experimental objects.

The next section details the proposed method, and the third section represents the experimentation and results. After that comes the conclusion in the fourth section.

2. Image Retrieval using MRMD Filtering in HSV Color Space

Fig. 1 represents the entire structure of the image retrieval system proposed in this paper. The procedure consists of the five steps as follows: Step 1 transforms a query RGB image to the HSV color image. Step 2 extracts color features in low and high frequency domains of H and S spaces to which MRMD filtering is applied, and extracts texture features in low and high frequency domains of a V space by MRMD filtering. Step 3 combines features extracted. Step 4 measures similarity between the combined query feature vector and each of the already-constructed DB feature vectors. Step 5 represents retrieved images in the order of higher rank from the image DB.

2.1 HSV Color Space

Humans describe objects by hue, saturation, and brightness when viewing objects with colors. As a subjective descriptor, brightness cannot actually be measured and therefore is described by representing quantity of light. The model related to this human vision is HSV (hue, saturation, value) color model [22-25]. In HSV color spaces, hue is a component representing a pure color, saturation is a component representing the purity of hue, and value is a component representing the relative degree of black or white mixed with a given hue.

Colors of an image have a characteristic of slow changes, so existing studies have usually used information from a low frequency domain. However, in this paper we use it together with information from a high frequency domain to include rapidly changing color information because various color images are targeted.

Textures of an image have a characteristic of rapid changes, so existing studies have usually used information from high frequency domains. However, in this paper we use it together with rough information from low frequency domains.

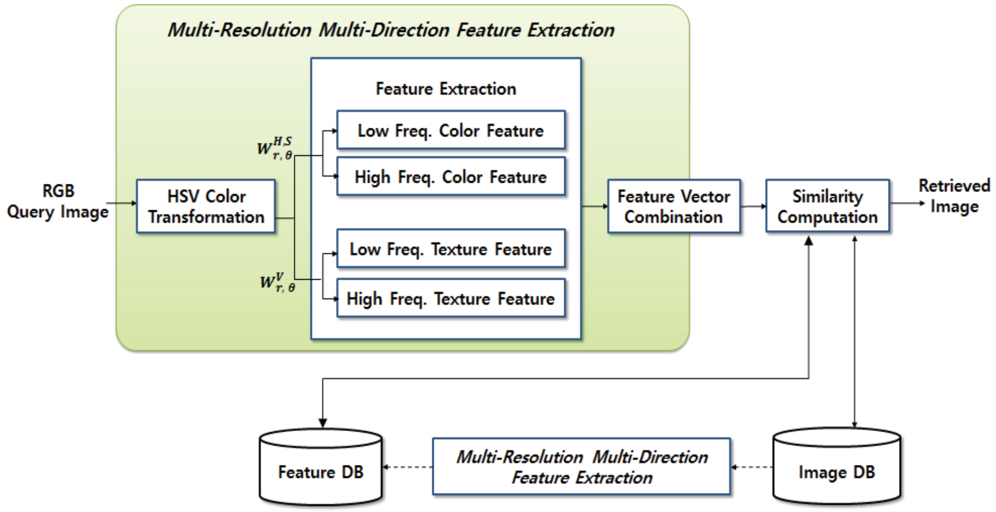

Fig. 1. The block diagram of the proposed image retrieval system.

2.2 MRMD Filtering

Generally, multi-resolution based methods decompose images into different resolutions [8-11]. Up to date, the methods using wavelet decomposition have been mainly used in methods extracting statistical data in sub domains. However, because it is conducted for only two directions (0°, 90°), this wavelet decomposition has no information for other directions. To supplement this defect, methods using Gabor wavelets have been proposed but this implementation requires a lot of computation and the research is limited to texture images with homogeneous patterns. In this paper, we propose a set of MRMD filters providing multi-resolution and multi-direction analysis, which is applicable to various images, supplementing existing defects.

Given an image f, general expression of an MRMD filter operation is defined as follows:

$$y_{r,\theta}(p) = \sum_{q \in \mathbf{Q}} h_{r,\theta}(q) \cdot f(p-q) \tag{1}$$

where p is the pixel position and $\mathbf{Q}$ is the support region of filtering.

If $h_{r,\theta}(q)$ is a high pass filter,

$$h_{r,\theta}(q) = \begin{cases} 1, & q = (0,0) \\ -1, & q = 2^{r-1} \cdot (cos\theta, sin\theta) \end{cases} \tag{2}$$

If $h_{r,\theta}(q)$ is a low pass filter,

$$h_{r,\theta}(q) = \begin{cases} 1, & q = (0,0) \\ 1, & q = 2^{r-1} \cdot (cos\theta, sin\theta) \end{cases} \tag{3}$$

where r is the resolution level and θ is the direction. $h_{r,\theta}$ is a filter with two taps, where one is in the center and the other is at the distance 2^{r-1} and the direction θ. If the total number of directions is N and the last resolution level is M, $\theta = \frac{2 \cdot \pi \cdot n}{N}$, $n \in \{0, 1, 2, \cdots, N-1\}$ and $r \in \{1, 2, \cdots, M\}$.

2.3 Feature Extraction Method using MRMD Filtering

This subsection proposes the feature extraction method using local energy, local correlation, color histogram and color autocorrelogram in MRMD-filtered frequency domains.

Parameters used in the experimentation of this paper are as follows: when applying MRMD filtering, we use only a 4-level resolution of a low frequency domain and all 1–4 level resolutions of high frequency domains; and 8 directions of a half circle, from 0° to 157.5° with 22.5° unit; and 4 quantized levels in the color histogram; and 8 quantized levels and 1 distance in the color autocorrelogram.

2.3.1 Feature extraction using local energy

The features for global statistics are extracted in low frequency domains on S and V spaces. The procedure for extracting local energy features can be divided largely into 4 steps. The conducting processes are as follows:

- Step 1: Transform a query image into the S component image I_S (or the V component image I_V).
- Step 2: Apply the MRMD low pass filtering in (1) with parameters of a resolution r and θ directions to the image I_S (or apply the MRMD low pass filter to I_V, in case of the V image).
- Step 3: Make the average image I_μ and the standard deviation image I_σ by computing average and standard deviation of pixel unit for the absoluter values of filtered images with θ directions and a resolution r. Pixel values of the image I_μ and the image I_σ are computed as follows:

$$I_{\mu}(p) = \underset{\theta \in \Theta}{mean} \left[\, | \, y_{r,\theta}(p) | \, \right] \tag{4}$$

$$I_{\sigma}(p) = \underset{\theta \in \Theta}{std} \left[\, | \, y_{r,\theta}(p) | \, \right] \tag{5}$$

where p is the pixel position, Θ is the set of all directions, and $y_{r,\theta}$ is the low frequency image filtered by (3). The operation std means standard deviation.

- Step 4: Compute the global average value and the global standard deviation value respectively for the image I_{μ} and the image I_{σ} in a resolution r. The expressions for the four feature values of a resolution r are as follows:

$$\mu_r^{I_{\mu}} = \underset{p \in \boldsymbol{P}}{mean} \left[\, I_{\mu}(p) \, \right] \tag{6}$$

$$\sigma_r^{I_{\mu}} = \underset{p \in \boldsymbol{P}}{std} \left[\, I_{\mu}(p) \, \right] \tag{7}$$

$$\mu_r^{I_{\sigma}} = \underset{p \in \boldsymbol{P}}{mean} \left[\, I_{\sigma}(p) \, \right] \tag{8}$$

$$\sigma_r^{I_{\sigma}} = \underset{p \in \boldsymbol{P}}{std} \left[\, I_{\sigma}(p) \, \right] \tag{9}$$

where $\boldsymbol{P}$ is the set of all pixel positions. $\mu_r^{I_{\mu}}$ and $\sigma_r^{I_{\mu}}$ are the global mean and the global standard deviation for the image I_{μ}. $\mu_r^{I_{\sigma}}$ and $\sigma_r^{I_{\sigma}}$ are the global mean and the global standard deviation for the image I_{σ}.

2.3.2 Feature extraction for local correlation

The features for local correlations are extracted in high frequency domains of H and V spaces, which have characteristics including local similarity information. The procedure extracting features for local correlations is similar to the statistical feature extraction method except for dealing with correlation coefficients. The procedure is as follows:

- Step 1: Transform a query image into the H component image I_H (or the V component image I_V).
- Step 2: Apply the MRMD high pass filtering in (1) with parameters of a resolution r and θ directions to the image I_H (or apply the MRMD high pass filtering to I_V, in case of the V image).
- Step 3: Make the images composed of correlation coefficients from high frequency images of θ directions. The expression for image correlation coefficient is as follows:

$$\rho_{r,\theta}(p) = \underset{t \in \boldsymbol{T}}{cor} \left[\, y_{r,\theta}(p-t), y_{r,\theta}(p-t-1) \, \right] \tag{10}$$

where the operation cor means correlation coefficient [26] between two images, and T a 3×3 window.

- Step 4: Make the average image I_μ^ρ and the standard deviation image I_σ^ρ by computing average and standard deviation of pixel unit for correlation coefficient images of θ directions for each resolution. Pixel values of the image I_μ^ρ and the image I_σ^ρ are computed as follows:

$$I_\mu^\rho(p) = \underset{\theta \in \Theta}{mean}\left[\rho_{r,\theta}(p)\right] \tag{11}$$

$$I_\sigma^\rho(p) = \underset{\theta \in \Theta}{std}\left[\rho_{r,\theta}(p)\right] \tag{12}$$

- Step 5: Compute the global mean and the global standard deviation respectively for the image I_μ^ρ and the image I_σ^ρ of each resolution. The expressions for the four feature values of each resolution are as follows.

$$\mu_r^{I_\mu^\rho} = \underset{p \in \boldsymbol{P}}{mean}\left[I_\mu^\rho(p)\right] \tag{13}$$

$$\sigma_r^{I_\mu^\rho} = \underset{p \in \boldsymbol{P}}{std}\left[I_\mu^\rho(p)\right] \tag{14}$$

$$\mu_r^{I_\sigma^\rho} = \underset{p \in \boldsymbol{P}}{mean}\left[I_\sigma^\rho(p)\right] \tag{15}$$

$$\sigma_r^{I_\sigma^\rho} = \underset{p \in \boldsymbol{P}}{std}\left[I_\sigma^\rho(p)\right] \tag{16}$$

2.3.3 Color histogram feature and color autocorrelogram feature extraction

Color histogram features are extracted in a low frequency domain of a H space. These features have a characteristic of representing global color property on an image. Color autocorrelogram features are extracted in a low frequency domain of a H space and a high frequency domain of a S space. These features have a characteristic with spatial correlation information of colors on an image.

The procedure of the color histogram feature extraction is as follows:

- Step 1: Transform a query image into the H component image I_H.
- Step 2: Apply the MRMD low pass filtering in (1) with parameters of a resolution r and θ directions to the image I_H.
- Step 3: Evaluate normalized histograms of M levels for the low frequency image $y_{r,\theta}$ of each θ direction in a resolution r:

$$H_{r,\theta}(i) = \frac{1}{N}\sum_{p \in \boldsymbol{P}} \delta\left(y_{r,\theta}(p) - i\right) \tag{17}$$

where $\delta(\cdot)$ is the Kronecker delta function which is 1 if input value is 0 and 0 otherwise and $y_{r,\theta}$ is the low frequency image quantized uniformly into M colors, $i \in \{0, 1, 2, \cdots, M-1\}$ indicates quantization level, p is the pixel position, and N is the size of the image $y_{r,\theta}$.

- Step 4: Make the average for normalized histograms of θ directions in a resolution r:

$$\mu(i) = \underset{\theta \in \Theta}{mean} \left[H_{r,\theta}(i) \right] \tag{18}$$

The procedure for the color autocorrelogram feature extraction is as follows:

- Step 1: Transform a query image into the H component image I_H (or the S component image I_S).
- Step 2: Apply the MRMD low pass filtering in (1) with parameters of a resolution r and θ directions to the image I_H (or apply the MRMD high pass filter to I_S, in case of the S image).
- Step 3: Evaluate color autocorrelograms with distance k for the low frequency image $y_{r,\theta}$ of each θ direction in a resolution r (or the high frequency image, in case of the S image):

$$\alpha_c^{(k)}(y_{r,\theta}) = Pr\left[\ \hat{y}_{r,\theta}(p) = \hat{y}_{r,\theta}(p') = c \ \mid \ |p - p'| = k \ for \ p, p' \in \boldsymbol{P}\ \right] \tag{19}$$

where $c \in \{0, 1, 2, \cdots, M-1\}$ indicates quantized color level and $\alpha_c^{(k)}(y_{r,\theta})$ indicates the probability that the colors of two pixels of distance k are c on the quantized image $\hat{y}_{r,\theta}$.

- Step 4: Make the average for M level color autocorrelograms of θ directions in a resolution r:

$$\mu(c) = \underset{\theta \in \Theta}{mean} \left[\alpha_c^{(k)}(y_{r,\theta}) \right] \tag{20}$$

These features can obtain higher retrieval accuracy when measuring similarity for each DB if applying weight.

3. Experimentation and Results

This section verifies through experimentation whether the proposed feature extracting method is superior to the existing methods in the aspect of retrieval performance. The images used in the experimentation are as follows: Corel DB including images of various objects and VisTex DB including homogeneous texture images; Corel_MR DB and VisTex_MR DB including multi-resolution images derived from Corel DB and Vistex DB; and Corel_MD DB and VisTex_MD DB including multi-direction images. Corel DB consists of 90 images in each of 11 classes, which are 990 images in total with the resolution of 192×128. VisTex DB consists of 16 images in each of 75 classes, which are 1,200 images in total with the resolution of 128×128. In Corel_MR DB, one-third is the same as the original DB and two-thirds are respectively decimated in $(1.5:1)^2$ and $(2:1)^2$ ratio for 90 images within each class. In VisTex_MR DB, one-fourth is the same as the original DB and three-fourths are respectively decimated in $(1.5:1)^2$, $(1.75:1)^2$ and $(2:1)^2$ ratio for 16 images within each class. Corel_MD DB and VisTex_MD DB consist of images rotated with the increment of 22.5° from 0° to 337.5° from Corel DB and VisTex DB, respectively [13].

With regard to the extracted features from the proposed method, the Mahalanobis distance measurement is used for similarity measurement on the experimental target images. The Mahalanobis distance is a measurement normalizing each component so as not to be governed by a specific component of a feature vector. The expression of the Mahalanobis distance is as follows [27]:

$$D\left(f^q, f^d\right) = \left(\sum_{i=1}^{n} \left| \frac{f_i^q - f_i^d}{\sigma_i} \right|^M \right)^{\frac{1}{M}} \tag{21}$$

where f_i^q is the i th component of a feature vector f^q of a query image and f_i^d is the i th component of a feature vector f^d of a DB image. M is the metric order and n is the feature vector dimension. σ_i is the standard deviation of the i th components of feature vectors in the entire feature DB.

Content-based image retrieval systems conduct a retrieval performance evaluation step after finishing the similarity measurement step. In this paper, we use precision vs recall which is used in many retrievals. The expressions for the precision and the recall are given as [28]:

$$p = \frac{|A(q) \cap R(q)|}{|A(q)|} \tag{22}$$

$$r = \frac{|A(q) \cap R(q)|}{|R(q)|} \tag{23}$$

where $|\cdot|$ is the size of a set, $A(q)$ is the set of retrieved images by a query image q, and $R(q)$ is the set of relevant images to q. That is, $|A(q) \cap R(q)|$ is the size of a set of retrieved and relevant images.

Evaluation of the proposed method of this paper is conducted by comparing with the methods of the well-known color histogram, the SCD and the CSD respectively in terms of precision vs recall and feature vector dimension.

Table 1. Color space and dimension of retrieval methods

Method	Color space	Dimension
Color histogram	RGB	128
SCD (scalable color descriptor)	HSV	128
CSD (color structure descriptor)	HMMD	128
Proposed	HSV	68

First of all, color space and dimension of the methods used in the experimentation are shown in Table 1. The proposed method has 68 dimensions combining color features of 48 dimensions and texture features of 20 dimensions and it means lower number of dimension than those of the compared methods.

Fig. 2 represents precision vs recall for the existing methods and the proposed method by graphs. In the graphs, the proposed method shows more excellent performance than the existing methods as showing the improvements of 37.86% and 16.1% on average in Corel DB and VisTex DB, 31.94% and 12.3% in Corel_MR DB and VisTex_MR DB, and 14.8% and 11.2% in Corel_MD DB and VisTex_MD DB than the color histogram method. Similarly, it also shows the improvements of 15.86% and 11.77% on average in Corel DB and VisTex DB, 12.22% and 8.63% in Corel_MR DB and VisTex_MR DB, and 0.38% and 6.6% in Corel_MD DB and VisTex_MD DB than the SCD of MPEG-7. Besides, it produces the improvements of 20.8% and 10.3% on average in Corel DB and VisTex DB, 15.96% and 7.4% in Corel_MR DB and VisTex_MR DB, and 1.76% and 4.9% in Corel_MD DB and VisTex_MD DB than the CSD of MPEG-7. The results say that the proposed method is robust for resolution and rotation variants and can retrieve not only homogeneous texture images but also artificial object images better than the existing methods.

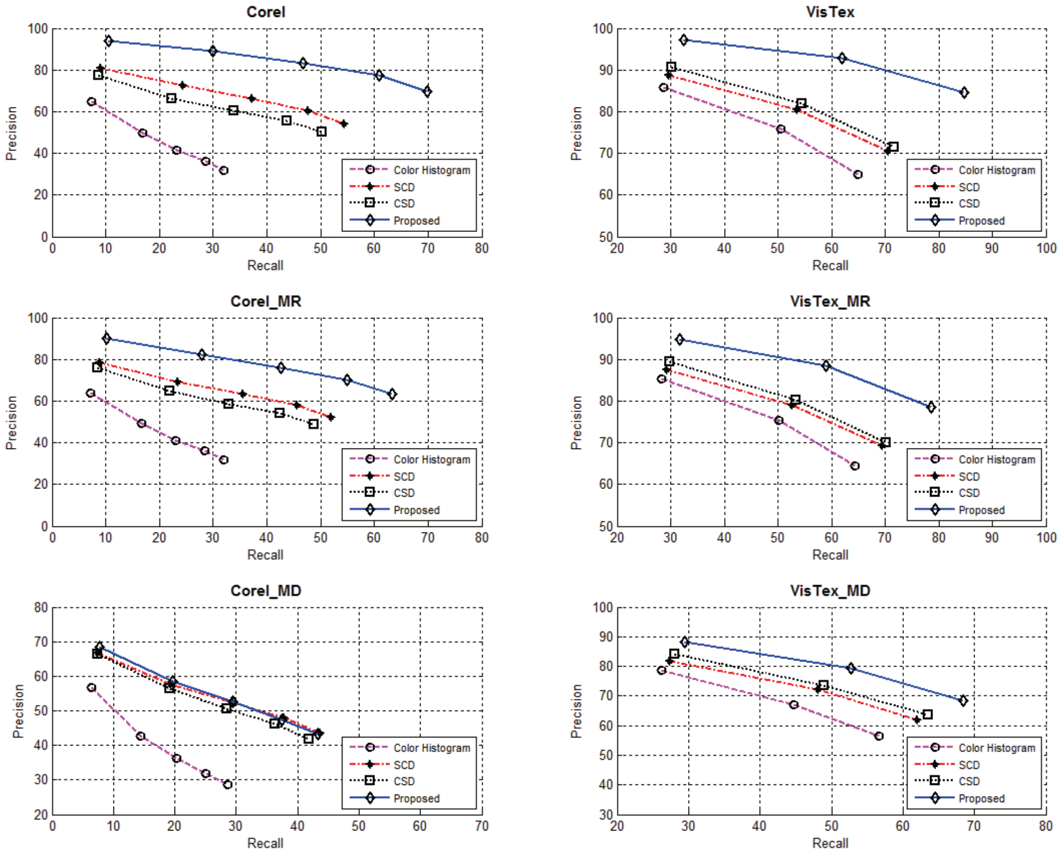

Fig. 2. The precision vs. recall for the existing methods and the proposed method.

4. Conclusion

In this paper, we have chosen a set of MRMD filters providing multi-resolution and multi-direction analysis, and presented the retrieval method combining color and texture features extracted from MRMD filtered images to increase retrieval accuracy. The color space used is HSV color space which has similar characteristics to the human visual system, and the presented method extracts global and local features from domains of low frequency and high frequency in each color space. In the experimental results, we confirmed that the proposed method shows a statistically significant improvement over the existing methods in aspects of retrieval accuracy and recall, and also further reduces feature vector dimension. Finally, the future direction for our research is toward devising a new method combining color and texture features with shape features so as to gradually apply for animal, face, etc., images not dealt with in this paper.

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