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Visual Feature Extraction Technique for Content-Based Image Retrieval

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ABSTRACT

This study has proposed visual-feature extraction methods for each band in wavelet domain with both spatial frequency features and multi resolution features. In addition, it has brought forward similarity measurement method using fuzzy theory and new color feature expression method taking advantage of the frequency of the same color after color quantization for reducing quantization error, a disadvantage of the existing color histogram intersection method. Experiments are performed on a database containing 1,000 color images. The proposed method gives better performance than the conventional method in both objective and subjective performance evaluation.

Keywords : CBIR, color histogram, homogram, feature vector, wavelet

1. INTRODUCTION

Content-based Image Retrieval(CBIR) has been widely used since the 1992 proposal of Kato[1]. In CBIR, user can retrieve, easily, images that he or she wants, by taking advantage of feature value representing visual properties like image color, shape, texture, etc. Therefore, the most important is effective extraction of such low-level visual features representing image as image color, shape, texture, etc[2].

In 1991, Swain and Ballad[3] proposed a color histogram method, a typical method extracting features by using color information. Color histogram is easy to calculate, and robust even about slight camera location change. However, its disadvantage is that images with different spatial color distribution can have the same color histogram. CCV(Color Coherence Vector)[4,5] techniques tried to compensate the disadvantage, but a lot of calculation takes too much time.

Texture is a visual pattern of similar properties, not of an only property like color or brightness, and a property that all substantial surfaces have[6]. In the early 1970s, Haralick[7] brought forward co-occurrence matrix as texture feature. The method took advantage of gray level as the spatial dependence of texture. First of all, it constructs a co-occurrence matrix based on distance and direction between image pixels. Then it extracts meaningful statistics from matrix for expressing texture.

Jacobs, etc.[8] took advantage of wavelet transformation, for the first time, in extracting feature vector. They made feature vector for each image channel R, G, and B by using Harr wavelet transformation fast to calculate. But this method has long transaction time because of too big feature vector dimensions.

Accordingly, this study has proposed a similarity

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measurement method using fuzzy theory, new color feature expression method, and visual-feature extraction method from wavelet domain, a transformation domain, for each band. And CBIR is embodied by extracted visual features.

Chapter 2 describes the proposed visual-feature extraction method, and similarity measurement method ; Chapter 3 shows a simulation result, and finally, Chapter 4 comes to a conclusion.

2. VISUAL-FEATURE EXTRACTION METHOD

2.1 Feature Extraction Method for Each Wavelet-Domain Band

The existing histogram method considered only the gray level value or color level value of each pixel within image, not spatial correlation between pixels ; therefore, even images with different spatial pixel distribution can have the same histogram. Fig. 2.1 shows the disadvantage of the existing histogram.

Here, Fig. 2.1 (a) and (b) have quite different spatial distribution ; however, both show the same histogram distribution as (c). As a result, using histogram can bring very different image retrieval.

In order to overcome the disadvantage of the existing histogram method, Cheng, etc.[9] applied pixel-based fuzzy homogeneity function to image segmentation. This study has tried to extract fuzzy homogeneity function using the frequency component of LL band, wavelet transformation domain, and apply it to image retrieval.

It has transformed wavelet by using 9/7 tap biorthogonal wavelet filter[10] ; then got LL, LH, HL, and HH band. N-number feature vectors have been extracted by LL band feature able to take advantage of sufficient spatial correlation in the form closely resembling an original image. A transaction process before extracting N-number features is as following.

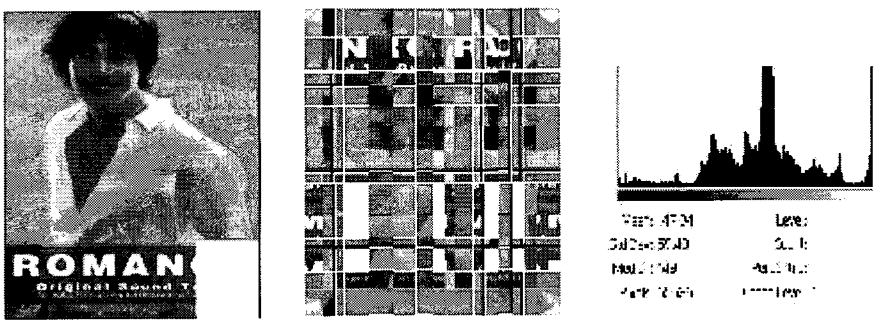
step 1. Input image is normalized to M× N size.
step 2. The normalized image is transformed into 1-level wavelet.
step 3. LL-band wavelet coefficients are normalized to L-level values.

If LL-band wavelet coefficients normalized to L-level values are defined as c(i, j), it will result in the following equation (1). Here, i and j mean wavelet coefficient index.

$$c(i,j) \in \{0,1,2,3,\cdots,L-1\}, \quad 0 \le i \le M/2,\ 0 \le j \le N/2 \quad (1)$$

Using normalized LL-band wavelet coefficients, L-number homogram values are obtained in the LL band of wavelet domain ; then stored in image database[18].

Also, the study extracted 3 feature vectors by high-frequency band in wavelet band. As energy is an instrument measuring the uniformity of brightness, the energy value of each band is



(a) A type image (b) B type image (c) Histogram

Fig. 2.1 Histogram technique

obtained and stored in image database by its relevant image feature vector. Energy value is obtained by the square value of each coefficient. Therefore, the energy value of each wavelet band is obtained by equation (2) - here B∈{*LH, HL, HH*}.

$$E(B) = \sum_{(i,j)\in B} c^2(i,j) \tag{2}$$

2.2 Color Feature Extraction Techniques

The existing color histogram takes advantage of only the frequency of the same color, not color component like relevant color R, G, or B value, or hue value. As a result, organizing color histogram gets to absorb quantization error, as it is, resulting from color quantization. Accordingly, the study has proposed a method using every color value and frequency in order to overcome this disadvantage.

It took advantage of HSV color space able to divide brightness and color difference for making color feature more obvious ; uniformly quantized H, S, V value respectively into 4, 2, and 2 values, and then divided into 16 color regions for dividing the image region including similar colors. The representative color and frequency of each divided region were extracted as its features, and each representative color had the average value R, G, and B of each region. Table 1 represent the frequency of each region and the values of RGB. Color histogram using the above is shown in Fig. 2.2.

Color feature extracted from image is expressed in the type of vector as the following equation (3).

$$\text{color featrue} = [r_i, g_i, b_i, p_i], \quad (i = 1, 2, \cdots, M) \tag{3}$$

Here, M means the total number of color ; p_i means the ratio value of a relevant color with r, g, or b ; they all satisfy $\sum_{i=1}^{M} p_i = 1$. The size of color feature vector extracted from one image is M×4 byte, occupying a tiny space.

2.3 Similarity Measurement

The purpose of CBIR system is retrieving the most similar image to query image within image database. Therefore, the method of obtaining similarity between query image and target image has a big influence on the performance of the total system. The study has proposed distance calculation (similarity calculation) method fit for 3 feature components like color, homogram, and energy value.

As the color distance calculation method using the existing color histogram takes advantage of only the frequency of the same color, not color components like relevant color values(R, G, or B), even similar visual images no longer have similarity because of color histogram movement by such component as illumination change. Thus, the study has proposed fuzzy color distance function for solving this problem resulting from not using relevant color values, a disadvantage of similarity measurement method in the existing color histogram ;

Table 2.1 Index of color histogram

Region	R	G	B	Frequency
1	255	0	0	340
2	30	80	180	1000
3	55	0	90	2000
..	..	..	..	..
..	..	..	..	..
..	..	..	..	..
16	0	255	33	730

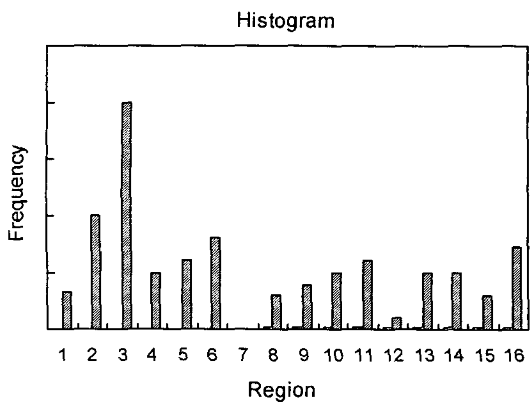


Fig. 2.2 Color histogram

color histogram is obtained by the already-proposed color feature extraction method.

$$D^1(q,t) = \sum_{m=0}^{M-1} \left| h_q(m) - h_t(m) \right| \quad (4)$$

Color histogram applies both the RGB value and frequency of each color to fuzzy color function, and measures similarity between query image and target image. If query image and target image are respectively I_1 and I_2, each image color feature can be expressed as [r, g, b, p]. At this time, similarity between the colors of two images is obtained by membership function like equation (5). If two colors are similar, equation (5) has a value of about 1 ; if not, it has 0.

$$\mu_A(c_1, c_2) = e^{\{-[(r_1-r_2)^2+(g_1-g_2)^2+(b_1-b_2)^2]\}} \quad (5)$$

Equation(6), distance function D^2 transformed by similarity between these two color values, can find similarity between two images.

$$D^2(I_1, I_2) = \sum_{i=1}^{B} p_{1i}^2 + \sum_{j=1}^{B} p_{2j}^2 - \sum_{i=1}^{B}\sum_{j=1}^{B} 2\mu(I_1, I_2) p_{1i} p_{2i} \quad (6)$$

Here, I_1 is the color feature of query image, I_2 the color feature of target image, and B the number of colors.

The homogram set, H, of one image has 128 bins like in {H(0), H(1), ⋯, H(127)} ; if 128 bins are all compared at the time of calculating homogram distance between two images, calculation gets to increase much more. Therefore, this study calculated homogram distance between two images by using the biggest 32 homogram values after arranging query image homograms according to frequency, not calculating similarity by the homogram set of query image. This is expressed in equation (7).

$$D_H(Q, I) = \sum_{t \in T_Q} \left| H_Q(t) - H_I(t) \right| \quad (7)$$

Here, Q means query image, and I target image. T_Q means 32 homogram indexes with the most biggest frequency of the homogram values of image Q.

Energy distance between query image and target image was obtained by equation (8) using general Euclidian distance.

$$D_E(Q, I) = \sum_{B \in \{LH, HL, HH\}} \left| E_Q(B) - E_I(B) \right| \quad (8)$$

The total distance between two images is obtained by the total difference in the energy value of each band of wavelet-transformed image.

3. SIMULATION RESULT

Fig. 3.1 shows feature vector database development system taking advantage of feature extraction techniques that this study has proposed. Above all, one input image is normalized to M× N size ; the normalized image is transformed into HSV color space for extracting color feature, then the image is divided into 16 color regions, and the representative color of each region is calculated ; color histogram is obtained by the above result. Color histogram is expressed in the form of vector, and stored in image feature vector database.

Also, color image is transformed into black and white image for calculating homogram and energy. Black and white image is decomposed into 1-level by wavelet transformation ; then feature vector fit for each band is extracted. First of all, LL band extracts 128 homogram vectors using spatial correlation between wavelet coefficients in the form closely resembling an original image ; The other high-frequency band LH, HL, HH, etc. extract 3 feature vectors by energy value, and store them in image feature vector database.

This study has used 1,000 natural images[11] such as buses, horses, flowers, characters with African scenes for background, European townscape, mountains, the sea, the seaside, etc. for evaluating the performance of content-based image retrieval system taking advantage of the feature extraction techniques and similarity measurement techniques

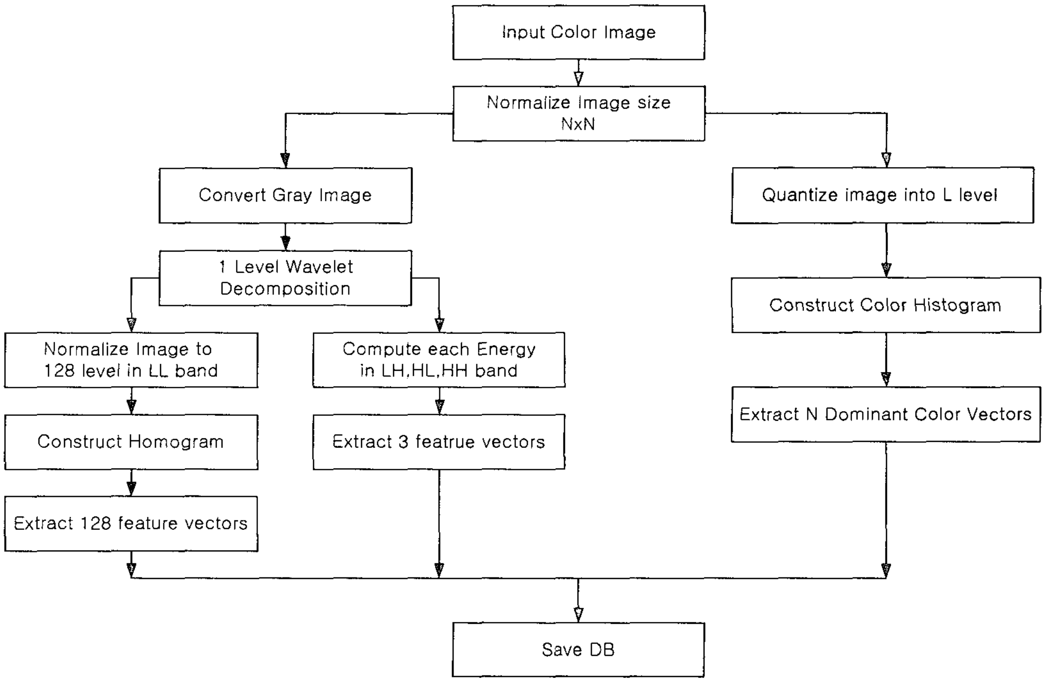


Fig. 3.1 The flowchart of feature vector database construction.

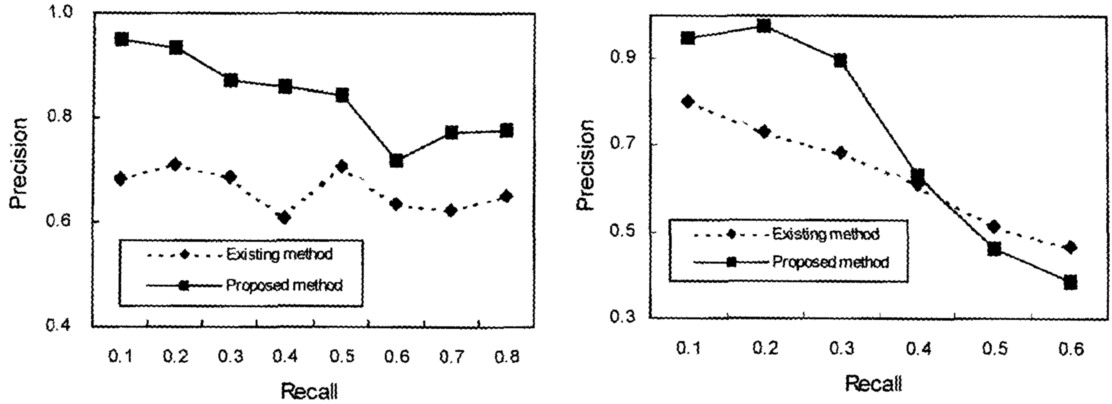
proposed here.

Also, it used a system absorbing both edge histogram method expressing high-frequency component and the existing Swain's histogram intersection method for evaluating the objective performance of CBIR system using the proposed feature extraction techniques. The existing system experimented with color histogram weight and edge histogram weight respectively 0.6 and 0.4, while the method proposed here has taken advantage of query transaction techniques by user definition, and experimented with color, homogram, and energy weight each as 0.4, 0.4, and 0.2. At this time, the constant value a, b, and c of equation (2) used for homogram extraction have become, respectively, experiment value 0, 64, and 128.

Fig. 3.2 shows the result of having retrieved, of 1,000 experiment images, ones similar to 10 query images voluntarily selected from bus-kind ones (a), and horse-kind ones (b). It has been proved that the proposed method has better average recall and average precision than the existing.

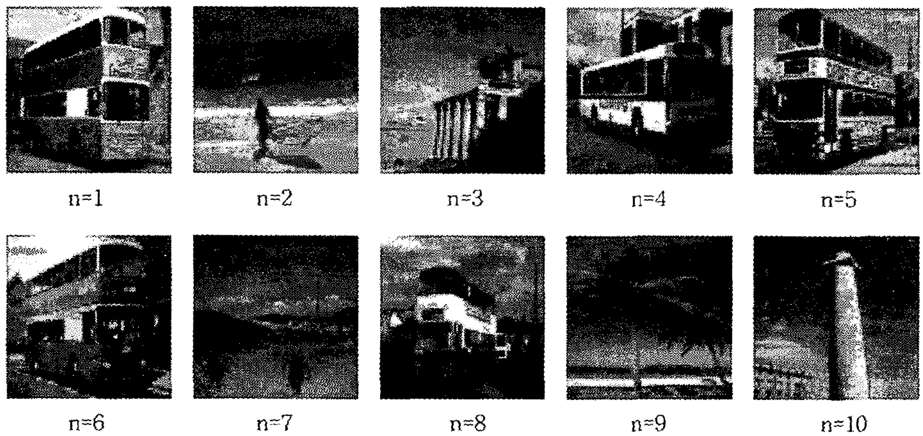
Also, when Fig. 3.3 has received bus image as query image for subjective estimation, (a) and (b) respectively show the result of retrieving the existing method and proposed method. As a result of retrieval, images have been expressed as index according to their similarity. That is, the lower the index of an image is, the more similar it is to query image. The existing method retrieved 5 images, like #1, #4, #5, #6, #8, etc. similar to query image (n=1), of the 10 retrieval images. On the other hand, the proposed method has showed better visual result than the existing one as it retrieved 9 similar images.

Also, when Fig. 3.4 has received horse image as query image for subjective estimation, (a) and (b) respectively show the result of retrieving the existing method and proposed method. As a result of retrieval, the existing method retrieved 8 images, like #1, #3, #4, #5, #6, #7, #8, #10. similar to query image(n=1), of the 10 retrieval images. On the other

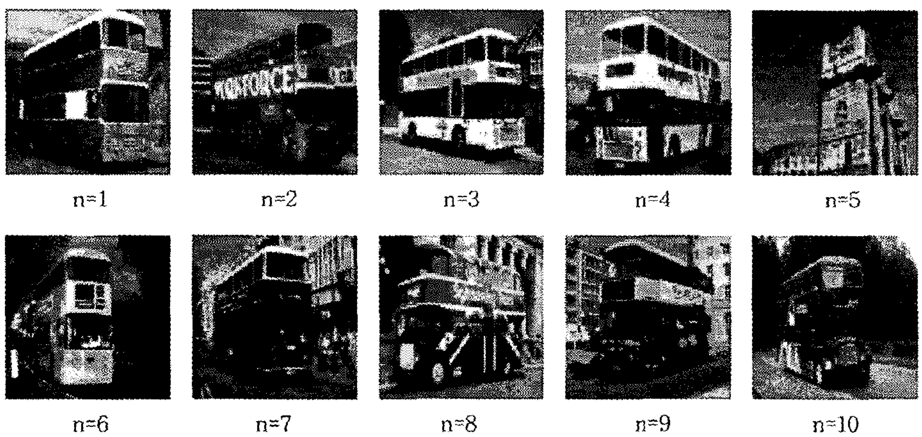


(a) bus image (b) horse image

Fig. 3.2 Simulation result(Recall vs. Precision)

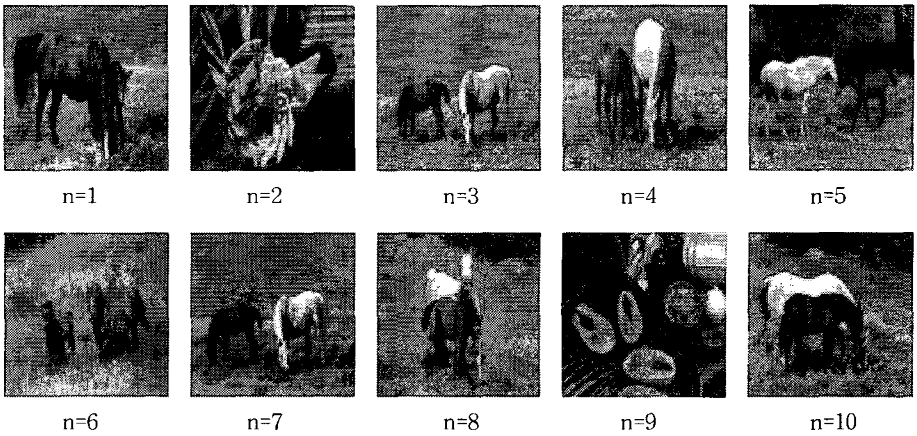


(a) Conventional method

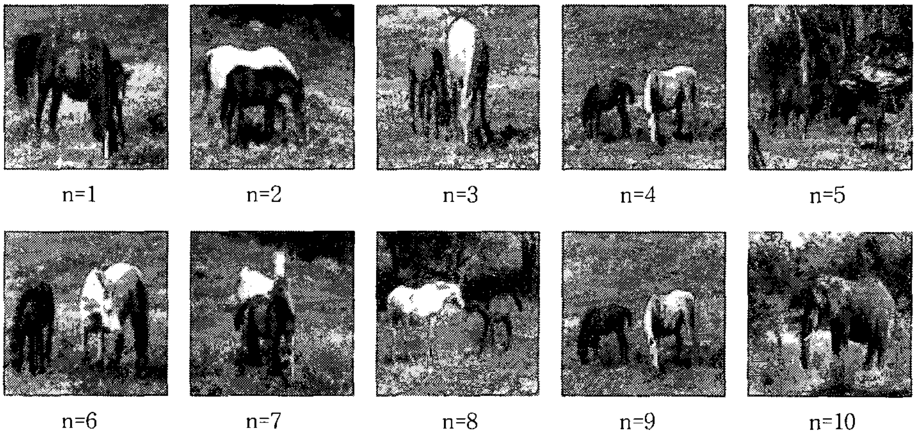


(b) Proposed method

Fig. 3.3 Simulation result(bus image)



(a) Conventional method



(b) Proposed method

Fig. 3.4 Simulation result(horse image)

hand, the proposed method has showed better visual result than the existing one as it retrieved 9 similar images.

4. CONCLUSION

The existing histogram techniques considered only pixel value, not spatial correlation ; even images with different spatial pixel distribution between each other can have the same histogram. And the existing color histogram method uses only the same color frequency, not color component, at the time of calculating relevant color similarity. As a result, it gets to absorb quantization error, as it is, resulting from color quantization for developing color histogram.

This study has proposed new color feature expression method and similarity measurement method in order to overcome the disadvantages of the above-mentioned existing methods. Above all, it has divided color image into 16 regions according to color similarity after transforming it into HSV color space for taking advantage of the color feature of image. In order to extract the representative color of 16 divided regions, the study calculated the RGB color component average value and color frequency of each region, then selected the representative value of a region similar to a relevant color, and stored it as feature vector. Also, when queried, it measured similarity between color images by fuzzy theory for calculating color feature vector distance. According to features by wavelet domain bands, it extracted N-number feature vectors by fuzzy homogeneity considering all spatial information between pixels, and wavelet coefficient in the lowest frequency band ; then extracted 3 feature vectors by the other high-frequency band energy value, and then stored them in database for using at the time of image retrieval.

The study experimented 1,000 color images by new feature extraction method and similarity retrieval method proposed here ; as a result, the new methods have proved to be much more precise in both objective performance evaluation and subjective performance evaluation method than the existing ones.

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