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Image Retrieval Using Fused Features

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***Abstract*—**The system is designed to show images which are related to the query image. Extracting color, texture, and shape features from an image plays a vital role in content-based image retrieval (CBIR). Initially RGB image is converted into HSV color space due to its perceptual uniformity. From the HSV image, Color features are extracted using block color histogram, texture features using Haar transform and shape feature using Fuzzy C-means Algorithm. Then, the characteristics of the global and local color histogram, texture features through co-occurrence matrix and Haar wavelet transform and shape are compared and analyzed for CBIR. Finally, the best method of each feature is fused during similarity measure to improve image retrieval effectiveness and accuracy.

***Keywords*—**Color Histogram, Haar Wavelet Transform, Fuzzy C-means, Co-occurrence matrix; Similarity measure.

I. Introduction

THE Content Based Image Retrieval (CBIR) retrieval will better than text retrieval because these CBIR will retrieve more similar image than the text retrieval. Content-based image retrieval (CBIR) is regarded as one of the most effective ways of accessing visual data [8]. The main idea of CBIR is to analyze image information by low level features of an image [3], which include color, texture, shape and space relationship of objects etc., and to set up feature vectors of an image as its index [2]. Retrieval methods focus on similar retrieval and are mainly carried out according to the multidimensional features of an image. To overcome the semantic gap a CBIR technique had been given by Deb et al. [4].

Shih et al. [10] proposed a method using signature of the object, with Object Detection or Separation and Normalization, the Shape Representations and Similarity Measurement with affine invariants were implemented. Within the last few decades, numerous novel CBIR techniques had been proposed [7]. A central issue to these approaches was the feature vector extraction.

Shape similarity measure where comparison of polygonal curves is based on distance between their turn angle representations, also called tangent space representation or turning function. Feature consisting of moment invariants and UNL Fourier feature gives the best results proposed by Mehtre et al. [3]. Hong et al. [11] proposed a novel method for the efficient object retrieval in videos. This method efficiently finds the objects and locates them in videos. But the objects sometimes cannot be distinguished from each other with only one type of feature descriptors. Wang et al. [5] present an effective color image retrieval method based on texture, which uses the color co-occurrence matrix to extract the texture feature and measure the similarity of two color images. But proposed method is superior to the gray-level co-occurrence matrix method and color histogram method. In attempt to further improve the CBIR technique we have presented an improved algorithm by extracting feature vector comprises of shape and color from image [9]. In this approach the image feature vector is then used to search the image in dynamic environment like Google or Yahoo search engine. Huang et al. described the prosperities of the images [6]. Zhang et al. considered the region segmentation problem as one that is still beyond current capabilities of computer vision research and proposed an alternative but feasible scheme [12]. Almeida et al. took study of the role color information played in image retrieval and described about global-based descriptors, partition-based descriptors, region-based descriptors, color-based descriptors, texture-based descriptors, shape-based descriptors, and motion-based descriptors [1].

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II. Comparing two Features of Color Based CBIR

Color based image retrieval is the most important method for CBIR. Color features are very stable and robust, and not sensitive to rotation, translation and scale changes. Color feature is simple to calculate. A color histogram is the most used method to extract color features.

A. Color Histogram Based CBIR

The global color histogram is a simple way of extracting image features. The global color histogram has both advantage and disadvantage. High effective calculation and matching are its main advantage and it is invariable to rotation and translation. The main drawback is two completely different images can get the same global color histogram, which will cause retrieval errors. The global color histogram can be calculated as follows:

Step 1. Convert the RGB image space into HSV space.

Step 2. Quantify the images.

H ={fix value 0 for h $\in$ [316, 360], fix value 1 for h $\in$ [1, 25], fix value for 2 h $\in$ [26, 40], fix value 3 for h $\in$ [41, 120], fix value 4 h $\in$ [121, 190], fix value for 5 h $\in$ [191, 270], fix value 6 for h $\in$ [271, 295], fix value 7 for h $\in$ [295, 315]}.

S = {fix value 0 for s $\in$ [0, 0.2), fix value 1 s $\in$ [0.2, 0.7), and fix value 2 for s $\in$ [0.7, 1]}.

V = {fix value 0 for v $\in$ [0, 0.2), fix value 1 v $\in$ [0.2, 0.7),

and fix value 2 for v ∈ [0.7, 1]}.
Step 3. Count each feature value.
Step 4. Euclidean distance is used to calculate similarity.

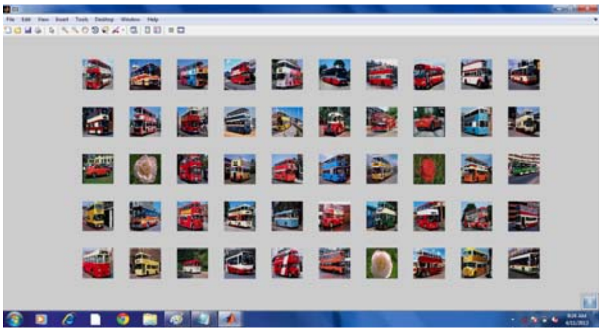
B. Block Color Histogram Based CBIR

The images are partition into n×n blocks. Each block will have less meaning if the block is too large and partition into so 3 × 3 will be more effective. Calculation of the color space converting, color quantization and normalized color features for each block are carried out.

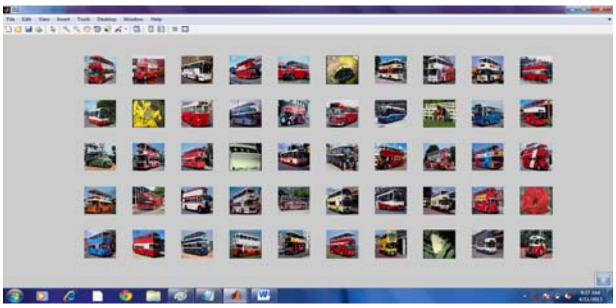
C. Comparing Two Color Features Based CBIR

Given an input image, two color based image retrieval approaches are used for results are shown as Fig. 1. From the results, it is obviously to see that the block color histogram is better than global color histogram because block color histogram will retrieve more similar images than block color histogram. Experiments show that the block color histogram is better than the global color histogram from the human visual perception from Fig. 1.

(a)



(b)



(c)

Fig. 1 Color based CBIR retrieval results (a) Input image for retrieval (b) Using global color histogram (c) Using 3 × 3 block color histogram

III. Comparing Two Features of Texture Based CBIR

A. Extracting Texture Features by Co-Occurance Matrix

Nc and Nr pixels in the horizontal and vertical directions present in the image. Assume Zc={1, 2, . . . , Nc} is a horizontal space domain and Zr= {1, 2, . . . , Nr} is a vertical space domain. When the direction θ and distance d are given, the matrix element P(i, j/d, θ) can be expressed by calculating the pixel logarithm of co-occurrence grey level i and j. Assume the distance is 1, θ equals 0°, 45°, 90°, 135° respectively. Moreover, the feature vector dimensions are also smaller.

There are five steps to extract the texture features

Step 1. Image Color Conversion

The color image will be converted to a grey-scale image by Y = 0.29 × R + 0.587 × G + 0.114 × B, where Y is the grey-scale value and R, G, B represent red, green and blue component values respectively. The grey-scale value is lies between 0 to 255.

Step 2. Grey-Scale Quantification

The corresponding co-occurrence matrix is 256 × 256 because the grey-scale value is 256. The grey-scale image should be compressed to reduce calculations is formed. 16 types of compression levels were chosen to improve the texture feature extracting speed.

Step 3. Feature Value Calculation

Four co-occurrence matrices are formed in four directions. The four texture parameters: capacity, entropy, moment of inertia and relevance are calculated. Finally, the means and standard deviations of each parameter are taken as each component of the texture features.

Step 4. Internal Normalization

Gaussian distribution Internal normalization implementation is done by Gaussian normalization approach in order to make each feature of the same weight, where hi,j′=hi,j–mjσj, where, mj is the mean and σj is the standard deviation. hi,j will be unitized on range [−1,1].

For an image li and its corresponding feature vector Hi = [hi,1, hi,2, . . . , hi, N].

Step 5. Texture Feature Comparison

The texture feature of each image is calculated and texture values are compared by Euclidean distance closer distance means higher similarity.

B. Extracting Texture Features by Transform Domain

There are several texture classification using transform domain features such as discrete Fourier transform (DFT), and discrete wavelet transforms (DWT). Fourier transform consist of breaking signals into sin waves of various frequencies. On the other hand, wavelet refers to decomposition of a signal function. Moments of wavelets coefficients in various frequency bands have been shown to be effective for representing texture.

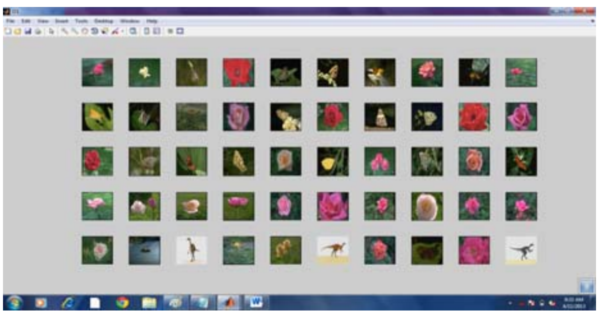
Wavelet transform computation involves recursive filtering and sub sampling; and at each level, it decomposes a 2D signal into four sub bands, which are often referred Low Low, Low High, High Low, and High High according to their frequency characteristics. Feature must be re present by energy in the high frequency bands of the Haar wavelet transform. Read the image into MATLAB. Calculate the mean of the block matrix operation. Partition the image to 4 by 4 block and finally concentrate the matrices to be a 3 dimensional.

Change to indexed image using color cube. Transform by using Haar Wavelet transform. Perform the one step decomposition (level one decomposition) using dwt2. Dwt2 means discrete wavelet transform and this if for one level decomposition of two dimensional data. Detail coefficients such as cA1, cH1, cV1, and cD1 from high pass filter. And transform back to display image coding (constructing the level-one approximation).Using color map of the color cube level-one approximation is constructed. Approximation co-efficient such as A1, H1, V1, and D1 from the coefficients. Approximation coefficient from low pass filter. The filter is either applied in spatial domain or frequency domain. And resize the matrices into normal size. Concatenate of the resize coefficient matrices into one matrix from 96*69 each, become 96*69*3. And finally concatenate into single 3 dimensional matrix.

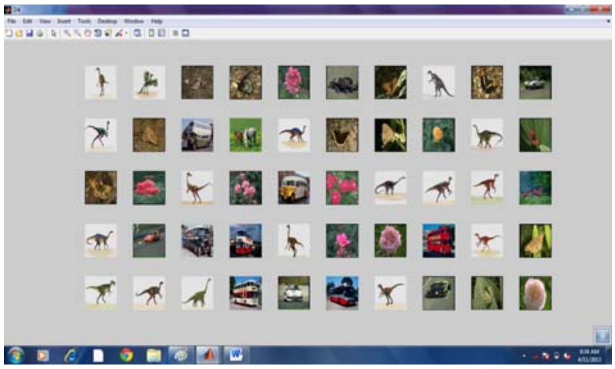
C. Comparing Two Texture Features Based CBIR

In co-occurance matrix, much work has been assigned feature descriptor. This texture is not very effective for classification and retrieval. In addition, these features are expensive to compute. So this texture is not used regularly in modern image applications. Haar transform is better reflection properties and coefficient in different frequency signal variations in different directions such as horizontal, vertical, and diagonal. Haar transform require less computation compared to other wavelet transform. Finally Haar transform is better than co-occurance matrix in field of retrieval an also in computation.

(a)



(b)



(c)

Fig. 2 Texture based CBIR retrieval results (a) Input image for retrieval (b) Using texture through co-occurance matrix (c) Using texture through Haar transform

When comparing the two texture features in our CBIR system. Given an input image, two texture based image retrieval approaches are adopted respectively, and the retrieval results are shown as Fig. 2. Experiments show that the Haar transform is better than the global color histogram from the co-occurance matrix from Fig. 2.

IV. Shape Feature

Use Segmentation is done by Fuzzy C-Mean clustering algorithm. Extracting object is converted into signature whose Fast Fourier Transform is calculated after successful segmentation boundary.

A. Signature Development

Step 1. Use the actual image, region mask and number of regions obtained using segmentation for signature development.

Step 2. Centroid, boundary, hole, and signature of the region mask are found from first step.

Step 3. Signature of each region from second step by calculating distance between boundary elements and centroid of the region. And signature is variant to translation

Step 4. Calculate the shape number of each region and then signature of that region mask is developed.

Step 5. Combining the signature of the region mask to generate the signature of the query image.

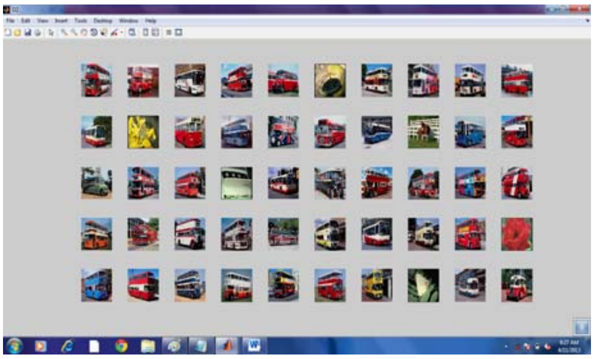
Step 6. Find the FFT after calculating signature of the image.

B. Experiment Results and Comparing with Color, Texture, and Shape Based CBIR

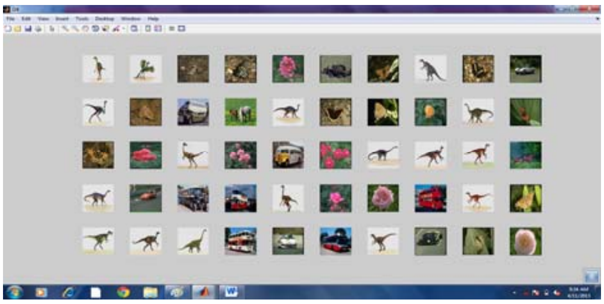
In Digital color image retrieval, the feature vector of each image in the image database will subtract the feature vector of target image separately as feature values. And the sum of the square of the result feature value is calculated to get the Euclidean distance. The images are queued according to the distance ordered from small to large. In order to test the retrieval effect by extracting texture features through Haar transform, the performance of the texture feature algorithm based on the Haar transform is taken to compare with the color-based retrieval, and shape retrieval which are shown in

Fig. 3. From the results, it can be see that the retrieval results are closed to the input image from the point of view of color when just using the color histogram. When only using texture features, the black–white image emerges. Though they are with quite different colors, the textures are very similar. From this comparison of experimental result, shape retrieval is better than the both color retrieval and texture retrieval from Fig. 3. And color retrieval is better than texture retrieval from Fig. 3.

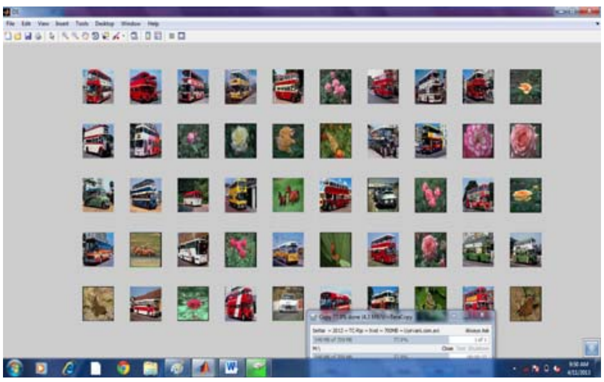
(a)



(b)



(c)



(d)

Fig. 3 CBIR retrieval results (a) Input image for retrieval (b) Using block color histogram (c) Using texture through Haar transform (d) Using Fuzzy C-Means Algorithm

V. CBIR System Using Color, Texture, and Shape Fused Features

In order to implement a fast and robust CBIR system, color, texture, and features are combined in the paper. The system was developed using MATLAB 2010 and MYSQL server 2012 served as the system database. Extracting color feature is work well in HSV color space. Block color histogram is better than global color histogram. So, Block color histogram alone used in fused CBIR system. Texture through Haar transform is better than texture through co-occurance matrix. So, Haar transform alone used in fused CBIR system. Based on the above image feature vectors, the color, texture, and shape features are fused by a linear weighted mode. The similarities measure is calculated by Euclidean distance in our work (Shown in Tables I-III).

TABLE I
COMPARATIVE STUDY OF LOW-LEVEL FEATURES AND COMBINED FEATURES AFTER OBSERVING SIMILARITY IMAGES OUT OF 50 RETRIEVED IMAGE

Image	GCH (F1)	BCH (F2)	Texture1 (F3)	Texture2 (F4)	Shape (F5)	F2+F3 (F6)	F2+F4+F5 (F7)
Butterfly	15	27	18	11	2	27	28
car	9	20	1	5	15	18	20
Horse	16	17	0	2	12	15	17
Dinosaries	50	50	3	17	49	49	50
Bus	45	44	0	7	29	4	44
Flower	16	21	31	9	31	21	21

TABLE II
PRECISION COMPARISON

Image	**GCH (F1)**	**BCH (F2)**	**Texture 1 (F3)**	**Texture 2 (F4)**	**Shape (F5)**	**F2+F3 (F6)**	**F2+F4+F5 (F7)**
Butterfly	0.151	0.273	0.181	0.111	0.020	0.272	0.282
car	0.909	0.202	0.010	0.050	0.151	0.181	0.202
Horse	0.161	0.171	0	0.020	0.121	0.151	0.171
Dinosaries	0.505	0.505	0.030	0.171	0.494	0.494	0.505
Bus	0.454	0.444	0	0.070	0.292	0.040	0.444
Flower	0.161	0.212	0.313	0.090	0.313	0.212	0.212

TABLE III
RECALL COMPARISON

Image	**GCH (F1)**	**BCH (F2)**	**Texture1 (F3)**	**Texture2 (F4)**	**Shape (F5)**	**F2+F3 (F6)**	**F2+F4+F5 (F7)**
Butterfly	0.3	0.54	0.36	0.22	0.04	0.54	0.54
car	0.18	0.4	0.02	0.1	0.3	0.36	0.4
Horse	0.32	0.34	0	0.04	0.24	0.3	0.34
Dinosaries	1	1	0.06	0.34	0.98	0.98	1
Bus	0.9	0.88	0	0.14	0.58	0.08	0.88
Flower	0.32	0.42	0.62	0.29	0.62	0.42	0.42

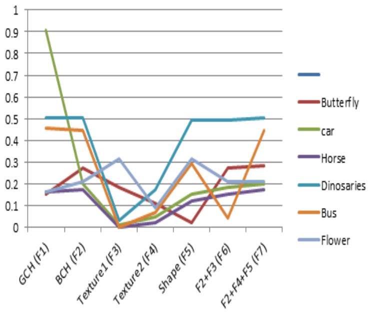


Fig. 4 (a) Precision comparison

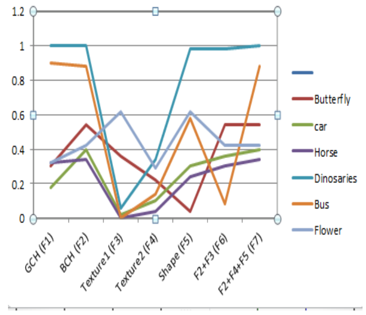


Fig. 4 (b) Recall comparison

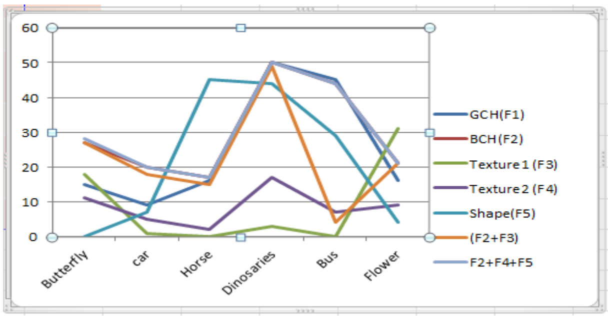
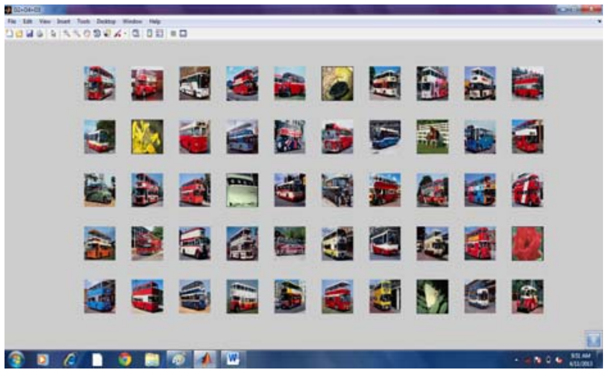


Fig. 5 Experiment and results after observing similarity images out of 50 retrieved image
GCH–Global Color Histogram, BCH – Block Color Histogram, TEXTURE1 – Texture Through Co-Occurance Matrix, and TEXTURE2 – Texture Through Haar Transform. Here, X-axis is no. of similarity image retrieved and Y-axis is no. of category of image.

(a)



(b)

Fig. 6 CBIR retrieval results (a) Input image for retrieval. (b) Using combine of global color histogram, texture through Haar transform, and shape through Fuzzy C-Means Algorithm

VI. Conclusions

After a studying and survey of the previous CBIR works, the paper explored the low-level features of color, texture, and shape extraction for CBIR. Comparing the two color histogram features, comparing the two texture features, and also comparing color, texture, and shape features, the paper implemented CBIR system using color, texture, and shape fused features (D2+D4+D5). Similar images can be retrieved quickly and accurately by input an image.

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