Content Based Image Retrieval Based on Global and Region Content of an Image

H. Kavitha
Assistant Professor Dept. of ISE
Siddaganga Institute of Technology,
Tumkur, India
kavitha.halappa@gmail.com

M.V.Sudhamani
Professor and Head Dept. of ISE
RNS Institute of Technology,
Benguluru, India
mvsudha raj@hotmail.com

ABSTRACT

In this paper we present efficient content based image retrieval system based on the visual features like texture and color. In our work the first step is the extraction of the texture features by using the Gabor filters form the whole image or for region formed after segmentation. Gabor filter (or Gabor wavelet) is widely adopted in image retrieval systems to extract texture features from images and has been shown to be very efficient. Therefore, we use the Gabor filter to extract global texture features from the image. In order to speed up retrieval the HSV color features are retrieved for both the entire image and the segmented regions. The experiments were carried out with COIL-100 and Wang's image dataset. The experimental results show that the current work is significantly better than the existing systems.

Keywords: Content based image retrieval, Region based features, Global based features, Texture, Color, Gabor filter.

INTRODUCTION

Content Based Image Retrieval (CBIR) is a combination of techniques to retrieve relevant images from the database based on the features of the images. CBIR is extremely useful in a plethora of applications such as publishing and advertising, historical research, fashion and graphic design, architectural and engineering design, crime prevention, med- ical diagnosis, geographical information and remote sensing systems, etc. The main goal of CBIR is efficiency during image indexing and retrieval, thereby reducing the need for human intervention in the indexing process.

Some of the existing CBIR systems extract features from the whole image not from certain regions of it; so, they are global features. Color and texture are the common global features. Image retrieval based on only the color features do not provide good results since the color has no relation with the content of the image. Different objects can have the same color, like tomato and red apple are both same in the color. This leads to the fact that global color features often fail to capture color distributions or textures within the image. D. Zhang [3] proposed a method combining both color and texture features to improve retrieval performance. In their work the database images are indexed using both types of features. During the retrieval process given a query image, images in the database are ranked based on the color features first. As a second step a number of top ranked images are selected and re-ranked according to their texture features. Two alternatives are provided to the user, one is the retrieval based on color features and the other is retrieval based on combined features. When the retrieval based on color fails, the user uses the other alternative which is the combined retrieval. Since the texture features are extracted globally from the image, they are not an accurate description of the image in some cases which degrades the system performance.

The drawback of the global feature is overcome by the region based approach. In the region based approach the image is decomposed into regions by segmentation. Region based approach does better since the region perception is nearer to human visual system. The well known region based retrieval systems are the Blobworld system [4] and the Natra system [5]. These two methods are based on the comparison of the individual regions in an image. For querying the image, the user is provided the segmented image. After that he is supposed to choose the region of interest and also has to specify the feature of interest like color or texture. Thus the user is given the option to compare the images. The region representation is however far behind the human semantic interpretation. The querying systems of this type will increase the burden of the user in choosing the query object, especially in cases where the texture is not obvious. The aim of our current work is to propose new CBIR system so that the semantic gap can be reduced. The remainder of the paper is organized as follows: In Section II the Global Content Based Approach system is dealt with. The Region Content Based Approach system is discussed in Section III. Section VI deals with the result and evaluation. We provide the conclusions and future works in Section V.

GLOBAL CONTENT BASED APPROACH

Where s and t are the filter mask size variables, g∗is the inn this section, we introduce our Global Content Based Approach (GCBA) system. This system defines the similarity between contents of two images based on global features like texture and color.

A. TEXTURE FEATURE

To extract the texture features from an image we have complex conjugate of the mother Gabor function, gmn and Gmn is the convolution result corresponding to the Gabor kernel at orientation m and scale n. Using Equations (5), (6) and (7) the mean μmn and variance σmn of the energy distribution E(m,n) of filters responses are computed.

$E(m, n) = \Sigma_x \Sigma_y \mid G_{mn}(x, y) \mid$ (5)

E(m, n)

used Gabor filter (or Gabor wavelet) and this has been shown to be very efficient. Manjunath and Ma [1] have shown that image retrieval using Gabor features outperforms µmn = pΣ Σ (Gp ∗q(x, y)(6)

µ)2 that using Pyramid structured Wavelet Transform (PWT)

σmn = | | − (7)

features, Tree structured Wavelet Transform (TWT) features and multi-resolution simultaneous autoregressive model features. Therefore, we use the Gabor filter to extract global texture features from the whole image. A total of twenty four wavelets are generated from the "mother" Gabor function given in Equation (1), using four scales of frequency and six orientations.

gmn (x, y) = a−m • g(x˜, y˜) (1) Where m and n are integers specifying the scale and orientation of the wavelets respectively, with m = 0, 1, 2, , M - 1, n = 0, 1, 2, ..., N - 1, M and N are the total number of scales and orientations, respectively, and

x˜ = a−m (x cos Θ + y sin Θ) (2)

y˜ = a−m (−x sin Θ + y cos Θ) (3)

Where a > 1 and Θ = nπ/N .

Redundancy is major consequence of the non-orthogonality of Gabor wavelets. It is addressed by choosing the parameters of the filter bank to be the set of frequencies and orientations that cover the entire spatial frequency space so as to capture texture information as much as possible in accordance with filter design. The lower and upper frequencies of the filters are set to 0.04 octaves and 0.5 octaves respectively, the orientations are at intervals of 30 degrees and the half-peak magnitudes of the filter responses in the frequency spectrum are constrained to touch each other. Note that because of the symmetric property of the Gabor function, wavelets with center frequencies and orientation covering only half of the frequency spectrum are generated. To extract texture feature from an image, we first convert the image from the RGB color space into gray level and implement the group of designed Gabor filters. Twenty four filtered images, Gmn (x, y), are produced by convolution of the gray level image and the Gabor filters as given in the equation 4.

x y mn mn

p ∗q

Finally the texture feature vector TG is obtained with 48 attributes:

TG = [µ00 σ00 µ01 σ01 µ02 σ02 • • • • • •µ35 σ35] (8)

The steps followed are summarized below:

1) Convert the RGB image into gray level image.
2) Construct a bank of 24 Gabor filters using the mother Gabor function with 4 scales and 6 orientations.
3) Apply Gabor filters on the gray level of the image.
4) Get the energy distribution of each of the 24 filters responses.
5) Compute the mean µ and the standard deviation σ of each energy distribution.

6) Return the texture vector TG , consisting of 48 attributes calculated at step 5. The attributes of the texture features vector may have different ranges. Therefore Min-Max normalization is used to make all the texture features have the same effect in measuring image similarity.

To test the similarity between a query image Q and a database image B based on their texture feature we use the Euclidian distance for its simplicity.

B. COLOR FEATURE

In the GCBA system we used global color histogram to extract the color feature of images. We adopt to use the HSV (Hue, Saturation and Value) color space for its simple transformation from the RGB (Red, Green and Blue) color space, in which images are commonly represented. The HSV color space is quantized into 11 bins for H, 11 for S and 11 for V. The similarity metric we used in deriving the similarity between two color histograms is the Histogram Intersection Technique (HIT). In this technique the similarity between two histograms is a floating point number between 0 and 1. Two histograms are equivalent when the similarity value is 1 and the similarity decreases as it approaches 0. Both of the histograms must be of the same size to have a valid similarity value. Let HQ and HB denote the histograms of

Gmn (x, y) = Σs Σt I (x − s, y − t)g∗(s, t) (4)

the query image and an image in the database respectively and S(HQ , HB) denote their similarity. Then S(HQ , HB) an be expressed as given in equation 9.

S(HQ , HB) = x X,y Y,z Z min(HQ (x, y, z), HB (x, y, z))

A. TEXTURE FEATURE

In our proposed RCBA system, we use the same features we have used in the GCBA system, which are texture and color, to represent each region extracted from the segmented image.

P X,y Y,z Z HQ (x, y, z), HB (x, y, z) P]

In this context, there is one problem to be considered when extracting texture features using Gabor filters. Trans- (9) where X, Y and Z are the arguments of the discretized color channels. This metric satisfies the associativity condi- tion. Finally the distance dc (Q, B), between the query image and the database image according to the extracted color feature is given by 10 equation.

dc (Q, B) = 1 − S(HQ , HB) (10)

C. IMAGE MATCHING AND RETRIEVAL

The similarity between a query image Q and a database image B is defined in term of the distance DG (Q, B) between them which is assessed according to the extracted texture and color features. Two images are equivalent when the distance value between them is zero and the similarity between them decreases as the distance increases. Using the texture distance dT and the color histogram distance dC we define the global distance DG (Q, B) as:

$$DG (Q, B) = wT\, dT + wC\, dC \qquad (11)$$

where wT and wC are weights for the texture and color distances respectively. We used wT = 0.35 for texture and wC = 0.65 for color followed by the experimental results by considering different values of wT and wC . The similarity between the query image and every image in the database is orms such as Gabor filtering require the input image to be rectangular, which is not always true for regions resulting from image segmentation. An instinctive way is to obtain an inner rectangle (IR) from a region on which filtering can be performed. This works when the size of the filtering mask is much smaller than the size of the IR. But many regions are small and the coefficients obtained cannot well describe the region. To solve this problem, we have adopted extended rectangle (ER) texture feature extraction method. By initial padding, our method extends an arbitrary shaped region into a larger rectangle onto which Gabor filtering is applied. Then a set of coefficients best describing the region is obtained, from which texture features can be extracted. In the literature there are many padding techniques such as mirror padding and object-based padding, we have chosen zero padding for its simplicity and low cost computation. As in the GCBA system, we implement a bank of Gabor filters with 4 scales and 6 orientations to extract texture features from the ER of an image region. Then we select the M largest coefficients in each of the 24 filtered output regions, since the high frequency components represent the object region and its boundary. By assuming spatial homogeneity of texture in each image region, the texture features are computed as the mean of the selected coefficients according to the formula in 2. calculated. The top similar target images are retrieved to the user.

$$\mu_{m,n} = m\, \Sigma x\, \Sigma y \mid Gmn (x, y) \mid \qquad (12)$$

REGION CONTENT BASED APPROACH (RCBA)

In region based systems the image is segmented using the Sobel operator and then features of the individual segment are extracted. During color feature comparison the distance of the segmented histogram of the query image and the segmented histogram of the database image are calculated using histogram intersection techniques. In the same way during the texture feature comparison, the Euclidian distance between the texture vector of the query image and the texture vector of the database image are calculated. Here we take two segments viz. foreground and background.

The entire above mentioned feature extraction techniques
are applied to the corresponding segments. Then the averages of the values of the distance vector of both the segments are obtained. This resultant distance vector average is the distance measure, on the basis of which we calculate the closeness between the query and resultant images.

$$TR = [\mu 00\ \mu 01\ \mu 02 \bullet \bullet \bullet \bullet \bullet \bullet \mu 35] \qquad (13)$$

Image region texture features may have different ranges therefore a normalization method should be applied on each of them. We use the Min-Max normalization the same as we did in the GCBA system.

B. COLOR FEATURE AND REGION AREA/IMAGE AREA RATIO

We use the HSV color space for color feature extrac- tion. As the image regions extracted from the image after segmentation are approximately color homogeneous, it is possible to use the average HSV value in each channel of all pixels in the region as its perceptual color. We also use the standard deviation for each color channel resulting in six color features. The Min-Max normalization is used to have the values of each color feature in the range [0, 1].

The last feature we used is the region area/image area ratio. We propose that the area occupied by a region in an image gives information about its importance which should be greater for regions with larger areas.

D. IMAGE SIMILARITY

Given a query image Q and a database image B. The overall distance between the two images Q and B is defined by the equation 15.

C. REGION MATCHING

An image region is described by a feature vector of 30

$$(D1(Q, B) + D2(B, Q))\ D(Q, B) = \quad 2 \ (15)$$

normalized attributes f1 to f30 . The first 24 features are for texture and f25 to f30 are for color. To measure the similarity between two images we have to compare each region in one image to all the regions of the other image. We use the Euclidian distance between the feature vectors to find the distance between regions. The distance dij between two image regions Ri and Rj is defined as:v

As compared with many existing similarity measures in the literature this definition strives to incorporate as much semantic information as possible and at the same time also achieves computational efficiency. Given this definition of distance, it is straightforward to compute the distance between a query image and all database images.

u 24 30
dij = uwT X(fki − fkj) + wC X (fki − fkj) (14)
t k=1 2 2
k=25

Where fki and fkj are the kth features of the regions Ri and Rj respectively and wT and wC are weights for texture and color features. We choose wT =1 and wC =2 because we have 24 texture features whereas the color features are only six and thus we have to increase the effect of such few features.

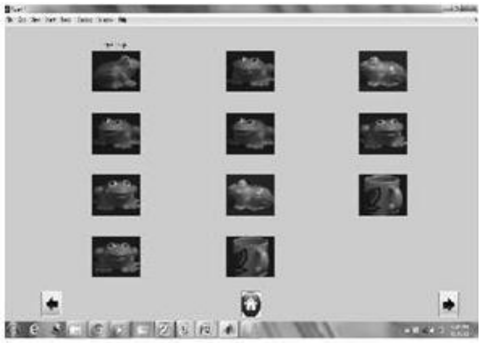

Fig.1 Images retrieved by the GCBA, first image is the query image followed by the retrieved images from COIL-100 dataset.

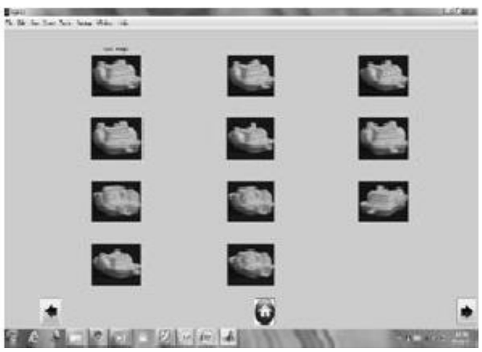

Fig.2 Images retrieved by the RCBA, first image is the query image followed by the retrieved images from COIL-100 dataset.

Fig.3 Images retrieved by the GCBA, first image is the query image followed by the retrieved images from Wang dataset.

Fig.4 Images retrieved by the RCBA, first image is the query image followed by the retrieved images from Wang dataset.

RESULTS AND SYSTEM EVALUATION

In this section the details about the dataset used for the experimental purpose and the results are discussed. In this work two datasets are used for experimentation namely Wang and COIL-100 dataset. These datasets are described in the section following.

A. Image database

The database we used in our evaluation is WANG database. It consists of 1000 image it's a subset of the Corel database

which has been manually selected to be a database of 10 classes of 100 images each. The images are of size 384×256 or 256×384 pixels. This database has been extensively used to test many CBIR systems because the size of the
database and the availability of class information allows for performance evaluation. The Columbia Object Image Library (COIL-100) is the other dataset used for the experimental purpose. COIL-100 is a database of 7,200 color images of
100 objects. This corresponds to 72 different orientation of each object. The precision recall pair is used to evaluate the proposed systems. Category GCBA
RCBA Precision Recall Precision Recall

CONCLUSION

In this paper we presented a content based image retrieval system that answers to an image query either by global features or region features. We used Gabor filter which is a powerful texture extraction technique to describe the content of image regions or the global content of an image. Color histogram as a global color feature and histogram intersection as color similarity metric. We have increased the effectiveness of the RCBA system by estimating texture features from an image region after segmentation instead of using the average value of group of pixels or blocks through the segmentation system can be used as the first option in our retrieval system. Since it gives accepted results and avoids the complex computations of the segmentation process and region comparison that are present in the RCBA system. RCBA system can be used next to further improve the retrieval results, in case the user is not satisfied.

Category	GCBA		RCBA	
	Precision	Recall	Precision	Recall
1	100.00	69.44	100.00	69.44
2	85.00	59.03	96.60	67.08
3	58.20	40.42	100.00	69.44
4	86.00	59.72	93.20	64.72
5	93.60	65.00	100.00	69.44
6	100.00	69.44	100.00	69.44
7	100.00	69.44	100.00	69.44
8	91.20	63.33	100.00	69.44
9	95.20	66.11	96.60	67.08
10	100.00	69.44	100.00	69.44
Average	90.92	63.14	98.64	68.50

TABLE.I Precision and Recall for the RCBA and GCBA system for the Coil-100 database

B. EVALUATION

The experiment is carried out by considering 10 random objects from each category from both the databases. The query image along with the retrieved images by applying the GCBA and RCBA techniques for COIL-100 dataset are shown in Fig. 1 and Fig. 2 respectively. Similarly for Wang dataset, the query image and its resultant retrieved images are depicted in Fig. 3 and Fig. 4 for the GCBA and RCBA techniques. The respective precision and recall of the GCBA and RCBA are given in Table 1 for COIL-100 dataset. From Table 1 it's evident that the RCBA performances better than the GCBA. The average precision and recall of the Wang's dataset for GCBA and RCBA are 86.5, 61.23, 89.1 and 67.56 respectively. The performance of the COIL-100 dataset is better compared to the Wang's dataset mainly because of the same background in all images in case of COIL-100 dataset.

REFERENCES

[1] R. C. Veltkamp, and M. Tanase, "Content-based image retrieval systems: A survey," Utrecht University Tech. Rep.,UU-CS-2000-34, [2004].

[2] B. Manjunath and W. Ma, "Texture features for browsing and retrieval of image data," IEEE Trans. Pattern Anal. Mach. Intell.,Vol. 18(8), pp. 837-842, [1996].

[3] J. Wang, G. Wiederhold, O. Firschein and X. Sha, "Content-based image indexing and searching using Daubechies wavelets," Int. J. Digital Libraries, Vol. 1, pp. 311-328, [1998].

[4] D. Zhang "Improving image retrieval performance by using both color and texture features," In Proc. IEEE 3rd Int. Conf. Image and Graphics (ICIG04), pp. 172-175, [2004].

[5] Chad Carson, Serge Belongie, Hayit Greenspan, and Jitendra Malik, "Blobworld: Image segmentation using Expectation-Maximization and its application to image querying," IEEE Trans. Pattern Anal. Mach. Intell., Vol. 24, pp. 1026-1038, [1999].

[6] N. Choudhary, Janak H. Patel, and Narendra Ahuja, "NETRA: A hierarchical and partitionable architecture for computer vision sys- tems," IEEE Trans. on Parallel and Distributed Systems, Vol. 4, pp. 1092-1104, [1993].

[7] H. Kavitha and Dr. M. V. Sudhamani, "Edge Detection of an Image based on Bi-Level Histogram Equalization and Ant Colony Optimiza- tion Technique", International Conference on Computer Technology and Science,New Delhi, pp 128-135, [2012].

[8] H. Kavitha and Dr. M. V. Sudhamani, "Content Based Image Retrieval - A Survey", International Conference on Computer Technology and Science,Nagpur,pp 35-42, [2012].

[9] H. Kavitha and Dr. M. V. Sudhamani, "A Survey of clustering algorithms for CBIR systems, National Conference on Computer Networks and Soft Computing,Tumkur, pp 53-56, [2012].

[10] H. Kavitha and Dr. M. V. Sudhamani, "Image retrieval **based on the Harris corner and edge** detection techniques", **IEEE International Conference on Com**munication, VLSI and **Signal Processing, pp.** 18**1-** 18**4, [**2013]**.**

[11] Sundaramoorthy, S., M. Kowsigan, J. Rajesh Kumar, and C. V. Arulkumar. "Semantic Keyword Search on XML." In International Journal of Engineering Research and Technology, vol. 1, no. 3 (May-2012). ESRSA Publications, 2012.