Content Based Image Retrieval Using Low Level Features of Automatically Extracted Regions of Interest

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***Abstract*— This paper proposes a region based image retrieval system using the local colour and texture features of image sub regions. The regions of interest (ROI) are roughly identified by segmenting the image into fixed partitions, finding the edge map and applying morphological dilation. The colour and texture features of the ROIs are computed from the histograms of the quantized HSV colour space and Gray Level co- occurrence matrix (GLCM) respectively. Each ROI of the query image is compared with same number of ROIs of the target image that are arranged in the descending order of white pixel density in the regions, using Euclidean distance measure for similarity computation. Preliminary experimental results show that the proposed method provides better retrieving result than retrieval using some of the existing methods.**

***Index Terms*— Content based image retrieval (CBIR); HSV color space; Regions of Interest; Colour histogram; Euclidean distance; GLCM.**

I. INTRODUCTION

The volume of image database is growing at an exponential rate with the steady growth of computer power, declining cost of storage and increasing access to Internet. To effectively manage the image information, it is imperative to advance automated image learning techniques. In the traditional method of text-based image retrieval the image search is mostly based on textual description of the image found on the web pages containing the image and the file names of the image [1]. The problem here is that the accuracy of the search result highly depends on the textual description associated with the image. Also un-annotated image collection cannot be searched. An alternate method is to retrieve image information based on the content of the image. The goal is to retrieve images that are semantically related to the user's query from a database. In Content based image retrieval systems the visual contents of the image such as colour, texture, shape or any other information that can be automatically extracted from the image itself are extracted and is used as a criterion to retrieve content related images from the database. The retrieved images are then ranked according to the relevance between the query image and images in the database in proportion to a similarity measure calculated from the features [2],[3].

Many early CBIR systems perform retrieval based on the global features of the query image [4],[5],[6]. Such systems are likely to fail as the global features cannot sufficiently capture the important properties of individual objects. Recently, much research has focused on region-based techniques [2],[3],[7] that allow the user to specify a particular region of an image and request that the system retrieve images that contain similar regions. Our research focuses on automatic identification of regions of interest and computing the feature vectors for comparison purpose. The regions of interest are roughly identified by segmenting the image into fixed partitions and finding the percentage of the object part in each partition.

II. REGIONS OF INTEREST EXTRACTION

The approximate regions of interest are detected by segmenting the image into fixed partitions and finding the percentage of the object part in each partition. Here the images are resized to 129x192 and divided into 3x3 equal sub-blocks. To identify the regions of interest/ prominent object regions, first the binary image is computed for the resized image and edge map is detected using Sobel edge filter. The gaps in the edge map are filled by morphological dilation using a 'line' structuring element that consists of three 'on' pixels in a row. The holes in the resultant edge map are then filled to identify the regions of interest. The white pixel regions roughly show the position of the object (Fig.1). A sub-block is identified as region of interest if the number of white pixels in that sub-block is greater than a certain threshold◀. Here we have taken ◀=30%. For example in Fig.1, regions 1, 3, 4, 5 and 8 are the ROIs. Only these sub-blocks take part in further computations for calculating the similarity. For each sub-block that is identified as ROI, the colour and

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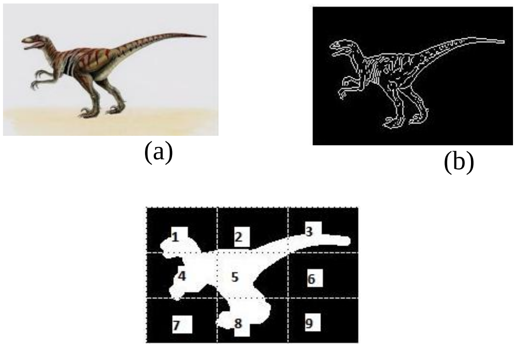
texture features are computed. Colour features are extracted from the histograms of quantized HSV colour space and texture features are computed from the gray-level co-occurrence matrix. Euclidean distance measure is used for calculating the distance between the query and the candidate images in the database.



(a) (b) (c)

Figure 1. Splitting the images into sub-blocks and identifying ROIs.

III. Feature Extraction

After identifying the image sub-blocks/ regions of interest, colour and texture features for each region are computed.

A. *Colour*

Colour is one of the most effective, simplest and widely used low level visual features employed in CBIR. As HSV colour space coincides better with human perception than the basic RGB colour space, we use HSV colour space for this work. For colour quantization, the HSV space is uniformly quantized to 18 bins for hue (each bin consisting of a range of 20 degrees), 3 bins for saturation and 3 bins for value. The histogram of each of these channels are extracted resulting in 24 colour feature vectors that are normalized in the range of [0,1].

B. *Texture*

Texture can be considered as repeating patterns of local variation of pixel intensities. Unlike colour, texture occurs in a region than at a point. A number of techniques have been used for measuring the texture features such as Gabor filter [8], fractals, wavelets, co-occurrence matrix etc. Using these texture features like contrast, coarseness, directionality and regularity can be measured. The gray-level co-occurrence matrix (GLCM) is a statistical method of examining texture that considers the spatial relationship of pixels [9]. It is a matrix showing how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. It is defined by $P(i,j|d, \theta)$, which expresses the probability of the couple of pixels at θ direction and d interval. Once the GLCM is created various features can be computed from it. The most commonly used features are contrast, energy, entropy, correlation and homogeneity (Table 1). We have taken d=1 and $\theta = 0$, 45, 90 and 135 for computing the texture features. Energy, contrast, correlation and homogeneity are calculated in all the four directions and entropy of the whole block only is computed resulting in 17 texture feature vectors for each sub-block.

TABLE I. Texture Features

Feature	Formula
Contrast	$\sum_{i,j} \lvert i-j\rvert^2 p(i,j)$
Correlation	$\sum_{i,j} (i-\mu i)(j-\mu j)p(i,j)/\sigma_i\,\sigma_j$
Energy	$\sum_{i,j} p(i,j)^2$
Entropy	$-\sum_{i,j} p(i,j)\, logp(i,j)$
Homogeneity	$\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j\rvert}$

IV. Similarity Measure

Euclidean distance metric is used for computing the similarity between the given pair of images.

$$d_{(I1,I2)} = \sqrt{(F_{I1} - F_{I2})^2} \tag{1}$$

Where, F_{I1} and F_{I2} are the feature vectors of image I_1 and I_2.

A. *Minimum Distance Computation*

For each ROI in the query image, the colour and texture features are computed and is compared with same number of ROIs of the target images that are arranged in the descending order of white pixel density in each region (Fig.2).

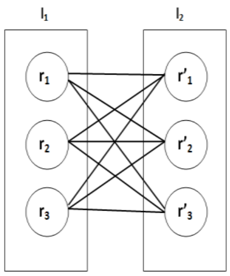


Figure 2. m regions of I_1 are compared with first m regions of I_2

Assume that image I_1 has m ROIs represented by R_1= {r1, r2,……,r_m} and I_2 has n ROIs represented by R_2={ r'_1, r'_2,……r'_n}. Let the distance between r_i and r'_j be d(r_i, r'_j) denoted as $d_{i,j}$. Every m region ri of R_1 is compared with first m regions r_j of R_2, that are arranged in the descending order of white pixel density in them. This results in 'm' comparisons for a single region in R_1

and m distance measures. These distances are stored in ascending order in an array and the minimum distance only is taken for the final computation of the distance D; the minimum distance between I_1 and I_2. Thus out of the m x n distances m lowest distances are added to get the distance D. This means that if image I_1 is compared with itself, D will be equal to zero. The algorithm for computing the minimum distance between two images is described below:

Input: R_1, R_2; the ROIs of the query and the target image.
Output: D, minimum distance between the query image I_1 and the target image I_2.
begin
  for each region in the query image I_1, *i*=1 to *m* **do**
    for first *m* regions in the target image I_2, j=1 to *m* **do**
      compute distance d[*j*]=d $_{i,j}$;
    end
    Sort distance array 'd' in ascending order;
    D=D+d[1];
  end
end
'd' is the array containing the distances between the r_i of R_1 with the *m* regions of R_2.

V. Experimental Results

The Wang's database of 1000 images consisting of 10 categories is used for evaluating the performance of the proposed method. Each category contains 100 images. A retrieved image is considered to be correct if and only if it is in the same category as the query. For each query, a preselected number (k) of images are retrieved which are illustrated and listed in the ascending order of the distance between the query and the retrieved images.

The precision and recall measurements are used here to describe the performance of the retrieval system. The precision (P) and recall (R) are defined as follows:

$$P(k) = \frac{n_k}{k} \text{ and } R(k) = \frac{n_k}{N} \tag{2}$$

Where k is the number of retrieved images, n_k is the number of relevant images in the retrieved images and N is the number of all relevant images in a particular category in the database. Also the average precision of the images belonging to the qth category Aq is given by

$$\overline{P_q} = \frac{\sum_{k\in A_q} P(I_k)}{|A_q|}, q = 1,2, \dots .10 \tag{3}$$

The final average precision is

$$\bar{P} = \sum_{q=1}^{10} \overline{P_q} /10 \tag{4}$$

Table.II shows the average precision of the retrieved images for different values of k. To evaluate the performance of the proposed method, we have compared the results with that of the method in [10] and global HSV histogram based retrieval. Table.III shows the average precision of the three methods when k=10. Fig.3 depicts the average precision of the proposed method for different values of k and that of the global HSV histogram based retrieval.

TABLE.II. Average Precision of retrieved images for different values of k

Category	P(100)	P(50)	P(20)	P(10)
Africa	40.85	52.38	64.85	72.22
Beaches	27.63	32.50	39.65	45.30
Buildings	28.86	35.84	46.30	54.00
Bus	61.36	75.92	83.15	86.30
Dinosaur	95.07	98.94	99.50	99.80
Elephant	34.83	44.00	55.55	65.50
Flowers	57.43	74.10	86.20	90.90
Horse	49.65	74.10	84.90	88.60
Mountain	21.46	42.92	29.45	35.10
Food	37.19	45.50	56.80	64.80
Average	**45.43**	**57.62**	**64.63**	**70.25**

TABLE. III Average Precision (k=10) of Retrieved Images For Different Methods

Category	Average Precision (k=10) of retrieved images using different methods		
	Global HSV Histogram	***Colour histogram + Gabor transform [7]***	***Proposed method***
Africa	66.76	79.50	72.22
Beaches	37.47	50.00	45.30
Buildings	48.2	46.80	54.00
Bus	64.4	51.70	86.30
Dinosaur	94.9	100	99.80
Elephant	46.9	61.70	65.50
Flowers	59.9	79.50	90.90
Horse	78.6	90.80	88.60
Mountain	45.4	28.40	35.10
Food	45.3	62.80	64.80
Average	**58.78**	**64.76**	**70.25**

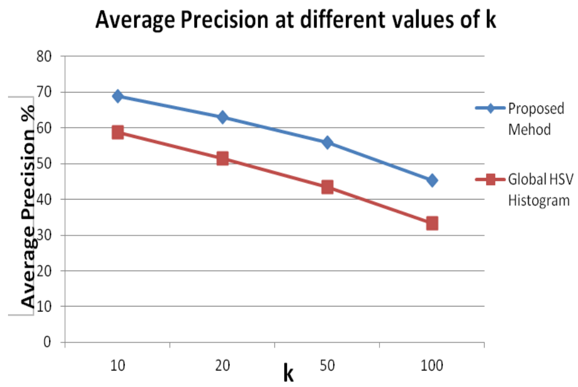


Figure 3. Average precision at different values of k.

Fig.4 shows the average precision- recall graph obtained by specifying the distance between query and target image <=9.0.

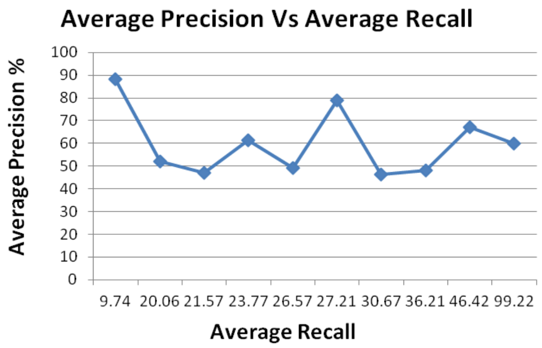


Figure. 4 Average precision Vs Average recall graph

Figure 5 and 6 depict the top 19 retrieved images for two sample query images using proposed method and global HSV histogram based retrieval. In each set, on top left corner is the query image and the retrieved images are listed according to their distance with the query image. It is seen that the proposed method provides more precise results than global HSV histogram based method.

(a)

(b)

Figure.5 Retrieved images. (a) Global HSV Histogram. (b) Proposed method

VI. Conclusion and Future Work

A content based image retrieval system using the color and texture features of the automatically extracted image sub-regions is proposed. Block-wise segmentation is used here as pixel-wise segmentation is computationally costly. The colour features are extracted from the histograms of the quantized HSV color space and texture features are computed from GLCM. Preliminary experimental results show that the proposed method provides better retrieving result than some of the existing methods. Future work aims at including the shape features and providing automatic feedback to improve the retrieval accuracy.

(a)

(b)

Figure.6 Retrieved images. (a) Global HSV Histogram. (b) Proposed method

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