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Content Based Image Retreival using HSV-Color Histogram and GLCM

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Abstract: Two of the main components of the visual information are texture and color. In this paper, a content-based image retrieval system (CBIR), which computes texture and color similarity among images, is presented. CBIR is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features. Color and texture are two important visual features of an image. This document gives a brief description of a system developed for retrieving images similar to a query image from a large set of distinct images. It follows an image segmentation based approach to extract the different features present in an image. These features are stored in vectors called feature vectors and compared to the feature vectors of query image and thus, the image database is sorted in decreasing order of similarity. An image is partitioned into sub-blocks of equal size as a first step. Color of each sub-block is extracted by quantifying the HSV color space into non-equal intervals and the color feature is represented by cumulative histogram. Texture of each sub-block is obtained by using gray level co occurrence matrix. A one to one matching scheme is used to compare the query and target image. Euclidean distance is used in retrieving the similar images. The efficiency of the method is demonstrated with the results.

Keywords: Content-based image retrieval (CBIR), Image retrieval, color, texture, cumulative histogram, gray level co-occurrence matrix (GLCM), Hue Saturation Value (HSV), Image search and Image similarity.

I. INTRODUCTION

Content-based image retrieval (CBIR) [1, 2, 3, 4, 5, 6] is motivated by the fast growth of digital image databases, which, in turn, require efficient search schemes. Content-based search will analyze the actual contents of the image. The term content refers to colors, shapes, textures, or any other information that can be derived from the image itself. The content based image retrieval techniques aim to respond to a query image with query similar resultant images obtained from the image database. The database images are preprocessed for extracting and then storing indexing corresponding image features. The query image also gets processed for extracting features which are compared with features of database images by applying appropriate similarity measures for retrieving query similar Images.. The CBIR system based on HSV color histogram [7] and GLCM texture. From the literature we came to know that the local features [4, 5, 6] play an important role in finding the similarity of images than global features [2, 3, 4]. So, in this paper, we present a technique for image retrieval based on local color and texture features [8, 9, 10]. Because Low level visual features of the images such as color and texture are especially useful to represent and to compare images automatically. In the concrete selection of color and texture description, we use color histogram, Gray-level co occurrence matrix.

Texture is also an important visual feature that refers to innate surface properties of an object and their relationship to the surrounding environment. Many objects in an image can be distinguished solely by their textures without any other information. There is no universal definition of texture. Texture may consist of some basic primitives, and may also describe the structural arrangement of a region and the relationship of the surrounding regions [17]. In our approach we have used the statistic texture features using gray-level co occurrence matrix (GLCM). The gray level co-occurrence matrix (GLCM) defined by Haralick[11] can reveal certain properties about the spatial distribution of the gray levels in the texture image. It denotes how often a pixel with the intensity value i occurs in a specific spatial relationship to a pixel with the value j. In GLCM , each element p (i, j) is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j. By default, the spatial relationship is defined as the pixel of interest and the pixel to its horizontally adjacent. In this work, four spatial relationships were specified: 0º, 45º, 90º and 135º. The number of intensity values in grayscale image is used scaling to reduce from 256 to 8, so the matrix size is 8 by 8.

So a technique is developed which captures color and texture features of sub-blocks of the image. For each sub block cumulative histogram and static texture features using GLCM are determined. A one to one integrated matching procedure is used to find the image similarity. The approach is the color and texture features are extracted from the each image into color and texture Vector. For better performance these two vectors are combined and form a feature vector of an image. In this approach segments the image into regions based on color and texture features. The regions are close to human perception and are used as the basic building blocks for feature computation and similarity measurement. The integrated region matching (IRM) algorithm [5] proposes an image-to-image similarity combining all the regions between the images. In this approach, every region is assigned significance worth its size in the image. A region is allowed to participate more than once in the matching process till its significance is met with. The significance of a region plays an important role in the image matching process. In either type of systems, segmentation close to human perception of objects is far from reality because the segmentation is based on color and texture. The objective of this paper is to develop a technique which captures local color and texture descriptors in a coarse segmentation framework. The image is partitioned into equal sized non-overlapping tiles. The features computed on these tiles serve as local descriptors of color and texture. The experimental evaluation is based on the 1000 COREL color image database.

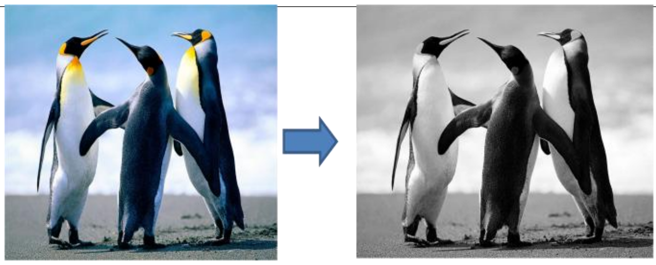
II. PROPOSED SYSTEM

The proposed system is based on color and texture features of image tiles with one to one matching. The algorithm for the proposed system is given below:

Input: 256×384 size image from database.
Output: Retrieved images from database.
Start:
Step 1: Pre-processing of the Image.
Step 2**:** Partitioning the image into sub-blocks.
Step 3: Compute Histogram.
Step 4: Compute GLCM (Gray Level Co-Occurrence Matrix).
Step 5: Feature vector construction for color and texture.
Step 6: Computing the Similarity.
Step 7: Image Retrieval.

A. Pre-processing of the Image

Pre-processing of the Image to reduce the total number of pixels per Image (without compromising the image quality) in order to reduce the total number of pixels per image and therefore decreasing the computation time. System based on an image size of 256×384. The main activities in this step are, Read an image and convert to Gray scale format. The images with other than 256X384 sizes are resized to 256X384.Figure 1 shown the preprocessing of image.



RGB Image (256×384) Gray Scale Image (256×384)

Figure 1.Pre-Processing of Image

B. Partitioning the image into sub-blocks

In this step an image is segmented into a collection of objects. An "object" is a set of pixels that are connected and have the same (quantized) color. When an image is inserted in the database, it is converted to a collection of objects and these attributes are automatically extracted. Firstly the image is partitioned into 6 (2X3) equal sized tiles as shown in Fig.2. The size of the tile in an image of size 256X384 is 128X128.

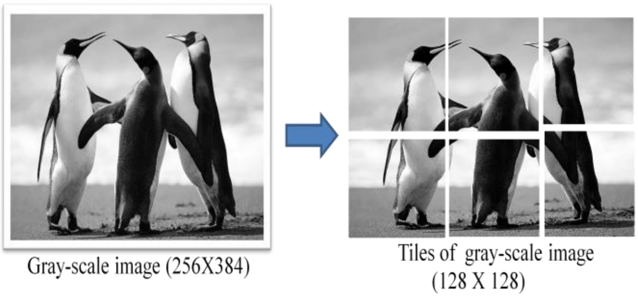


Figure. 2 partitioned image

C. Compute Histogram

During this step following actions are done, Color Space Conversion, Color Quantization and Compute Histogram. In color space conversion, Translate the representation of all colors in each image from the RGB space to the HSV space. In the HSV color space [12], hue is used to distinguish colors, saturation is the percentage of white light added to a pure color and value refers to the perceived light intensity. Therefore we have opted the HSV color space to extract the color features according to hue, saturation and value. In color quantization, for every image in the database, colors in the HSV model are quantized, to make later computations easier. Color quantization reduces the number of distinct colors used in an image. In compute histogram (Sequence), for every quantized image, a color histogram is calculated, which is a frequency distribution of quantized HSV values of each pixel of an image. For each tile construct cumulative HSV color histogram. A color histogram is a representation of the distribution of colors in an image. For digital images, a color histogram represents the number of pixels that have colors in each of a fixed list of color ranges that span the image's color space, the set of all possible colors.

We observed that HSV color space is better than the RGB color model for our approach using the following quantization scheme where each component is quantized with non-equal intervals: H: 8 bins; S: 3 bins and V: 3 bins. Finally we concatenate 8X3X3 histogram and get 72-dimensional vector [16]. To reduce the number of zeros in the histogram, we adopted the cumulative histogram. The procedure is as follows: In the HSV color space, each component occupies a large range of values. If we use direct values of H, S and V components to represent the color feature, it requires lot of computation. So it is better to quantify the HSV color space into non-equal intervals. At the same time, because the power of human eye to distinguish colors is limited, we do not need to calculate all segments. Unequal interval quantization according the human color perception has been applied on *H, S, and V* components.

Based on the color model of substantial analysis, we divided Hue into eight parts. Saturation and intensity is divided into three parts separately in accordance with the human eyes to distinguish [12, 13, 14]. In accordance with the different colors and subjective color perception quantification, quantified hue (H), saturation (S) and value (V) are showed as equation 1.

$$H = \begin{cases} 0 if h \in [316, 20] \\ 1 if h \in [21, 40] \\ 2 if h \in [41, 75] \\ 3 if h \in [76, 155] \\ 4 if h \in [156, 190] \\ 5 if h \in [191, 270] \\ 6 if h \in [271, 295] \\ 7 if h \in [296, 315] \end{cases} \qquad S = \begin{cases} 0 if s \in [0, 0.2) \\ 1 if s \in [0.2, 0.7) \\ 2 if s \in [0.7, 1) \end{cases} \qquad V = \begin{cases} 0 if v \in [0, 0.2) \\ 1 if v \in [0.2, 0.7) \\ 2 if v \in [0.7, 1) \end{cases} \quad (1)$$

D. Compute GLCM

The gray level co-occurrence matrix (GLCM) defined by Haralick[11] can reveal certain properties about the spatial distribution of the gray levels in the texture image. It denotes how often a pixel with the intensity value i occurs in a specific spatial relationship to a pixel with the value j. In one GLCM, each element p (i,j) is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j. Four GLCM texture features are commonly used which are given below, Energy, Contrast, Correlation, and Homogeneity. GLCM is composed of the probability value, it is defined by which expresses the probability of the couple pixels at θ direction and d interval. When θ and d is determined, is showed by P(i, j). Distinctly GLCM is a symmetry matrix and its level is determined by the image gray-level. Elements in the matrix are computed by the equation shown below:

$$P(i, j|d, \theta) = \frac{P(i, j|d, \theta)}{\sum_i \sum_j P(i, j|d, \theta)} \quad (2)$$

In this paper, four texture features are considered. They include energy, contrast, correlation and homogenity.Energy is a texture measure of gray-scale image represents homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

$$\text{Energy} \quad E = \sum_x \sum_v P(x, y)^2 \quad (3)$$

Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth. Contrast is large means texture is deeper. Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. Range = [0 (size (GLCM, 1)-1) ^2] .Contrast is 0 for a constant image.

$$\text{Contrast} \quad I = \sum \sum (x - y)^2 P(x, y) \quad (4)$$

Correlation measures image texture randomness, when the space co-occurrence matrix for all values is equal, it achieved the minimum value; on the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random. Returns a measure of how correlated a pixel is to its neighbor over the whole image. Range = [-1 1].Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image.

$$\text{Correlation (C)=-}\sum_x \sum_y P(x, y) \log P(x, y) \quad (5)$$

Homogeneity measures number of local changes in image texture. It measures local changes in image texture number. Its value in large is illustrated that image texture between the different regions of the lack of change and partial very evenly. Here $p(x, y)$ is the gray-level value at the coordinate (x, y). Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Range = [0 1] Homogeneity is 1 for a diagonal GLCM.

$$H = \sum_x \sum_y \frac{1}{1+(x-y)^2} P(x,y) \tag{6}$$

Four texture features are computed for all the tiles of an image and is used as feature descriptor.

E. Feature vector construction for color and texture.

In accordance with the quantization level above, three dimensional feature vectors for different values of H, S, V with different weight to form one-dimensional feature vector named G:

$$G=Qs\ Qv\ H + Qv\ S + V \tag{7}$$

Where *Qs* is quantified series of S, *Qv* is quantified series of V. Here we set *Qs*=*Qv* =3, then

$$G = 9H + 3S + V \tag{8}$$

Finally we concatenate 8X3X3 histogram and get 72-dimensional vector. At the same time, because the power of human eye to distinguish colors is limited, we do not need to calculate all segments. In this way, three-component vector of HSV form One-dimensional vector, which quantize the whole color space for the 72 kinds of main colors. So we can handle 72bins of one-dimensional histogram. This quantification can be effective by reducing the computational time and complexity. It will be much of the deviation of the calculation of the similarity if we do not normalize, so we must normalize the components to the same range. The process of normalization is to make the components of feature vector equal importance. In accordance with the quantization level, 3-dimensional feature vector for different values of H, S, and V is converted to 1-dimensional vector. This quantizes the whole color space for the 72 kinds of main colors. So we can handle 72bins of 1-dimensional histogram.

F. Computing the Similarity

Find the distances between feature vector of query image and the feature vectors of target images using normalized Euclidean distance. The similarity between sub-blocks of query and target image is measured from two types of characteristic features which includes color and texture features to formulate the graph. Matching of the sub-blocks is done based on one to one matching. Two types of characteristics of images represent different aspects of property. So during the Euclidean similarity measure, when necessary the appropriate weights to combine them are also considered. Therefore, in carrying out Euclidean similarity measure we should consider necessary appropriate weights to combine them. We construct the Euclidean calculation model as follows:

$$D(A, B) = \omega 1 D(FCA, FCB) + \omega 2 D(FTA, FTB) \tag{9}$$

Here ω1 is the weight of color features, ω2 is the weight of texture features, *FCA* and *FCB* represents the normalized 72-dimensional color features for image A and B. For a method based on GLCM, *FTA* and *FTB* on behalf of 4- dimensional normalized texture features correspond to image A and B.Here, we combine color features and texture features. The value of ω through experiments shows that at the time ω1=ω2=0.5 has better retrieval performance.

G. Image Retrieval

The process of retrieving images is based on the sorting of Euclidean distances, Retrieve first 20 most similar images with minimum distance. Finally, the accepted images are displayed in the order of similarity score. The proposed scheme is shown in figure 3

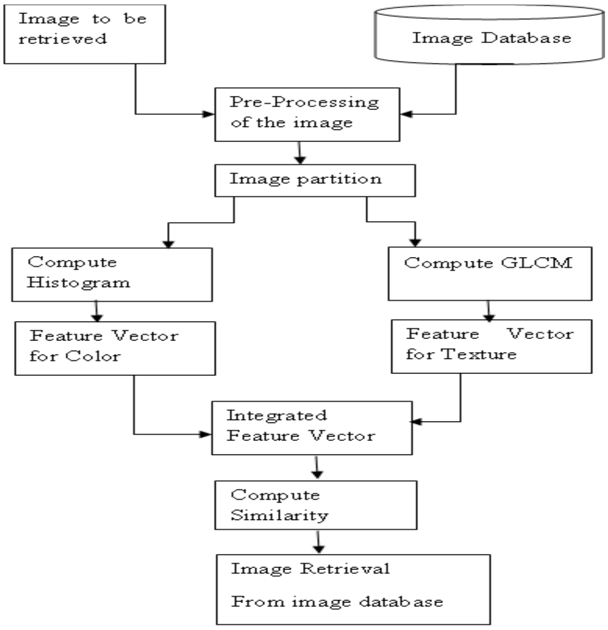


Figure 3.Proposed Scheme

III. Experimental Setup and Results

A. Test database

Wang's dataset comprising of 1000 Corel images with ground truth. The image set comprises 100 images in each of 10 categories. The images are of the size 256 x 384 or 384X256. But the images with 384X256 are resized to 256X384.

3.1 Feature set

The feature set comprises color and texture descriptors computed for each sub-block of an image as we discussed in section 2.

3.2 Results

The results are benchmarked with some of the existing systems using the same database. The quantitative measure is given below

$$p(i) = \frac{1}{100} \sum_{1 \le j \le 1000, r(i,j) \le 100, ID(j) = ID(i)} 1 \qquad (10)$$

Where *p (i)* is precision of query image I, ID (i) and ID (j) are category ID of image I and j respectively, which are in the range of 1 to 10. The r (i, j) is the rank of image j. The average precision *pt* for category ***t*** **(**1≤t≤10) is given by

$$p_t = \frac{1}{100} \sum_{1 \le i \le 1000, ID(i) = t} p(i) \qquad (11)$$

The experiments were carried out on a Core i3, 2.4 GHz processor with 4GB RAM using MATLAB. The comparison of proposed method with other retrieval systems is presented in the Table 1. These retrieval systems are based on HSV color, GLCM texture and combined HSV color and GLCM texture. Our sub-blocks based retrieval system is better than these systems in all categories of the database. Table1. Comparison of average precision obtained by proposed method with other retrieval systems. In our data base, there are ten categories. In each class of images, one can observe the improvement in the average precision value by our proposed method when compared with other techniques.

Table1. Average precision

Class	Average Precision			
	HSV color	GLCM Texture	HSV color +GLCM Texture	HSVcolor +GLCM Texture of image sub-blocks(proposed method)
Africa	0.36	0.21	0.34	0.41
Beaches	0.27	0.35	0.21	0.32
Building	0.38	0.50	0.24	0.37
Bus	0.45	0.22	0.51	0.66
Dinosaur	0.26	0.29	0.39	0.43
Elephant	0.3	0.24	0.26	0.39
Flower	0.65	0.73	0.81	0.87
Horses	0.19	0.25	0.28	0.35
Mountain	0.15	0.18	0.20	0.34
Food	0.24	0.29	0.25	0.31

The graph in Figur.4 shows the Comparison of average precision obtained by proposed method with other retrieval systems.

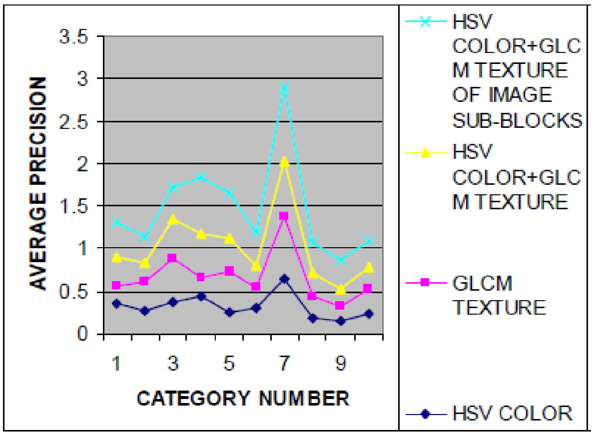


Figure 4.Average Precision of various image retrieval methods

IV. Conclusion

In this paper a new image retrieval method based on HSV color and GLCM texture features of image sub-blocks with one to one matching is proposed. We combined color and texture features with normalized Euclidean distance. Our experimental results demonstrate that the proposed method based on color and texture features of image sub-blocks has better retrieval performance compared with the Image retrieval system using only HSV color, only GLCM texture and combined HSV color and GLCM texture. As further studies, the proposed retrieval method is to be evaluated with other integrated matching techniques.

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