International Journal of Research (IJR)
e-ISSN: 2348-6848, p- ISSN: 2348-795X Volume 2, Issue 09, September 2015
Available at http://internationaljournalofresearch.org

Digital Library: The YUV Component Information Based on the Image Retrieval Performance by Using Both Color and Texture Features

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ABSTRACT

Region of interest (ROI) plays an important role in image analysis. In this paper, an efficient approach for content based image retrieval combining both color and texture features using three ROIs is proposed. Region based feature have shown to be more effective than global features as they are capable of reflecting users specific interest with greater accuracy. However success of region based methods largely depends on the segmentation technique used to automatically specify the region of interest (ROI) in the query. Apart from this user can also specify ROI's in an image. The ROI image retrieval involves the task of formulation of region based query, feature extraction, indexing and retrieval of images containing similar region as specified in the query. In this paper state-of-the-art techniques for ROI image retrieval are discussed.Firstly, segment image to three parts using K-means algorithm. Secondly, select three ROIs from the three parts and then extract color features and texture features of ROIs. The similarity of two images will be determined by the similarities between pairs of ROIs.The experimental results demonstrate that the proposed method is encouraging with a successful retrieval rate.

Introduction

Content based image retrieval (CBIR) has been an active research topic in the last few years. Shape, texture and color are three main features that are being used in CBIR systems. Many researchers applied texture in finding similarities between images in a database. In QBlC[1] system, Ni black et al. used features including color, texture and shape, and for texture, coarseness, contrast and directionality are used. In the Photo book [2],Pent land et al. applied features based on appearance 2D shape and texture proprieties, and they used Laws' texture energy maps to extract textural features and introduced a global signature based on a sum of weighted Gaussian to describe the texture. R.S. Torres, E.M. Picado and L.F. Costa[3] used a shape descriptor called contour saliences to realize shape based image retrieval. A. Benazza-Benyahia et al.[4] extracted image texture features with lifting wavelet schemes. Y.J. Song et al.[5] used a new color histogram to extract color feature. There are also many algorithms combine two or three features among of shape, texture and color. D.S. Zhang[12] firstly ranked images using color features and then re-ranked the top ranked images according to their texture features. S.K. Saha, A.K. Das and B. Chanda[13] used a texture co-occurrence matrix and fuzzy index of major colors to improve performance. All the above methods have received great achievements, but sometimes their features do not work for CBIR, especially for color nature images. Most retrieval systems rely on global image characteristics but they more often fail due to the lack of higher-level knowledge about what exactly was of interest to the user in the query image. On the other hand, most retrieval systems use color as image features. However, nature image retrieval using color features often gives disappointing results because in many cases, images with similar colors do not have similar content. The color set and texture set can be combined to create an even more powerful characterization of image content. In this paper, a novel approach is proposed for color and texture based retrieval using three ROIs. The processing of selecting ROIs is simple and the computation is fast because it makes partial match. It first use K-means algorithm to segment image to three regions and then respectively select one ROI from every region. The end, extract color features and texture features from three ROIs. The similarity of two images will be determined by the similarities between pairs of ROIs.

2. Extraction of features

2.1. Color features

There are many color spaces for image processing, such as RGB, CMY, HSV and MTM [13]. To extract color features, we use the hue histogram of HSV color space. In order to use HSV space, color values are converted from RGB space into HSV space using the following transforms, here we just give hue value formula.

When R≠G or R≠B

$$H = \arccos \frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}} \qquad (1)$$

When B>G

$$H = 2\pi - \arccos \frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}} \qquad (2)$$

After transformation, hue value is between 0 to 2π. In order to avoid complex computation, the hue value level is normalized to 12. In this paper proposed method, we just compute ROI's hue histograms as color features for retrieval.

2.2. Texture features :

The gray level co-occurrence matrix(GLCM) defined by Haralick [8] 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 I, 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.

$$p(i,j) = \frac{\#\{(p1,p2) \in I \mid p1 = i \; \& \; p2 = j\}}{\# I} \qquad (3)$$

In order to estimate the similarity between different gray level co-occurrence matrices, many statistical features extracted from them were proposed [9]. In this study we use the four of them: energy, entropy, contrast and

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e-ISSN: 2348-6848, p- ISSN: 2348-795X Volume 2, Issue 09, September 2015
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homogeneity. In this paper proposed method, the keystone is ROI, so just construct GLCMs of ROIs, and compute four statistical features of ROIs for retrieval.

3. Proposed method:

In a natural image, there may be a lot of object regions, but from the perspective of human vision, people generally only pay attention to 1~3 object regions. In our work, we first segment image to three parts, then select three ROIs from different parts, finally extract color features and texture features of ROIs to make partial match. The similarity of two images will be determined by the similarities between pairs of ROIs. We use a simple clustering algorithm: K-means algorithm to segment image to three parts according to gray value.

3.1. Image segmentation using K-means algorithm:

K-means is one of the simplest unsupervised learning algorithms that solve the clustering problem. Simply speaking it is an algorithm to classify or to group your objects based on features into K number of group[8]. K is positive integer number. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid. Thus, the purpose of K-means clustering is to classify the data.

$$J = \sum_{j=1}^{\varphi} \sum_{i=1}^{n} \| x_i^{(j)} - c_j \|^2 \qquad (4)$$

Formula 4 is an indicator of the distance of the n data points from their respective cluster centers[7], where || xi (j) - cj ||2 is a chosen distance measure between a data point xi (j) and the cluster centrecj. In this paper proposed method, we firstly divided image to 32 by 32 segments with size 4 by 4, we can not get a exact segmentation result if the size is very large; and then compute average gray value of every segment; because we need three RIOs, so the average gray values are segmented into three groups using K-means clustering algorithm, this means we use this algorithm with K=3. After segmentation, there are just three values in the segmentation image

3.2. Selection of ROI:

A Region of Interest, often abbreviated ROI, is a selected subset of samples within a dataset identified for a particular purpose[10]. Considering both the segmentation quality and computational cost, in this paper we propose a simple and efficient approach to extract ROI. After using K-means clustering algorithm, the original image was segmented to three regions, one region only has one gray value, showed in Fig.2. In Fig.2, the sample image is segmented three parts: region 1, region 2 and region 3. All pixels of region 1 gray value is 208; All pixels of region 2 gray value is 163; All pixels of region 3 gray value is 69. We select one ROI with size 32 by 32 from every region, the ROI has the maximum number of pixels which has same gray value with this region. Furthermore ROI1 is in the largest region of three regions; therefore, it is very important when calculating two images distance.

Most image-related tasks can process a subset of the pixels in an input image. Depending on the task, the selected pixels may either be a fairly arbitrary region, or only a regular subimage of the input image.

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The task parameter, region, which gives the region-of-interest consists of a combination of subcommands. Each subcommand specifies either a sub region or the units of the coordinates used in subsequent sub-commands.

The sub regions selected by multiple subcommands are effectively `OR-ed' together to form the overall region. That is, the overall region selected is the `union' (not intersection) of the sub regions.

For comparatively simple regions, combining subcommands is quite adequate. However for complex regions, a cursor-based program, cgcurs, may be the most convenient for generating the subcommands

Region specification is composed of one or more of the following subcommands. Each subcommand can be abbreviated to uniqueness, and subcommands are separated by a comma.

images(*z1,z2*)

This selects the image planes *z1* to *z2* inclusive. *z2* is optional, defaulting to the same value as *z1*.

quarter(*z1,z2*)

This is somewhat like the images command, except that it selects only the central quarter of each plane. Both *z1* and *z2* are optional.

box(*xmin,ymin,xmax,ymax*)(*z1,z2*)

This subcommand selects the pixels within a box whose corners are *xmin, ymin,xmax* and *ymax*. *z1* and *z2* are optional, and are the same as in the imagesubcommand. If the (*z1,z2*) part is missing, a default is used (generally all planes are selected).

polygon(*x0,y0,x1,y1,x2,y2,...*)(*z1,z2*)

This gives the vertices of a polygon. box(*xmin,ymin,xmax,ymax*) is equivalent to poly(*xmin,ymin,xmax,ymin,xmax,ymax,xmin,ymax*). *z1* and *z2* are the same as with the images and boxes subcommands.

mask(*name*)

This selects pixels according to the mask given by the mask item in the dataset *name*.

4. Retrieval performance:

When image is retrieved, sometimes only partial regions are real interest to the researcher. In this paper proposed method, we just select three regions as retrieval keywords from different parts of image. So the emphases are the process of selecting three ROIs and extracting their features. The first one is that divide image to 32 by 32 regions with size 4 by 4 and compute average gray value of every region. The second step is image segmentation. Using K means algorithm with K=3 cluster average gray value of all regions, so the image is segmented to three regions. The third step is extracting ROI. In here, we use the method which is proposed at section 3.2 to extract three rectangular regions with size 32 by 32. These partial regions are the key of image retrieval. The fourth, respectively compute hue histograms of three ROIs as color feature vector, and then construct four directions gray level co-occurrence matrices for every ROI, and compute their four statistical features as texture feature vector. The four statistical features are contrast, entropy, energy and inverse difference moment. They measure respectively the amount of local variations, disorder, texture uniformity and homogeneity in an image. The end, regard the partial region's feature as feature vector of

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the image, and obtain distance measures using Euclidean distance. Because we compute distance between query image's three ROIs and database image's three ROIs and all ROI were extracted two features: color feature and texture feature, so the process of compute distance is not an easy process. Fig.3 shows it. In Fig.3, d11c is the color feature distance between query image ROI1 and database image ROI1, d11t is the texture feature distance between query image ROI1 and database image ROI1, d11 is the distance between query image ROI1 and database image ROI1, etc. the distance between ROI is a sum of color distance and texture distance with weight, the weight is decided by user; w1 is color feature's weight, w2 is texture feature's weight; if query image has prominent texture characteristics, example leopard images , zebra images, etc, w2 should be given a large value:0.7~0.9; otherwise if query image has prominent color characteristics, example cherry images, etc, w1 should be given a large value:0.7~0.9; for general query image, w1 and w2 are given 0.5. We first compute all color distances and texture distances between query image's ROIs and database image's ROIs: d11c, d11t, d12c, d12t…, and then compute all distances between query image's ROIs and database image's ROIs: d11, d12, d13, d21…, save the minimum distance to dis1. Next compute dis2 just use ROIs which are not used when compute dis1. Use same method to compute dis3. The distance between query image and database image is sum of dis1, dis2 and dis3.

5. Experimental result

5.1. Test database The test database consists of 300 nature images withsize 128 by 128; It consists of 5 classes, including cherries, jokul,landscape, footway and palaestra.

5.2. Performance results

The samples of retrieval results are shown in Fig.1 nin every result, we select the 20 most similar images inorder and the first image is the query image,

CONCLUSION :

In this paper, a novel color and texture based retrieval of color natural image algorithm using three ROIs was proposed. The first advantage is that clustering algorithm: K-Means method is used to the image retrieval system. It segments image to three parts using K-Means clustering algorithm, and use a simple, speedy method to extract three ROIs from different parts; the second advantage is that it does partial match for retrieving image, this makes the speed and accuracy of the retrieval are improved. The third advantage is the method of computing many-tomany relationships distance, query image has three ROIs, database image has three ROIs and all ROIs have two features, this method can compute the best distance between query image and database image. It gives encouraging results when comparing its retrieval performance to texture based retrieval using one ROI algorithm

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