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Image Retrieval Using Relative Location of Multiple ROIS

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Abstract: Image retrieval is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image and the system will return images "similar" to the query. The similarity used for search criteria could be meta tags, color distribution in images, region/shape attributes, etc. Recently, region based image retrieval has been improved which measures the similarity of the images without proper consideration of the spatial layouts of the ROIs and thus fails to reflect the intent of the user. To meet the challenges, we propose Image Retrieval Method using Relative Location for Multiple Region of Interest (ROI), a similarity measurement using the relative layouts of the ROIs. In contrast to the earlier CBIR, the multiple ROI is specifically designed for the user to choose multiple region of interest from the image and retrieve it. Features of Multiple ROI are the images are divided into blocks of certain sizes to measure the similarities with the target image. In addition to CBIR using multiple ROIs, we extract the texture and object shape features.

Key words: Retrieval, location, attributes, blocks, shape features

INTRODUCTION

Image retrieval methods can be broadly divided into those using text information included in the images and those based on the contents of images themselves. Recently, using images on the internet rapidly increases, additional information such as text attached to images is often unavailable hence the need for retrieval methods based on the contents of images has been on the increase.

Content-based image retrieval is a technology that in principle helps to organize picture archives by their visual content. With the rapid growth of computing power and digital image acquisition devices available, how to effectively retrieval digital images in a large library is still a highly challenging (Datta *et al*., 2008).

In recent years, the construction of region-based visual signature was attracted more attention (Chen and Wang, 2002; Chen and Wang, 2004). Image segmentation is a key step to acquire a region-based signature. However, content-based image retrieval that confront many image types, some of them even have not a clear object, so some strategies for dealing with this problem is to reduce dependence on accurate image segmentation for a practical image retrieval system (Carson *et al*., 2002).

The methods of selecting ROIs from images are divided into methods in which the retrieval system recognizes key objects in the images and automatically specifies them as ROIs (Prasad *et al*., 2004) and those enabling the user to choose ROIs directly (Tian *et al*., 2002; Moghaddam *et al*., 2001). If the system automatically designates ROIs, they may not correspond to the regions that the user wishes to retrieve.

To overcome the issues, we propose the Image retrieval using relative location of multiple region of interest. For this purpose, images are divided into coordinate planes with four quadrants centering on the basis ROI to determine which quadrants individual ROIs are located in. Retrieval systems are just as important in CBIR as the feature calculation methods. In this paper, the proposed retrieval system will adopt various methods to retrieve images from the database based on the user selected multiple regions of interest.

Literature review: For region of interest based image retrieval, the user should specify the required region from the images. In contrast to image-based query systems, region-based systems do not treat each image as an atomic and indivisible entity but rather work at the subimage level by extracting, indexing and comparing image regions and corresponding features. Region information can be used not only to locate relevant (Lakshmi-Ratan). Initial systems tackled the content-based image retrieval problem by using color histograms, texture and shape features. The first systems

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from this class were the QBIC system (Niblack *et al*., 1993) (Flickner) from IBM, the Virage system (Gupta and Jain, 1997) by Virage Inc. and the Photobook system (Pentland *et al*., 1995) from the MIT Media Lab.

MATERIALS AND METHODS

The architecture of the system is described by its functionalities and components. The overall system architecture is shown The above overall system architecture (Fig. 1) describes about the image retrieval based on the query image and the target image. The query image is given as input by the user. The query image is segmented by dividing the images into regions. Second, the feature extraction of the image is done based on the color and shape of the image. Next the user intended multiple region of interest is extracted from the image and the output is taken as region 1-3, etc. The extracted regions are loaded in the image search and the most related target images are retrieved in the system.

Segmentation of images: Image segmentation is one of the most important steps leading to the analysis of the processing images. The main goal is to divide an image into parts that have a strong correlation with the objects or areas of the real world that are contained in an image. Image segmentation means grouping and clustering pixels according to the similarity criterion of some features or set of features and then dividing the image into some non-overlapping regions which have some coherence. Multi-scale local features are to obtain more representative and robust features and avoid the impact of noise. The dominant foreground region of an image is the region which occupies most of the space in the image foreground.

Feature extraction: Feature extraction is a special form of imensionality reduction. When the input data to an algorithm is too large to be processed, the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. From the segmented image, we need to extract features from each region. Features (color, texture, Normalized area (Narea), location and shape) of each region are used to describe the content of the image.

Feature normalization: For feature normalization, this method chooses to use the Gaussian normalization method. Let, Fi = (fi1, ..., fik, ..., fiq) be the feature vector representing the ith image in the database. We compute the mean, uk and standard deviation, σ of the k-th feature dimension. We then normalize the feature vectors to N(0,1) according to:

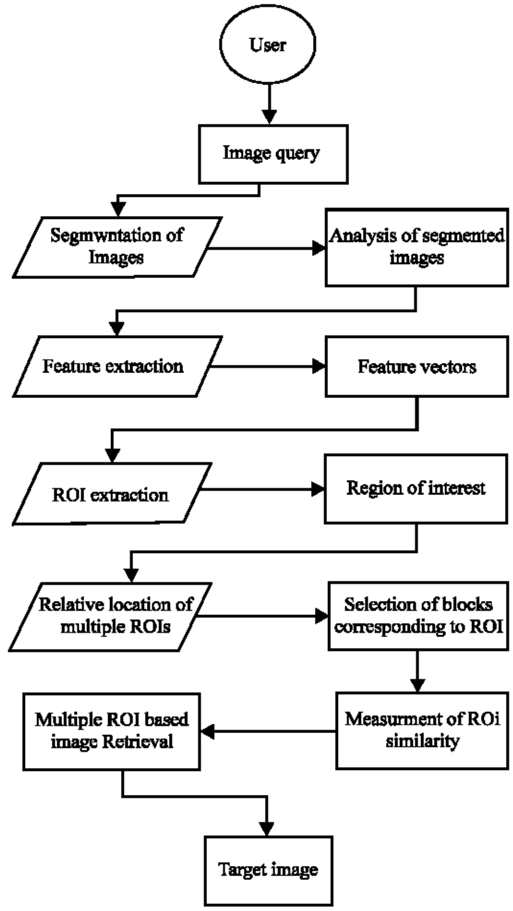

Fig. 1: The proposed method for image retrieval for multiple ROIs

$$Fi = (fi1\text{-}u1/K\sigma1,\ldots,fikuk/K\sigma k,\ldots,fiq\text{-}uq/K\sigma q)$$
$$= (f'i1,\ldots,f'ik,..f'iq)$$

Color feature extraction: We extract the average color (Ar, Ag, Ab) of the RGB color space from each region instead of color histogram in order to reduce the storage space. The color distance ($d_{Q,r}^{c}$) between the Query (Q) and the target region (r) is measured by the city-block distance:

$$d^{c}_{Q,r} = |Ar_Q - Ar_r| + |Ag_Q - Ag_r| + |Ar_Q - Ar_r|$$

Texture feature extraction: This method choose the Discrete Wavelet Transformation (DCTWT) as the texture feature. By BWF, we can obtain a fst and precise directional feature compare with multi resolution method and get the same size of low pass and high pass images from the original image. Each high pass image is decomposed again into X-Y directional sub images. The distance in texture ($d_{Q,r}^{r}$) between two regions, Q and r is computed by city block distance:

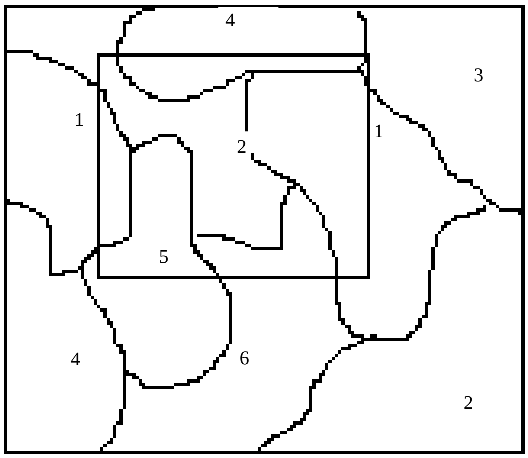

Fig. 2: Illustration of an ROI (lined box inside) select from a segmented imagine

$$d^{r}_{Q,r} = |Yd_Q/Xd_Q - Yd_r/Xd_r|$$

Normalized area feature extraction: Feature NArea is defined as the number of pixels (NP) of a region divided by the image size. The distance in Narea ($d^{NArea}_{Q,r}$) between Query (Q) and target region(r) is computed by city block distance: $d^{NArea}_{Q,r} = |NP_Q - NP_r|$.

ROI extraction: As mentioned earlier in the study, our proposed method allows users to impose their desired requirements on the query image. That is the user is asked to capsulate their desired requirements on the query image using any desired shape. Once, the ROI is selected, the proposed method will perform the image analysis. The match between the user selected ROI and each target image from the database is based on similarity comparisons between the extracted features. Our proposed method allocates the constrains in the process of query, and reflects the user specification by ignoring other parts of the sample and only taking into account the selected ROI (Fig. 2).

Relative location for multiple ROIS: The region of interest based image retrieval are used for selecting ROI corresponding blocks and reflects the relative location of ROIs in distance measurement to improve the accuracy of image retrieval.

Block selection of ROI: For ROI-based image retrieval, the user should be able to select ROIs directly to reflect his/her interest on the retrieval process. To use the feature values of blocks, it is instrumental to determine blocks overlapping with ROIs first which can be done in the following two ways: first, the feature values of blocks overlapping with ROIs are fully reflected. Second, the proportion of overlap between ROIs and blocks is taken into account (Fig. 3).

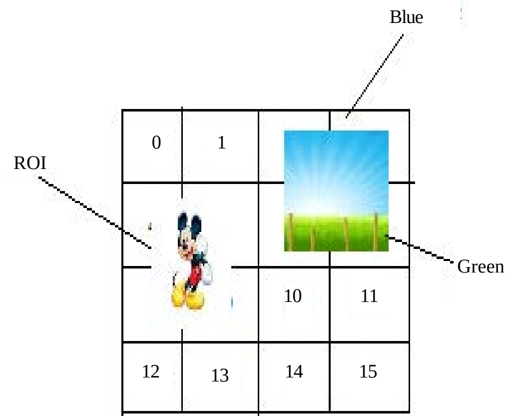

Fig. 3: Comparison of ROI and image block locations

For example, let us assume as illustrated in Fig. 3 that the blocks are divided into 4×4 and that the ROIs overlap with blocks are # 0, 1, 2, 4, 5, 6, 8, 9 and 10.

Similarity measurement: Similarity between ROIs of the query image and the target image is measured by the feature values of ROI-overlapping blocks of the query image and the distance from the target image. The degree of similarity becomes greater when the measured distance has a smaller value. The similarity is measured by obtaining the list of blocks in the query image corresponding to ROIs (R_b) and scanning the target image m times by the unit of blocks to find the nearest block list to b R. The distance is determined by the similarity measure between ROIs and the query image. This can be written as equation:

$$SD(R_b, I^j) = \min(RD_i(R_b, I^j_{bi})),\ i=1,...,m$$

The SD (R_b, I^j) measures the degree of similarity between R_b and target image and I_j represents the jth image of the image database. The RD (R_b, I^j_{bi}) measures the distance between R_b and each block list I^j_{bi} in the target image I_j). I^j_{bi} means the ith block list of the jth image that corresponds to R_b. In RD (R_b, I^j_{bi}), the similarity of blocks is measured using different similarity calculation methods by the property in use. For SD (R_b, I^j), the smallest value (i.e., min value) is applied among the distances calculated by scanning blocks from the target image and comparing them m times.

Table 1: Overall average recall and precision for all decomposition level for all class images

DTCWT decomposition level	Average precision	Average recall
1st	26	70
2nd	55	43
3rd	60	46
4th	80	40

RESULTS AND DISCUSSION

Implementation: The precision and recall is calculated for proposed methods and average recall and average precision is plotted against decomposition level for each category image. Database of 800 images of 8 different classes is used to check the performance of the algorithms developed. The query image and dataset image matching is done using Euclidean distance which is given Eq. 1. The average precision and average recall is calculating by using following Eq. 2 and 3:

$$Ed(Q,I) = (\Sigma^{M-1}_{M=0}|HQ-HI|^{r})^{1/r} \quad (1)$$

Where:

Q = Query image
I = Dataset image
H_Q = Feature vector query image
H_I = Feature vector dataset image
M = Total No. of components in the feature vectors

The average precision for images belonging to the qth category (Aq) has been computed by:

$$P_q = \sum_{k \in aq} P(I_K)/|(A_q)|, \; q = 1,2,...5 \quad (2)$$

Finally, the average precision is given by:

$$P = \sum_{q=1}^{5} Pq/5 \quad (3)$$

Table 1 gives overall average recall and average precision for all decomposition levels for all class of images. It also shows the plot of overall recall and precision against the decomposition level. On the plot it is observed that precision for the 4th level decomposition level is very good and recall for the 1st level is very good.

CONCLUSION

In this study, we have investigated a region-based approach, which uses multiple ROIs as a key to retrieve images. The methods using statistical and hierarchical analysis on the multiple ROI query results proved very flexible to model the nature of images with two ingredients: the feature distribution of the regions and the analysis of the multiple regions query results. Experimental results show that the multiple ROI query strategies perform better than other existing methods, such as those using global features and single ROI. Our findings indicate that the results from the segmentation are the most crucial portion of the system. The user selected ROIs are projected onto the segmented image and as a consequence, the regions selected by the user are analyzed.

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