Image Retrieval Using Low Level Features of Object Regions with Application to Partially Occluded Images

E.R.Vimina[1,*] and K. Poulose Jacob[2]

[1] Department of Computer Science, Rajagiri College of Social Sciences, Kochi, Kerala, India
vimina_er@yahoo.com
[2] Department of Computer Science, Cochin University of Science and Technology, Kochi, Kerala, India
kpj@cusat.ac.in

Abstract. This paper proposes an image retrieval system using the local colour and texture features of object regions and global colour features of the image. The object regions are roughly identified by segmenting the image into fixed partitions and finding the edge density in each partition using edge thresholding and morphological dilation. The colour and texture features of the identified regions are computed from the histograms of the quantized HSV colour space and Gray Level Co- occurrence Matrix (GLCM) respectively. A combined colour and texture feature vector is computed for each region and Euclidean distance measure is used for computing the distance between the features of the query and target image. Preliminary experimental results show that the proposed method provides better retrieving result than retrieval using some of the existing methods. Also promising results are obtained for 50% and 75% occluded query images.

Keywords: Content Based Image Retrieval, GLCM, Colour histogram.

1 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

* Corresponding author.

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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][9]. 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][6]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 object regions and computing the feature vectors for comparison purpose. The object regions are roughly identified by performing morphological operations on the image and segmenting the image into fixed partitions.

2 Object Region Identification

The images are resized to 128×192 and divided into 3×3 equal sub-blocks. To identify the object regions, first the grayscale image is computed for the resized image and edge map is detected using Sobel edge filter with a threshold value of τ (τ <1 so that the edges are boosted). The gaps in the edge map are bridged by dilating it with 'line' structuring element, that consists of three 'on' pixels in a row, in the 0, 45, 90 and 135 directions. The holes in the resultant image are then filled to get the approximate location of the objects. The objects are identified correctly if the background is uniform.

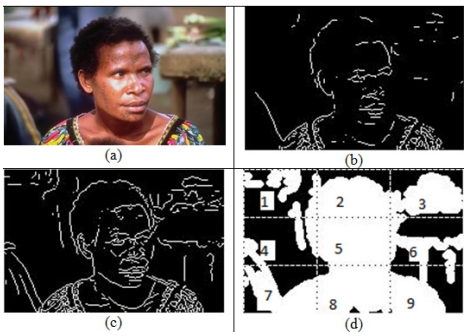


Fig. 1. (a)Original image (b)Edge map after sobel edge filtering (c) Edge map after edge thresholding (d)Region identification

A sub-block is identified as region of interest (ROI) if τ'% of the sub-block is part of the object region. Ie., if the number of white pixels in that sub-block is greater than τ', it is identified as a region of interest. Here we have taken τ'=30%. For example in Fig.1, regions 2,3,5,7,8 and 9 are the ROIs. Only these sub-blocks take part in further computations for calculating the similarity along with the global colour features of the image. For each sub-block that is identified as ROI, the colour and 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.

3 Feature Extraction

After identifying the image sub-blocks/ prominent regions of object, colour and texture features for each region are computed. We have used HSV colour space for extracting the colour features. The HSV space is uniformly quantized to 18 bins for hue, 3 bins for saturation and 3 bins for value. The histogram of each of these channels are extracted resulting in a 24 dimensional colour feature vector that is normalized in the range of [0,1]. For each image both global and local colour features are extracted.

Texture features are computed using the gray-level co-occurrence matrix (GLCM) [7]. 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. We have taken d=1 and Θ = 0, 45, 90 and 135. 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.

4 Similarity Measure

Euclidean distance is used for computing the similarity between the given pair of images. It is given by,

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

where FI1 and FI2 are the feature vectors of image I1 and I2.

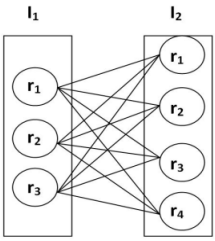


Fig. 2. Each ROI of image I_1 is compared with that of I_2

For each ROI in the query image, the colour and texture features are computed and is compared with each ROIs of the target images (Fig.2). Assume that image I_1 has m ROIs represented by R_1= {r_1, r_2,……,r_m} and I_2 has n ROIs represented by R_2={ r'_1, r'_2,……r'_n}. Let the distance between ri and r'j be d(ri,rj) denoted as di,j. Every region ri of R_1 is compared with every region rj of R_2. This results in 'n' comparisons

for a single region in R_1 and n 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 distance between I_1 and I_2. Thus out of the m × 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: R1, R2; the ROIs of the query and the target image
Output: minimum distance between I1 and I2
begin
  for each region in the query image I1, i=1 to m do
    for each region in the target image I2, j=1 to n 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 n regions of R_2. The final distance between I1 and I2 is given by

$$D' = D + d_{global\_colour\_feature} \tag{2}$$

Where, $d_{global\_colour\_feature}$ is the Euclidean distance between the global colour feature vectors of I_1 and I_2.

5 Experimental Results

The Wang's image database [9] 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 of images are retrieved which are illustrated and listed in the ascending order of the distance between the query and the retrieved images.

The results of the proposed method is compared with that of [10] and [11] in terms of average precision. Precision (P) of N retrieved results is given by

$$P(k) = n_k / N \tag{3}$$

Where N is the number of retrieved images, n_k is the number of relevant images in the retrieved images.

Table1. shows the average precision of the retrieved images for different methods.

Table 1. Average Precision (N=20) of retrieved images using different methods

Category	Jhanwar et al[11]	Hung and Dai's [10]	Proposed method
Africa	0.4525	0.4240	0.6747
Beaches	0.3975	0.4455	0.3655
Buildings	0.3735	0.4105	0.4645
Bus	0.7410	0.8515	0.8445
Dinosaur	0.9145	0.5865	0.9830
Elephant	0.3040	0.4255	0.6030
flowers	0.8515	0.8975	0.8565
Horse	0.5680	0.5890	0.8750
Mountain	0.2925	0.2680	0.3005
Food	0.3695	0.4265	0.6005
Average	**0.5264**	**0.5324**	**0.6568**

5.1 Retrieval of Partially Occluded Images

Further to evaluate the efficiency of the proposed method, we have partially occluded the query images and presented to the retrieval system. For this purpose 10 randomly chosen images from each category are occluded 50% and 75% and presented as query images to the proposed system and the global features based retrieval system for comparison purpose. Experimental results show that the proposed method outperforms retrieval using global features based method. Table 2. shows retrieved results for 50% occluded query images for different values of N and Table 3. shows the same for 75% occluded query images.

Table 2. Average precision (N=20) of retrieved images for 50% occluded query images

Category	Global HSV Histogram+GLCM Texture	Proposed Method
Africa	0.8608	0.8204
Beaches	0.4090	0.3045
Buildings	0.4200	0.6175
Bus	0.6675	0.8350
Dinosaur	0.9675	0.9525
Elephant	0.3525	0.3975
flowers	0.9900	0.8750
Horse	0.6295	0.8550
Mountain	0.2795	0.3022
Food	0.4000	0.5850
Average	**0.5977**	**0.6545**

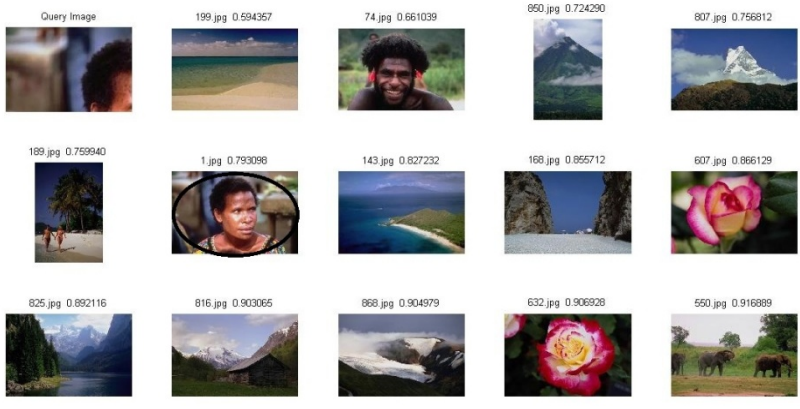
Table 3. Average precision (N=20) of retrieved images for 75% occluded query images

Category	Global HSV Histogram+GLCM Texture	Proposed Method
Africa	0.5337	0.7625
Beaches	0.2750	0.2475
Buildings	0.4162	0.4950
Bus	0.5537	0.7887
Dinosaur	0.9225	0.8800
Elephant	0.2000	0.2862
flowers	0.8962	0.7900
Horse	0.4987	0.6212
Mountain	0.1587	0.2175
Food	0.3400	0.4525
Average	**0.4795**	**0.5541**

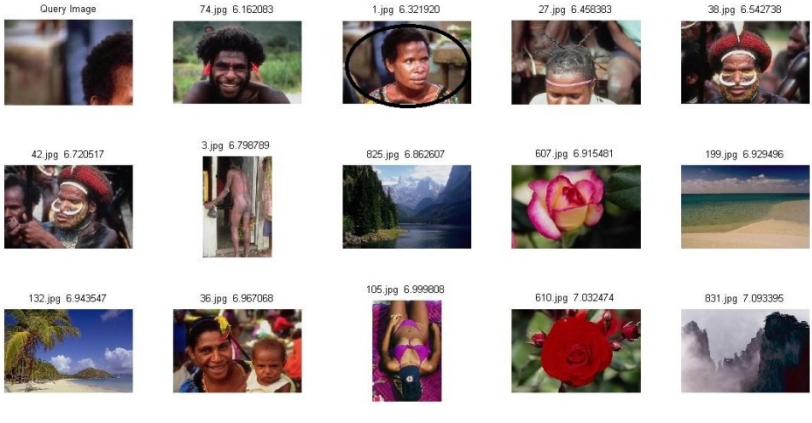
(a)

(b)

Fig. 3. Retrieved images using query images occluded by 50%. (a) Using global colour histogram and texture features.(b) Using proposed method.



(a)



(b)

Fig. 4. Retrieved images using query images occluded by 75%. (a) Using global colour histogram and texture features.(b) Using proposed method.

Fig.3. depicts the top 14 retrieved images for sample query images occluded 50% using proposed method and global HSV histogram+ GLCM texture 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. (a) shows the retrieved results using global colour and texture features and (b) shows that using the proposed method. Fig.4 depicts the same for the 75% occluded query images. The marked image is the original image part of which is given as query.

6 Conclusion and Future Work

A content based image retrieval system using the colour and texture features of automatically extracted object regions is proposed. The colour features are extracted from the histograms of the quantized HSV color space and texture features are computed from GLCM. Experimental results show that the proposed method provides better retrieving result than some of the existing methods. Unlike other sub-block based retrieval systems that require all the sub-blocks to participate in similarity comparison, the proposed method requires only the identified sub-blocks be compared with that of the candidate image sub-blocks reducing complexity and time required for retrieval. Preliminary results of the 50% and 75% occluded query images using the proposed method also outperforms that using global colour and texture features. Future work aims at the generation of fuzzy rules that may improve the retrieval precision.

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