Content Based Image Retrieval by Shape, Color and Relevance Feedback

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Abstract: Efficient content based image retrieval has been proposed in this study by combining shape and color features and relevance feedback. In this era of digital communication, images are everywhere and these images consist of shape and color. For true image representation it is necessary to represent the shape correctly semantically. Only in this case accurate matching and retrieval can be performed. In these days navigation through image databases is very common. For correct image search and retrieval, the proposed method has been proved to be efficient and having better performance with the help of experimental results. Proposed method has also been compared with existing state of art methods that clearly shows its outperformance.

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1. Introduction

Image has achieved a very important place as a source of information sharing in this age of digital communication. "A picture is worth a thousand words", directs a human mind towards interpreting the numerous and complex ideas through a single image. In this context the thing that matters is the perception i.e., how two people perceive the meaning or content described in the image. It is termed as semantic of image. Millions of digital images exist in the form of image databases or repositories in the world. Search is one of essential and key operations of database systems. Similarly anyone may need a specific image at any time according to the need or idea from these image repositories. As true perception is very important for image presented as source of information sharing, similarly true interpretation of image information is necessary for image matching and search. For the sake of these true interpretations of images, content based image retrieval (CBIR) systems have been devised through which the images are interpreted via the contents presented in the image. These contents are best possibly extracted in the form of digital attributes known as features. Some possible ways of extracting features from the image are color, shape, texture, order statistics etc. In this study a new state of art method has been built based on a new shape features extraction method, color histogram and relevance feedback. These three features have been combined to get advantage of their individual powerful characteristics at the same time and it comes up as a strong and efficient image description method for image matching and retrieval.

2. Existing Work

A number of methods have been existed for image retrieval in literature as color descriptor, shape descriptor and methods with relevance feedback. Color descriptors use the color intensities of image existed in the form of RGB or in converted color spaces like HSV, HSL, and CMYK etc. Three approaches are used in extracting color information of images; first one considers the color of images globally, second one divides the image into partitions and takes the color information from individual segments and the third one divides the image into segments via segmentation algorithm [1]. Color histograms have been used for image matching [2]. Traditional color histograms use the binning methods and weight of each bin refers to the number of pixels falling into that bin. These methods do not take into account color distributions. In [3] an adaptive approach has been proposed to address the color distributions. Mathematical morphology based color descriptions have been defined in [4]. Local binary patterns combined with color histogram have been implemented for fast image matching and retrieval in [5].

Shape descriptors take the shapes presented in the image into account and convert the boundary or region information of these shapes into features. Fourier descriptors (FD) have been implemented in many applications of shape description due to their prominent features of simple derivation, normalization and noise robustness [6]. The curvature scale space descriptor (CSS) converts shape boundary into a 1D signal and performs analysis of this signal in scale space [7]. In [8] scale normalization has been performed on complex vector obtained from shape boundary. MPEG-7 adopted two dimensional region based shaped descriptor named ART that is moment based [9]. In [10] ART descriptor has been proposed by normalized magnitudes of ART coefficients and achieved rotational invariance with these coefficients. Translation invariance is obtained by defining the center of polar coordinate system as the center of mass of the object. [11] performed recognition task by image moments (IM) which are scaling, translation and rotation invariant and is also invariant to general affine transformation.

Relevance feedback deals with user responses on the images retrieved that which images are of user's interest or more relevant and improves the degree of relevancy of image retrieval on the basis of these synthesis. In [12, 13] relevance feedback approach has been adopted by weighting the positive and negative examples and online features selection respectively. In [14] the interactive image retrieval has been introduced by active learning methods. [15] combined state vector machine and Gaussian mixture model for relevance feedback approach.

Rest of the paper has been arranged in four sections from section 3 to 6. Section 3 contains the detailed proposed method, section 4 includes experimental results and discussion, section 5 concludes the method overall and section 6 presents the bibliography used in this study.

3. Proposed Work

The idea is based on the architecture that there exists an image repository containing a number of images on one hand and on the other hand there is an image for which image search is needed which is termed as query image. The need is to retrieve those images from image repository which are similar to query image in terms of contents. The building blocks are features of shape and color and relevance feedback. For shape features newly defined shape descriptor has been used as described in Section 2.1, color features are obtained through widely used color histograms and relevance feedback has been implemented by probability computation without bothering the user by any feedback queries or surveys. The architecture of the proposed technique has been presented in Fig.1 with the prominent operations and flow of operations.

3.1. Shape Descriptor

Gradient of images are calculated for each image that is included in image collection and residing on disk. For this purpose, the most popular and commonly used canny [16] edge detector has been used. Standard equations have been shown in expressions 1 to 4. In Fig.2 an image has been shown with its gradient image.

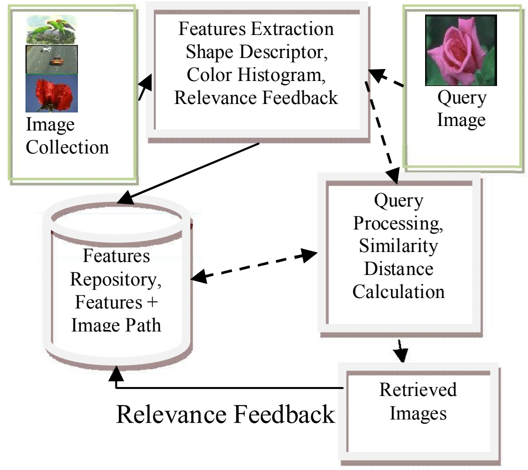


Figure 1. General Architecture of Proposed Method

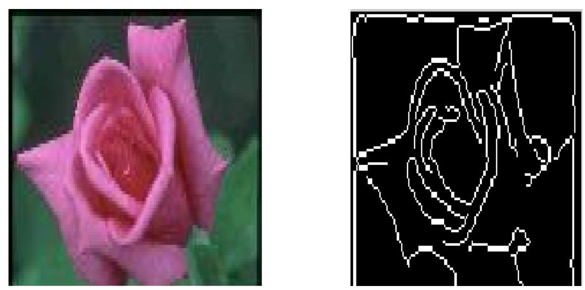
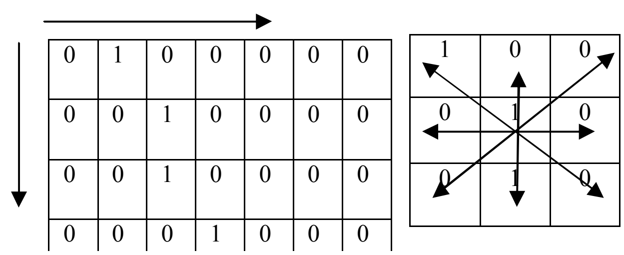


Figure 2. Color Image and Its Gradient Image



(a) Image Sliding **(b) 3x 3 Neighborhoods**

Figure 3. Image Sliding and 3x3 Neighborhood

$$G(x) = e^{-(\frac{x^2}{2\sigma^2})} \quad (1)$$

$$G'(x) = (-\frac{x}{\sigma^2})e^{-(\frac{x^2}{2\sigma^2})} \quad (2)$$

$$f_x(x, y) = G_x * I(x, y) \quad (3)$$

$$f_y(x, y) = G_y * I(x, y) \quad (4)$$

Gradient image consists of the values '0' and '1', '0' for inner pixel and '1' for edge pixel respectively. Starting from top left corner and proceeding in left to right and top down fashion pixel by pixel, a 3x3 neighborhood for each pixel is selected as shown in Fig.3. A code is extracted from the 3x3 neighborhood based on edge pixel and inner pixel as shown in Fig.4.

1	0	0	
0	1	0	100010010
0	1	0	
1	0	1	
0	0	0	101000011
0	1	1	
1	0	1	
1	1	1	101111001
0	0	1	

Figure 4. 3x3 Traces with Codes

These codes are saved as feature vectors in database where each code corresponds to one cell of feature vector. Length of feature vector depends on the size of image, more the size of image more the length of feature vector.

3.2. Color Histogram

Color histogram computes the number of occurrences of a particular color intensity that is probability mass function. It can be defined by the following expression:

$$t_{R,G,B}(a,b,c) = M.P(R = a, G = b, B = c) \quad (5)$$

Where M is maximum number of color intensity. In this case it is 255 because 8-bit color images have been used and P is probability that is obtained by counting the color intensities of specific range of a color. Some color images with corresponding color histograms have been shown in Fig.5.

3.3. Relevance Feedback

Relevance Feedback is a mechanism in which user response is considered i.e., what response the user gives to the retrieved results. In this scenario user is presented with the retrieval results and asked to set the system parameters to improve the relevance and performance of the system. According to user's suggestions system tries again to retrieve the results. In this study a new smart technique has been used in which a probability is associated with each image. This probability is ratio of each image selected by user to the total no. of times image retrieved so far. This can be shown by the following expression:

$$\rho = \frac{\mathrm{A}}{\mathrm{T}} \quad (6)$$

$$\mathrm{A} = no.of\ times\ an\ image\ selected\ by\ user$$
$$\mathrm{T} = total\ \mathrm{n}o.of\ times\ image\ retrieved\ so\ far$$

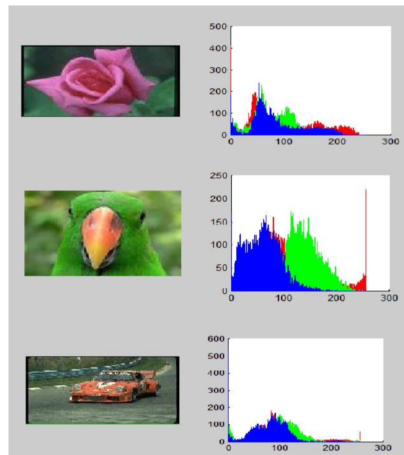


Figure 5. Color Images and Corresponding Color Histograms

3.4. Distance Calculation and Image Retrieval

Two distance formulae have been used for the proposed method; one is Hamming distance and the other is Euclidean distance. The first one is used for measuring the distance of codes obtained from the shape descriptor and the second one is used for measuring the distance of color histograms of query image and database resident images. If Q is the query image and I be the database resident image then the Hamming distance is computed by the following equation:

$$d^H(q,i) = \sum_{k=1}^{n} \left[v_{q,k} \neq v_{i,k} \right] \quad (7)$$

Each cell of feature vector of query image is summed up without carry with the cell of feature vector of database resident images. Hamming distance exactly tells change in two values. If 60% or more entries of feature vectors of query image and database image are found to be similar then the images are considered to be relevant. K is number of cells in feature vector.

Euclidean distance is computed by the following expression.

$$d^2(t_Q,t_I)=\sum_{R}\sum_{G}\sum_{B}(t_Q(a,b,c)-t_I(a,b,c))^2 \qquad (8)$$

Smaller the distance similar the images; the images designated as relevant images after calculating the Hamming distance are sorted according to histogram distance calculation and presented to user. Whenever the user selects any retrieved image the probability associated with it changes and next time if that images is included in retrieved images it is on top of these images. This means that images are retrieved by shape descriptor described and then sorted according to color distance from query image and again sorted according to probabilities selected in the past.

4. Results & Discussion

To evaluate the performance of proposed method, the system used consists of 2.27 GHz i3 Processor, 2 GB RAM, 32-bit Windows 7 OS and Mat lab 7.0 as a tool used. Corel database [17, 18] of ten thousand images has been used. Ten thousand images have been divided into several categories like cars, landscapes, animals, birds, waterfall, desert etc. Each category contains 100 to 150 images.

Widely accepted precision and recall rates have been used as quantification measures to prove the strength of proposed method. These measures can be defined by the following expressions:

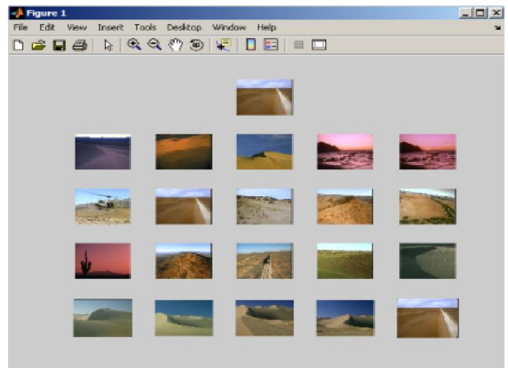
P = Relevant retrieved images/Total retrieved images

R = Relevant retrieved images/Total images in that category

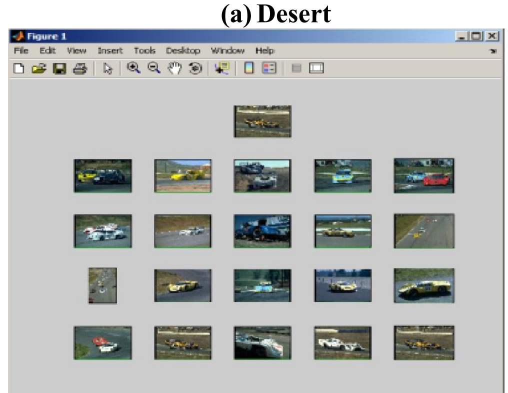
A good balance between precision and recall is necessary for better system performance and a higher degree of relevancy as well. Precision measures the relevancy of retrieved images with respect to number of those which have currently been retrieved. Recall measures the overall performance of system. It encounters the degree of relevancy from images retrieved to total number of images belonging to category of query image. In case of huge image databases it is difficult to maintain a good recall, therefore usually the system is judged from precision's point of view. Proposed method achieves precision from 68% to 88% and recall from 62% to 71% for different categories which is a very improved performance.

Fig. 6 shows the top 20 results of retrieved images visually. To maintain a good balance between precision and recall the system has been designed to retrieve 100 images per search click.

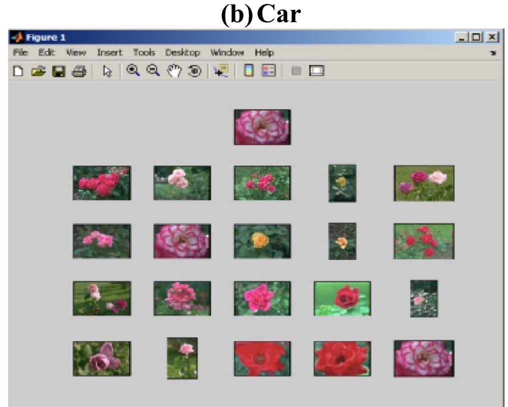
For comparison of two different CBIR systems like testing environment it is necessary that image database, number of images to be retrieved and nature of features must be the same otherwise it is very difficult to compare two CBIR systems or image descriptors. However for showing the outperformance of proposed system, it has been compared with four famous shape descriptors FD, ART, IM and CSS.



(a) Desert



(b) Car



(c) Flower

Figure 6. Top 20 Retrieval Results for Query Images Desert, Car and Flower

Though these descriptors are different in operational nature but they have been implemented for same database in same testing environment and an average precision has been computed and used for comparison. Fig.7 and Table 1 show the comparison graph visually and numerically respectively which clearly show that proposed system has better performance.

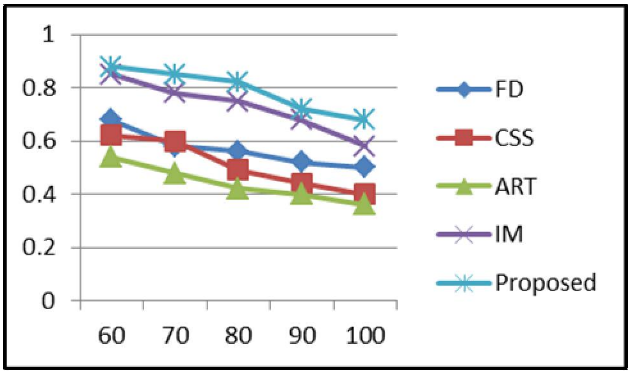


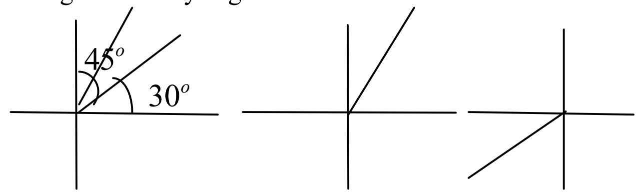
Figure 7. Comparison Results of Average Precision Rates, Test Image Categories: Car, Flower, Desert, Retrieved Images 60, 70, 80, 90 & 100

Table 1. Comparison of Average Precision

Retrieved Images	FD [6]	CSS [8]	ART [10]	IM [11]	Proposed
60	0.68	0.62	0.54	0.85	0.88
70	0.58	0.60	0.48	0.78	0.85
80	0.56	0.49	0.42	0.75	0.82
90	0.52	0.44	0.40	0.68	0.72
100	0.50	0.40	0.36	0.58	0.68

4.1. Robustness to Geometric Transformation

Geometric transformation like rotation, scaling and translation plays a critical role in designing of shape descriptors. An efficient shape descriptor must be robust against these geometric attacks. The proposed solution efficiently copes with the geometric attacks. Neighborhood in context of edges remains the same although a rotational, positional or a change in size has been occurred. Its simplest proof is sketching a line. From Fig.8 one can easily see that the line was at 30˚ and then rotated by 15˚ and now the line is at 45˚. Its edge is same. Any pixel on this line will always have same neighborhood and will generate same codes. If line is resized let's suppose by 20%, there must be 60% or more features that remain similar due to same code generation. From Fig.8 (c) it can also be observed that positional change does not make any difference because it is concerned with the edges and not with the whole image. In all cases it does not affect the code generated by edges.



(a) Rotation (b) Scaling (c) Translation

Figure8. Robustness to Geometric Attacks, in all cases code generated by shape descriptor remains same

5. Conclusion

In this study an image descriptor has been devised that combines the shape and color features and relevance feedback together to attain the powerful and efficient performance. All elements of these features contribute positively and strongly with their powerful features and the shortcomings are covered up by each other's strengths. As a result, a powerful image descriptor has been achieved that is robust to geometric attacks, has higher degree of relevancy and a good and acceptable balance between precision and recall. It records the user responses but does not involve user or bothersome user for selecting the parameters or for any feedback survey or clicks. Moreover, the features are simplest to calculate and to populate into the database. Their simplicity leads to simple distance calculation and decision making. Image matching is performed efficiently and strongly by the proposed shape descriptor.

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