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Result Analysis on Content Base Image Retrieval using Combination of Color, Shape and Texture Features

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Abstract

Image retrieval based on color, texture and shape is an emerging and wide area of research scope. In this paper we present a novel framework for combining all the three i.e. color, texture and shape information, and achieve higher retrieval efficiency using dominant color feature. The image and its complement are partitioned into non-overlapping tiles of equal size. The features drawn from conditional co-occurrence histograms between the image tiles and corresponding complement tiles, in RGB color space, serve as local descriptors of color, shape and texture. We apply the integration of the above combination, then we cluster based on alike properties. Based on five dominant colors we retrieve the similar images. We also create the histogram of edges. Image information is captured in terms of edge images computed using Gradient Vector Flow fields. Invariant moments are then used to record the shape features. The combination of the color, shape and texture features between image and its complement in conjunction with the shape features provide a robust feature set for image retrieval. The experimental results demonstrate the efficacy of the method.

Keywords

CBIR, Image Retrieval, Cluster, Dominat Color

1. Introduction

In this computer age, virtually all spheres of human life including commerce, government, academics, hospitals, crime prevention, surveillance, engineering, architecture, journalism, fashion and graphic design, and historical research use images for efficient services. A large collection of images is referred to as image database. An image database is a system where image data are integrated and stored [1].Image data include the raw images and information extracted from images by automated or computer assisted image analysis.

In text-based retrieval, images are indexed using keywords, subject headings, or classification codes, which in turn are used as retrieval keys during search and retrieval [2]. Text-based retrieval is non-standardized because different users employ different keywords for annotation. Text descriptions are sometimes subjective and incomplete because they cannot depict complicated image features very well. Examples are texture images that cannot be described by text. Textual information about images can be easily searched using existing technology, but requires humans to personally describe every image in the database. This is impractical for very large databases, or for images that are generated automatically, e.g. from surveillance cameras. It is also possible to miss images that use different synonyms in their descriptions. Systems based on categorizing images in semantic classes like "cat" as a subclass of "animal" avoid this problem, but still face the same scaling issues [3].

The Content Based Image Retrieval (CBIR) technique uses image content to search and retrieve digital images. Content-based image retrieval systems were introduced to address the problems associated with text-based image retrieval. Content based image retrieval is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features [4]. The main goal of CBIR is efficiency during image indexing and retrieval, thereby reducing the need for human intervention in the indexing process[5]. The computer must be able to retrieve images from a database without any human assumption on specific domain.

We provide here an overview of Image Compression Technique. The rest of this paper is arranged as follows: Section 2 describes about Recent Scenario; Section 3 shows the proposed approach; section 4 shows the result analysis; Section 5 describes Conclusion.

2. Literature Review

In 2005, Xiaojun Qi et al. [6] propose a novel fusion approach to content-based image retrieval. In their retrieval system, an image is represented by a set of color -clustering-based segmented regions and global/semi-global edge histogram descriptors (EHDs). As a result, the resemblance of two images is measured by an overall similarity fusing both region-based and global/semi-global-based image level similarities. In their approach, each segmented region corresponds to an object or parts of an object and is represented by two sets of fuzzified color and texture features. A fuzzy region matching scheme, which allows one region to match several regions, is then incorporated to address the issues associated with the color/texture inaccuracies and segmentation uncertainties. The matched regions, together with the simple semantics for determining the relative importance of each region, are further used to calculate the region-based image level similarity. The global/semi-global EHDs are also incorporated into our retrieval system since they do not depend on the segmentation results. These EHDs not only decrease the impact of inaccurate segmentation and but also reduce the possible retrieval accuracy degradation after applying the fuzzy approach to the accurate segmentation for images with distinctive and relevant scenes. The Manhattan distance is used to measure the global/semi-global image level similarity.

In 2008, N. S. Vassilieva [7] presents a survey of common feature extraction and representation techniques and metrics of the corresponding feature spaces. Color, texture, and shape features are considered. A detailed classification of the currently known features' representations is given. Experimental results on efficiency comparison of various methods for representing and comparing image content as applied to the retrieval and classification tasks are presented by the author.

In 2011, Chandan Singh et al. [8] proposed a novel solution to content based image retrieval system. Local features extraction is done by computing histograms of distances from edge lines to the centroid of edge image, where edge lines are detected using Hough transform. It is a robust and effective method according to the authors. It provides association among adjacent edge points, which representtheirlinearrelationshipwitheachother.Zernike momentsareused to describe the global features. They have applied algorithms for the fast computation of Hough transform and Zernike moments to make our system fast and efficient. Bray–Curtis similarity measure is applied to compute the similarity among images. A large number of experiments is carried out to evaluate the system performance over six standard databases, which represent various kinds of images.

In 2011, Daniel Carlos et al. [9] present the Distance Optimization Algorithm (DOA), aiming to improve the effectiveness of Content-Based Image Retrieval (CBIR) systems. DOA Considers an iterative clustering approach based on distances correlation and on the similarity of ranked lists. Their algorithm explores the fact that if two images are similar, their distances to other images and therefore their ranked lists should be similar as well.

In 2011, Xiang-Yang Wang [10] proposed effective and novel color image retrieval based on color, texture and shape. They firstly apply quantization algorithm for cluster merging. Second the spatial texture features are extracted using steerable filter decomposition. Finally they apply pseudo-zernike moments of an image for the shape descriptor. According to the author they provide an efficient and robust capability of image retrieval after applying the above techniques.

3. Proposed Approach

In many texture analysis applications it is desirable to have features that are invariant or robust to rotations of the input image. As the LBPP,R patterns are obtained by circularly sampling around the center pixel, rotation of the input image has two effects: each local neighborhood is rotated into other pixel location, and within each neighborhood, the sampling points on the circle surrounding the center point are rotated into a different orientation.

In this paper we propose a combination of color, texture and shape based approach. The basic local binary pattern operator, introduced by Ojala et al. [13], was based on the assumption that texture has locally two complementary aspects, a pattern and its strength. In that work, the LBP was proposed as a two-level version of the texture unit [14] to describe the local textural patterns.

The original version of the local binary pattern operator works in a 3×3 pixel block of an image. The pixels in this block are threshold by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighbourhood consists of 8 pixels, a total of 28 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighbourhood. Our approach is shown in figure 4 and Figure 5.

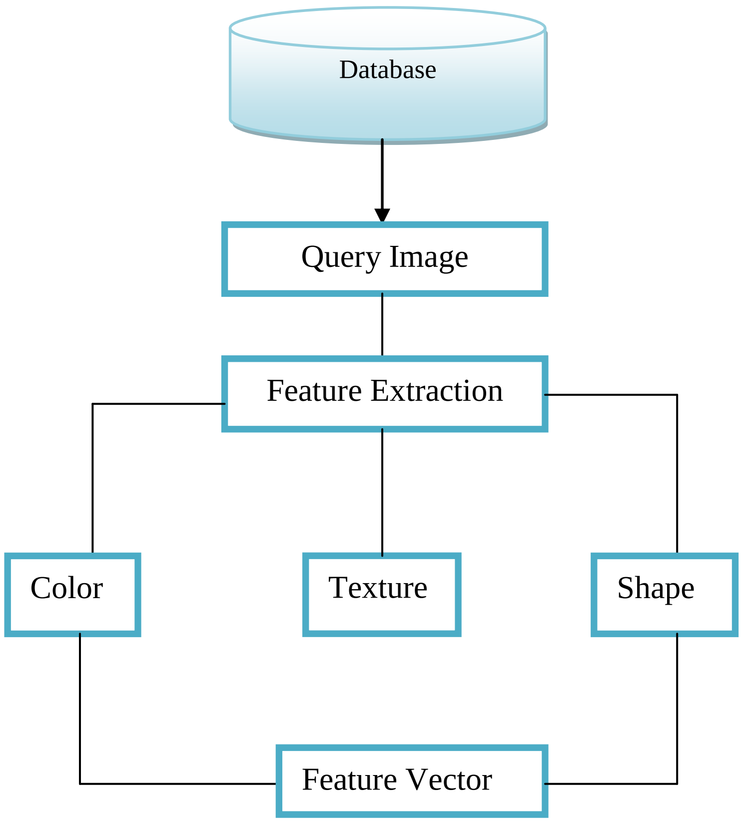

Figure 1: Indexing

In our approach Query Image is retrieved for feature extraction. Based on the dominant color we extract the features which are the combination or clusters of combinations of color fetched. Before extracting the color feature of an image, all pixels on database images are categorized into similar types of groups according to the similarity of their colors. All images are quantized to these similar colors in RGB color space. A color will be selected from predefined colors which are very near to image pixel color and it will be stored as new color pixel in the image. Color distance C_D is calculated using Euclidean distance formula, as specified below:

$$C_D = \min\left(\sqrt{(R_P - R_{iT})^2 + (G_P - G_{iT}) + (B_P - B_{iT})^2}\ \right)$$

$$I = 1 \ldots\ldots K$$

Using R_P, G_P, B_P as red, green, and blue components of intensity values of the pixel and R_{iT} , G_{iT}, B_{iT} are the corresponding values of the color entry in the table.The color having highest percentage is determined as dominant color of the block. Three dimensional Dominant color together with its percentage is stored as a color feature. For similarity comparison, we have used Euclidean distance, d using equation below.

$$d = \sqrt{\left(F_Q[i] - F_{DB}[i]\right)^2}$$

Where $F_Q[i]$ is the i^{th} query image feature and F_{DB} [i] is the corresponding feature in the feature vector database. Here, N refers to the number of images in the database.

In many texture analysis applications it is desirable to have features that are invariant or robust to rotations of the input image. As the Local Binary pattern are obtained by simply integrating with the dominant colors and the effects will be sampled based on similarity measures given by the above equation. RGB is of 8 bit, so the combination is of 2^{24}. The combination of each color is repented in the combination and the feature extracted based on the dominant color. Color is chosen or selected in such manner so that their percentage is color features, which are based on the 5 dominant colors. In our approach we reduce the number of colors in the five color combination, which is the centroid of the combination of the five clusters. We use the histogram of edges. n = histc(x,edges) counts the number of values in vector x that fall between the elements in the edges vector (which must contain monotonically nondecreasing values). n is a length(edges) vector containing these counts. No elements of x can be complex.n(k) counts the value x(i) if edges(k) <= x(i) < edges(k+1). The last bin counts any values of x that match edges(end). Values outside the values in edges are not counted. Use -inf and inf in edges to include all non-NaN values.

For matrices, histc(x,edges) returns a matrix of column histogram counts. For N-D arrays, histc(x,edges) operates along the first nonsingleton dimension. n = histc(x,edges,dim) operates along the dimension dim. [n,bin] = histc(...) also returns an index matrix bin. If x is a vector, n(k) = sum(bin==k). bin is zero for out of range values. If x is an M-by-N matrix, then
for j=1:N,
n(k,j) = sum(bin(:,j)==k);end

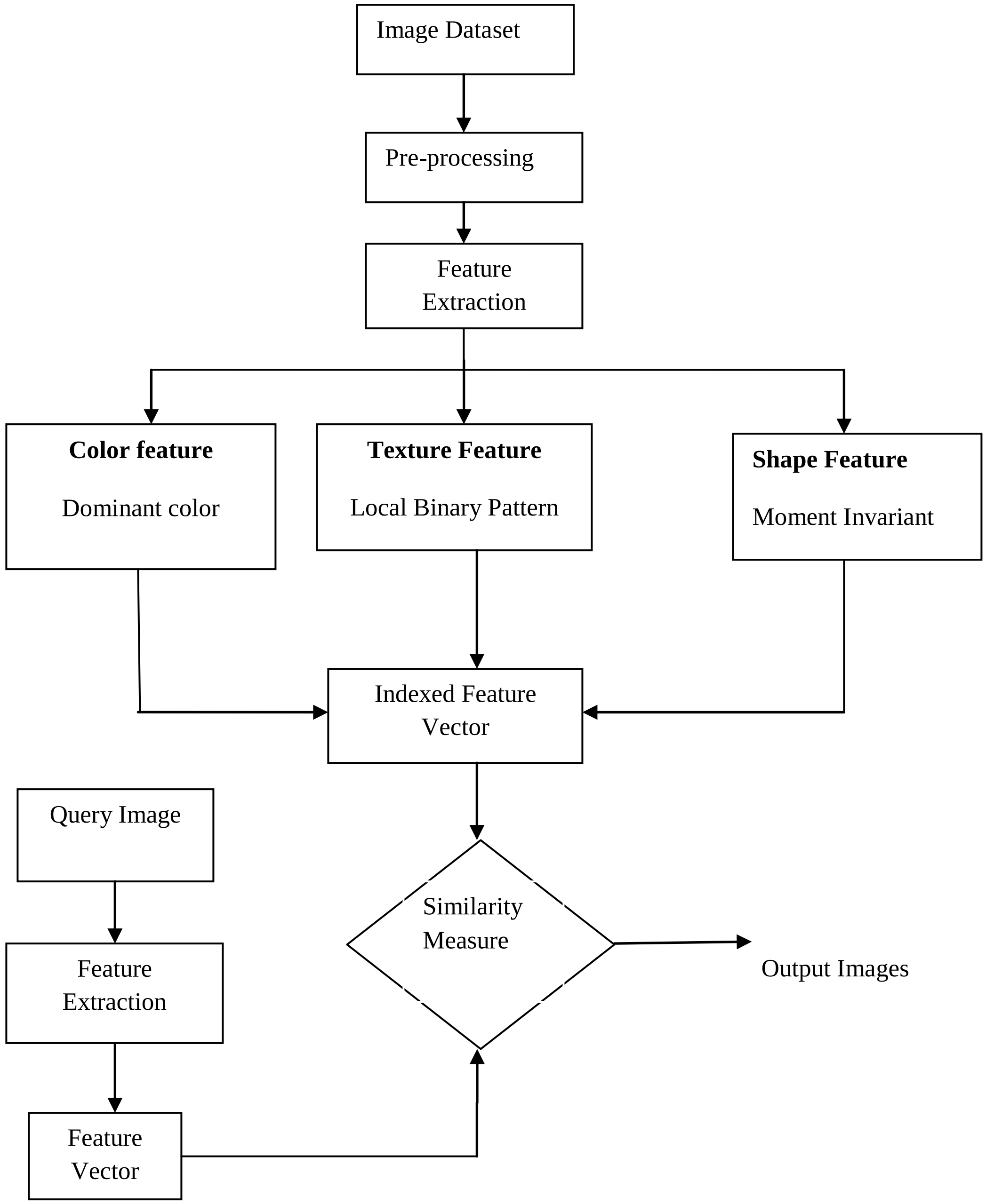

Figure 2: Working Procedure

Finally by the above approach we find better retrieval in comparison to the traditional approach.

4. Result analysis

For comparison we consider the database of James Z. Wang [15] which is the collection of 1000 Databases. There is 10 categories in the database. We consider each category one by one for comparison. First category we taken that is an African man. The result based on the African man is shown in Figure 3. Figure 4 is taken the category of sea. The next category is shown in Figure 5 which is of Building. The category of Bus is shown in figure 6. The category of dinosaur is considered in figure 7. The category of elephant is taken in figure 8. The category of rose is taken in figure 9. The category of horse is taken in figure 10. The category of mountain is taken in figure 11. Finally the category of food is taken in figure 12.

We take the entire above category separately and find the similar retrieval of images. When we apply our algorithm in the above database, then we observe that our result is better in comparison to the traditional approach. All the retrievals are shown below.

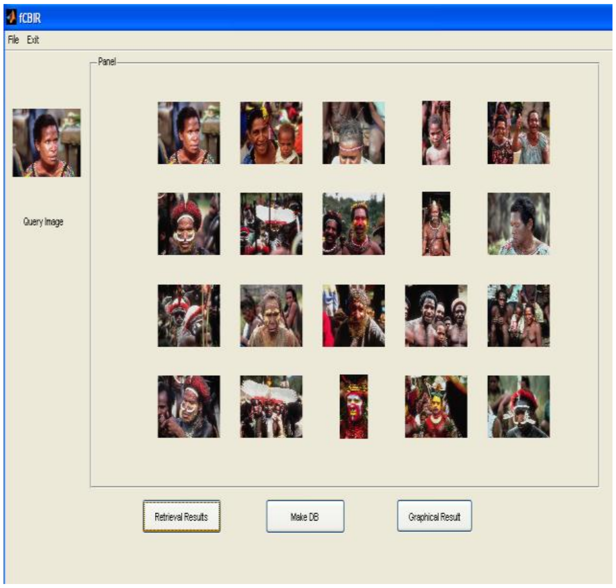

Figure 3: Category 1

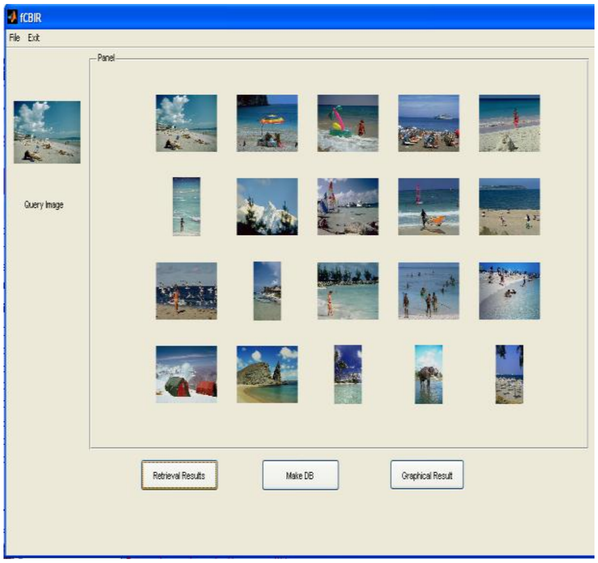

Figure 4: Category 2

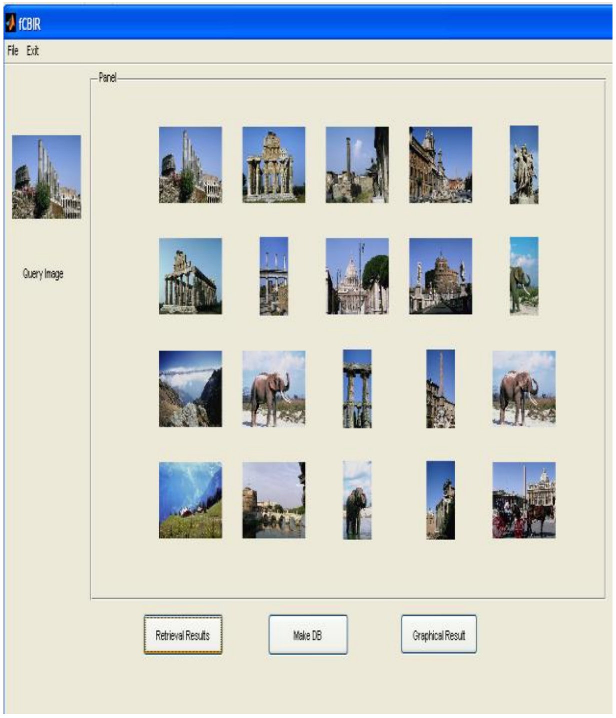

Figure 5: Category 3

Figure 6: Category 4

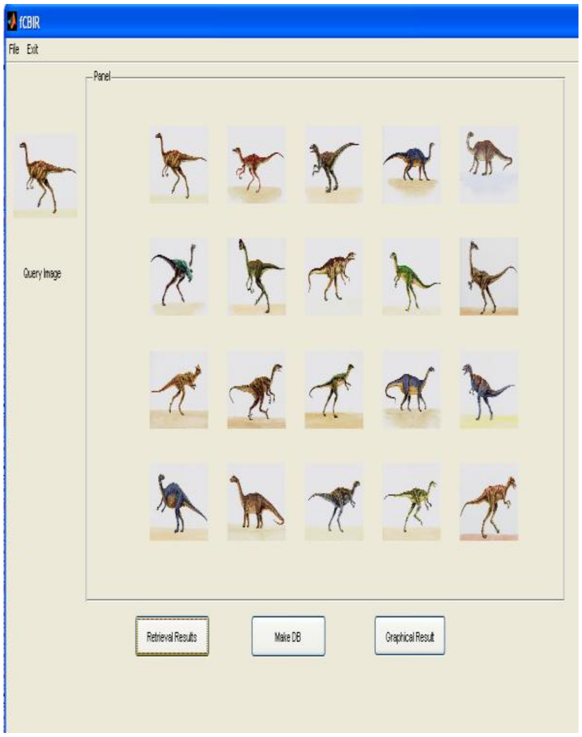

Figure 7: Category 5

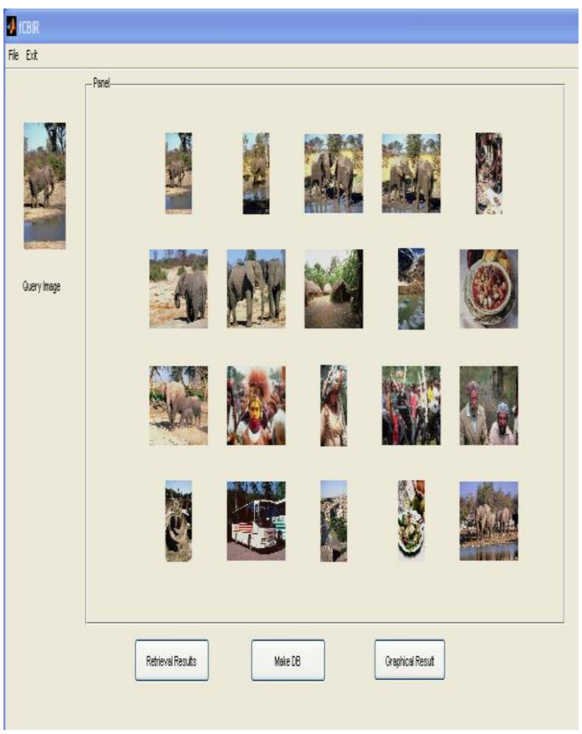

Figure 8: Category 6

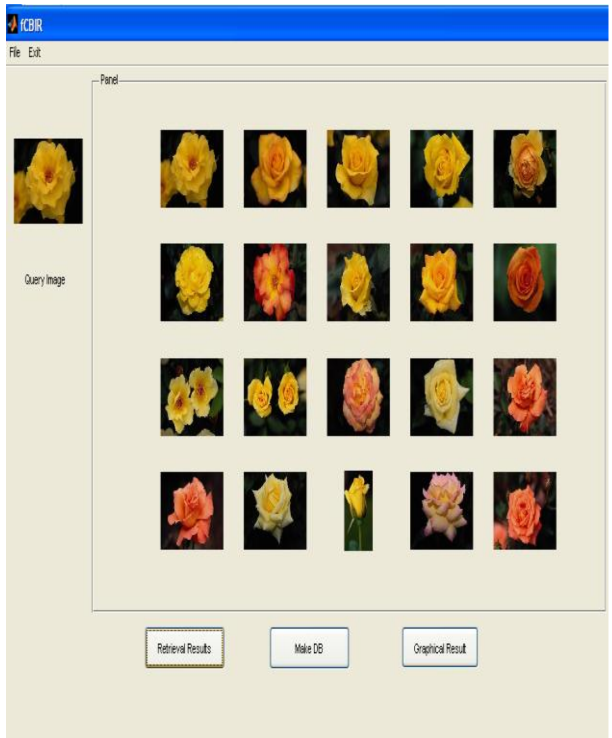

Figure 9: Category 7

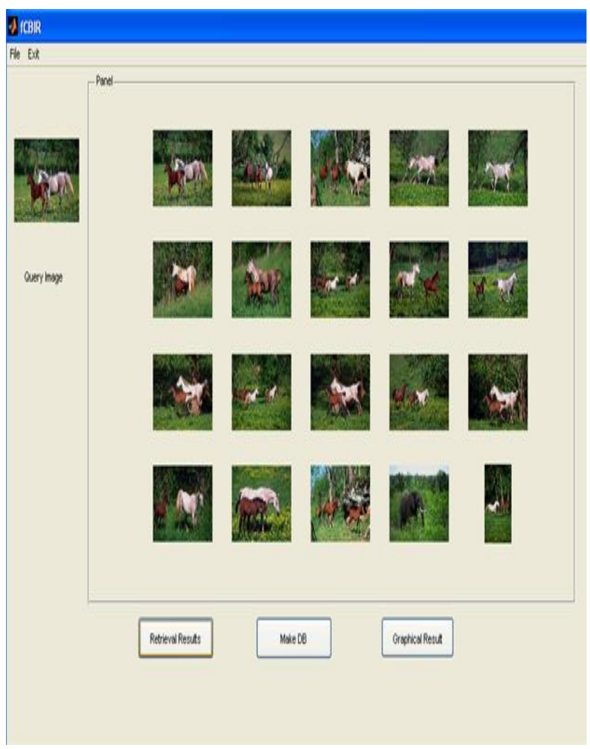

Figure 10: Category 8

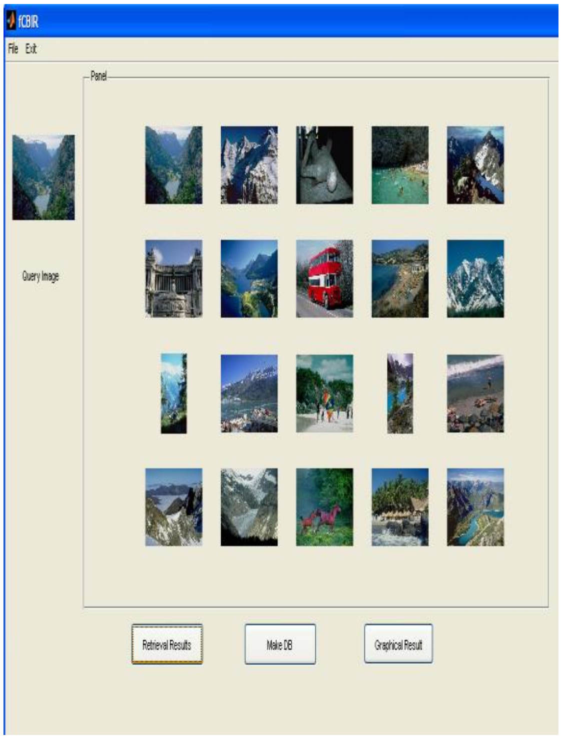

Figure 11: Category 9

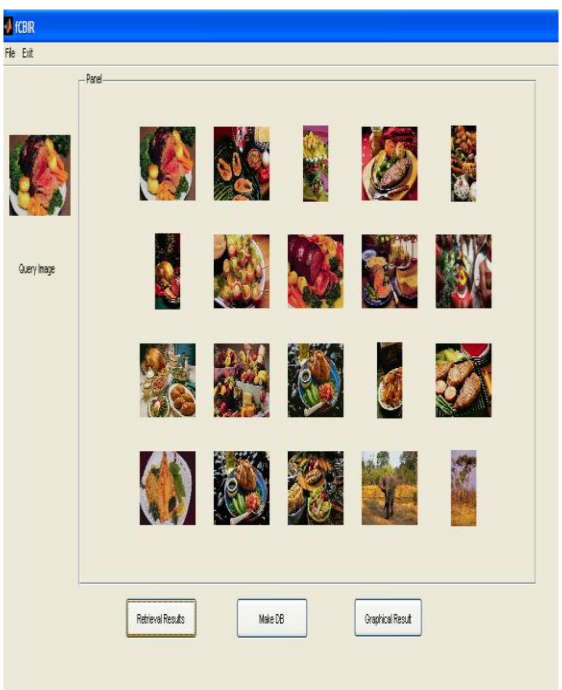

Figure 12: Category 10

Evaluation of an information retrieval system generally focuses on two things:
1. How relevant are the retrieved results? (precision)
2. Did the system retrieve many of the truly relevant documents? (recall)
Precision is the percentage true positives in the retrieved results. That is:

Precision=tp/tp+fp or tp/n
where n is equal to the total number of images retrieved (tp + fp).
Recall is the percentage of the airplanes that the system retrieves. That is:

Recall =tp/tp+fn
For example, with 3 true positives, 1 false positive, 4 true negatives, and 2 false negatives, precision = 0.75, and recall = 0.6.

A good way to characterize the performance of a classifier is to look at how precision and recall change as you change the threshold. A good classifier will be good at ranking actual airplane images near the top of the list, and be able to retrieve a lot of airplane images before retrieving any geese: its precision will stay high as recall increases. A poor classifier will have to take a large hit in precision to get higher recall. Usually, a publication will present a precision-recall curve to show how this tradeoff looks for their classifier.

By the above formullas of precision and recall we can plot Figure 13 and Figure 14, which is better from the traditional techniques. We also calculate the precision which is shown in table 1.

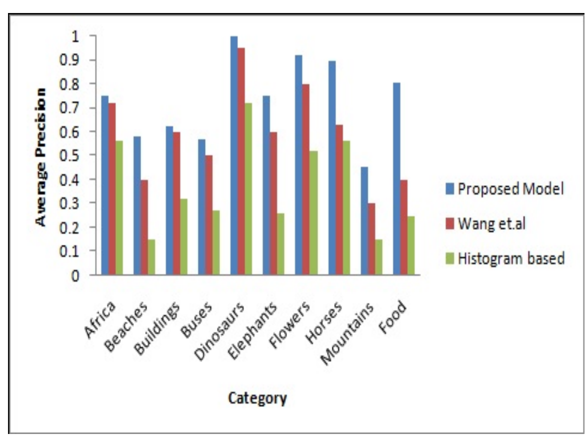

Figure 13: Average Precison

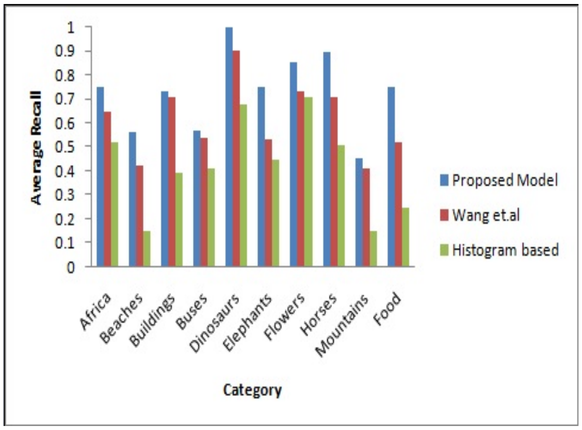

Figure 14: Average Recall

Table 1: Comparison Table

Category ID	Class	Proposed Model	Wang et.al	Histogram based
1	Africa	**0.748**	0.72	0.56
2	Beaches	**0.582**	0.4	0.15
3	Buildings	**0.621**	0.6	0.32
4	Buses	**0.57**	0.5	0.27
5	Dinosaurs	**1**	0.95	0.72
6	Elephants	**0.751**	0.6	0.26
7	Flowers	**0.923**	0.8	0.52
8	Horses	**0.896**	0.63	0.56
9	Mountains	**0.451**	0.3	0.15
10	Food	**0.803**	0.4	0.25

5. Conclusion

Users needing to retrieve images from a collection come from a variety of domains, including crime prevention, medicine, architecture, fashion and publishing. Remarkably little has yet been published on the way such users search for and use images, though attempts are being made to categorize users' behaviour in the hope that this will enable their needs to be better met in the future. So in our paper we present an efficient way of image retrieval based on the combination of color, texture and shape. By using wang database, we compare our technique with the previous algorithm and we found that our algorithm is better than the previous.

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