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A new technique for Image retrieval using its contents

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Summary

Most of the early researches on content -based image retrieval (CBIR) have been focused on developing effective global features. While these researches establish the basis of CBIR, the retrieval performance is still far from users' expectations.

The main reason is acknowledged to be the gap between low-level features and high-level concepts. To narrow down this semantic gap, an additive technique has been widely used: region-based features to represent the focus of the user's perceptions of image content.

The primary intent of this paper is to develop a system for efficiently retrieving similar images on the basis of their visual content from large image repositories. Studies on the benefit of various computational features in the description of visual contents of an image and on the grouping of features leading to successful retrieval results are the basis for the development of an image indexing and retrieval algorithm in this paper. This research, presents an elegant and efficient system for content-based indexing and retrieval of images. The global and region features are extracted from the images and are used in indexing the same. Tree data structures are used in indexing the extracted region features. The proposed system makes use of the following image processing techniques: color space conversion, quantization, denoising, edge detection and segmentation.

الخلاصه

كثيرا ما استخدمت البحوث السابقه التي تتعلق باسترجاع الصور بناءا على محتوياتها الخصائص العامه من اجل فهرسة الصور المتشابهه. وبالرغم من ان هذه البحوث شكلت الاساس لنظم استرجاع الصور بناءا على محتوياتها ، الا انها ظلت بعيده عن طموحات المستخدم وتصوره لنظام استرجاع صور جيد، وذلك بسبب الفجوه الكبيره بين خصائص المستوى الواطيء وخصائص المستوى العالي ولتقليل حجم هذه الفجوه، تم استخدام تقنية الخصائص المناطقيه لتمثل اهتمام المستخدم وادراكه لمحتويات الصورة. أن غاية هذا البحث هو تطوير نظام كفوء لاسترجاع الصور المتشابهه المخزونه اعتمادا على محتوياتها(محتويات الصوره).تمت الدراسه للاستفاده من الخصائص المتنوعه المستخدمه لوصف محتويات الصوره ولتجميع الخصائص للحصول على نتائج استرجاع جيده واستخدمت هذه الخصائص كأساس لخورارزمية الفهرسة واسترجاع الصور. في هذا البحث تم تقديم نظام كفوء لفهرسة واسترجاع الصور على اساس محتوياتها. تم الاستفاده من

الخصائص المناطقيه والعامه للصوره من اجل فهرسة الصور المتشابهه. كذلك استخدمت هياكل بيانات من نوع الشجره في فهرسة الخصائص المناطقيه المستخلصه. استخدم النظام المقترح تقنيات معالجة الصور التاليه: تحويل المدى او النظام اللوني، تقليل القيم اللونيه،ازالة التشويش، تحديد الحواف والتقسيم.

1. Introduction

Image databases have become popular among domains such as medical image management, multimedia libraries, document archives, art collections and more [1] owing to the recent advancements in data storage and image acquisition technologies. This has led to the increase in demand of the image retrieval systems capable of indexing and retrieving huge amounts of images on basis of their visual contents [2]. The problem of searching identical images from large image repositories on basis of their visual contents is called Content-Based Image Retrieval(CBIR) [3] . The term 'content' in CBIR refers to colors, shapes, textures, or any other information that can be possibly obtained from the image itself and 'Content Based' denotes that the search will consider the concrete contents of the image [4]. Indexing remarkably affects the speed of data access besides supporting the accuracy for retrieval process and thus is a significant factor in image database systems. Content-based image indexing intends to facilitate automatic identification and abstraction of the visual content of an image. Generally the collections of images are represented as a set of feature vectors [5]. There are two significant phases in the CBIR: 1) Indexing Phase where in the image information like the color, shape or texture is enumerated into features that are consequently stored in an index data structure along with a link to the image of origin. 2) Retrieval phase, wherein the searching of an image in the CBIR index necessitates the description of the properties of the image of interest either by supplying a sample image or denoting the image features [1].

2. background of Image Retrieval Systems

Since the early 1990s, content-based image retrieval has become a very active research area. Many image retrieval systems for commercial or researches have been built. Most image retrieval systems support one or more of the following options.

1. Random browsing
2. Search by example
3. Search by sketch or color layout
4. Search by text (including key word or speech)
5. Navigation with customized image categories
6. Relevance feedback for interactive searching

There is a rich set of search options today, but systematic studies involving actual users in practical applications still need to be done to explore the trade-off among the different options mentioned above. Here, I selected representative systems in image retrieval and highlight their distinct characteristics.

1. QBIC: QBIC (Query By Image Content)[6-7], is the first commercial CBIR system developed by IBM. Its structure and techniques used have made a great effect on most of the later image retrieval systems. QBIC supports queries based on example images, user-constructed sketches and drawings, and selected color and texture patterns, etc. QBIC also takes into account of the high dimensional feature indexing. In its indexing subsystem, KLT is first used to perform dimension reduction and then R*- tree is used as the multidimensional indexing structure. In the system, text-based keyword search can be combined with content-based similarity search.
2. Photobook: Photobook [8] is a set of interactive tools for browsing and searching images developed at the MIT Media Lab. Photobook consists of three subbooks from which shape, texture, and face features are extracted, respectively. Users can then query, based on the corresponding features in each of the three sub-books. The Photobook implemented human perception in image annotation and retrieval. Since there was no single feature which can best model images from each and every domain, and a human's perception is subjective, they proposed a "society of model" approach to incorporate the human factor. Experimental results show that this approach is effective in interactive image annotation.
3. VisualSEEK and WebSEEK: VisualSEEK [9] is a visual feature search engine and WebSEEK[10] is a World Wide Web oriented text image search engine, both of which are developed at Columbia University. Main research features are spatial relationship query of image regions and visual feature extraction from compressed domain. The visual features used in their systems are color set and wavelet transform based texture feature. To speed up the retrieval process, binary tree based indexing algorithms is also developed.

3.The proposed System Architecture

The architecture of the proposed content-based image indexing and retrieval system has been revealed and explained in the following .

3.1 Content-Based Image Indexing System

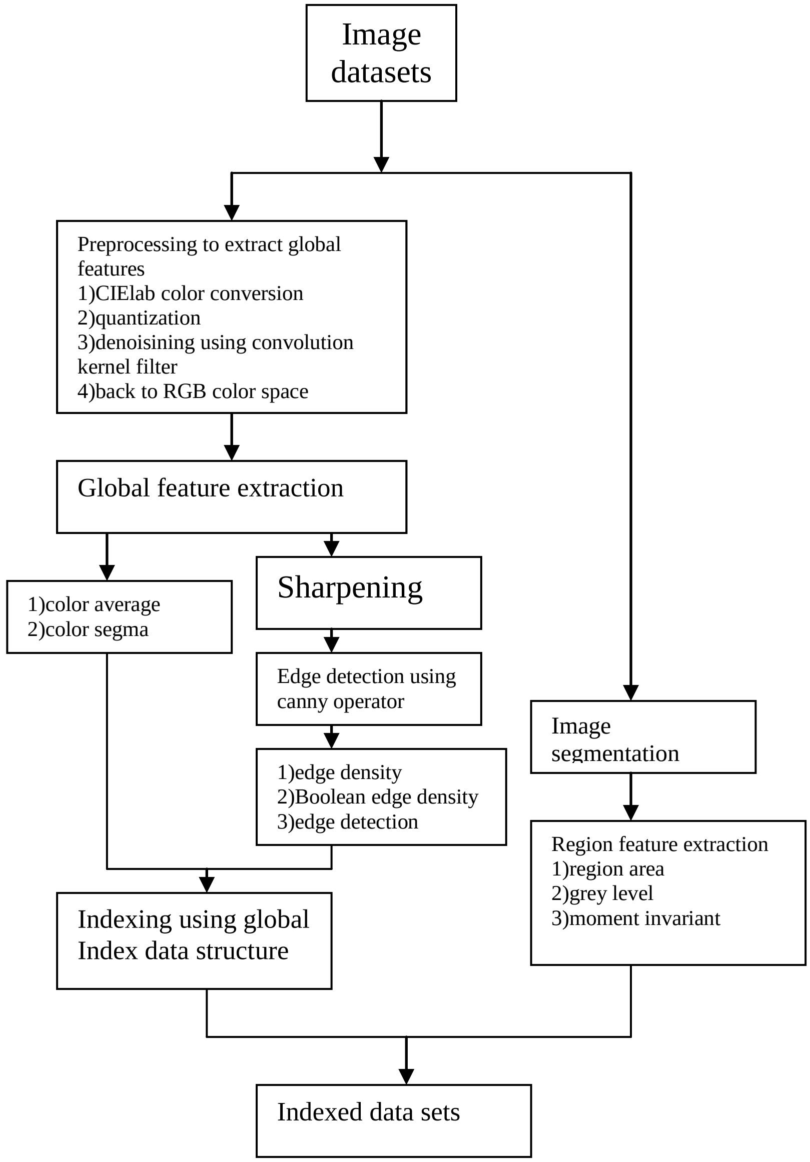

Fig1.the architecture of content based image indexing system

The architecture of the proposed content-based image indexing system is depicted in Figure 1. The system architecture shows the series of processes involved in the extraction of global and region features and indexing them using tree structures. The global features extracted include: color average, color sigma, edge density, Boolean edge density and edge direction. The region features extracted include: region area, moment invariants and grey level. In order to calculate edge related global features, edge detection is performed using sharpening then applying canny operator. The images are then segmented so as to extract region features.

3.2 Content-Based Image Retrieval System

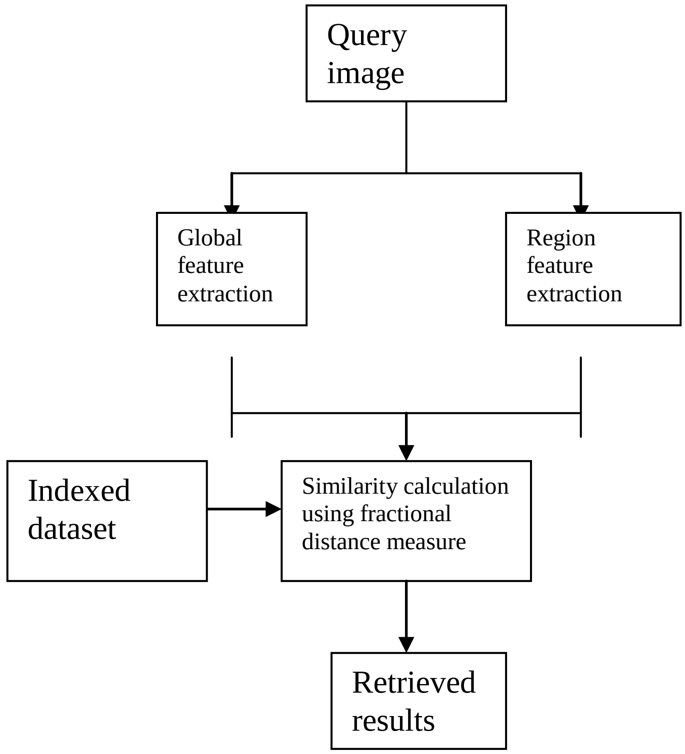

Fig.2.The architecture of Content-Based Image Retrieval System

Figure 2 shows the architecture of the proposed contentbased image retrieval system. The process of retrieval involves the determination of similarity amid a query image and the images present in a dataset. In the retrieval system, the global and regional features are extracted from the query image using the steps as in indexing. The similarity between the query image's features and the dataset image's features is computed using fractional distance measures. Owing to the fact that different features have different levels of significance to differentiate with query image, a weighting scheme is utilized by the retrieval system. Analogous to the indexing process, this system also segregates the process of determining similarity into two sections name the global section and the region section. Global section makes use of only the global features to determine similarities whereas the region section makes use of region features alone. This is followed by the computation of an average value of similarity amid the global and region sections thus arriving at a single value for each comparison between query image and dataset image. Eventually the similarity values determined against the datasets are sorted in ascending order by the system. As a result, the set of images with minimal similarities will come up first denoting that these are similar to those in the theoretical query image.

4. Global Features Extraction

Features that are determined by considering the whole image instead of separate regions or segments are called global features. Before extracting global features, the images in the dataset are preprocessed. Preprocessing comprises the following: color space conversion, quantization and denoising. The global features extracted from the images are: Color average, Color Sigma, Edge density, sharpening, Boolean edge density and Edge direction. Edge detection is performed using canny operator for the calculation of edge related features.

4.1 Preprocessing of Images

It is mandatory for an image to be digitized in amplitude for computer processing and features extraction (color). The motive is to reduce the color space besides acquiring the ability to localize color information spatially. We have performed quantization in CIELab color space. Extraction of global features becomes easy when the color space is reduced.

The preprocessing stage of global feature extraction comprises the following steps:

• RGB to CIELab color space conversion
• Quantization
• Denoising using Convolution Kernel filter
• CIELab to RGB color space conversion

4.1.1 RGB to CIELAB Color Space Conversion

The first step in preprocessing is the conversion of the images from RGB to CIELab color space [11], RGB to CIELAB is as follows

$\boldsymbol{X} = 0.412453\boldsymbol{R} + 0.357580\boldsymbol{G} + 0.180423\boldsymbol{B}$

$\boldsymbol{Y} = 0.212671\boldsymbol{R} + 0.715160\boldsymbol{G} + 0.072169\boldsymbol{B}$

$\boldsymbol{Z} = 0.019334\boldsymbol{R} + 0.119193\boldsymbol{G} + 0.950227\boldsymbol{B}$

Based on the definition, $\boldsymbol{L^*a^*b^*}$ is defined as

$$\begin{aligned} \boldsymbol{L^*} &= 116\boldsymbol{f}(\boldsymbol{Y/Y_n}) - 16 \\ \boldsymbol{a^*} &= 500[\boldsymbol{f}(\boldsymbol{X/X_n}) - \boldsymbol{f}(\boldsymbol{Y/Y_n})] \\ \boldsymbol{b^*} &= 200[\boldsymbol{f}(\boldsymbol{Y/Y_n}) - \boldsymbol{f}(\boldsymbol{Z/Z_n})] \end{aligned}$$

where

$$\boldsymbol{f}(\boldsymbol{q}) = \begin{cases} \boldsymbol{q^{1/3}} & \textbf{if } \boldsymbol{q} > \mathbf{0.008856} \\ \boldsymbol{7.787q} + \mathbf{16/116} & \textbf{otherwise} \end{cases}$$

$\boldsymbol{X_n, Y_n,}$ ***and*** $\boldsymbol{Z_n}$ represent a reference white as defined by a CIE standard illuminant, $\boldsymbol{D_{65}}$ in this case, and are obtained by setting $\boldsymbol{R = G = B} = 100(\boldsymbol{q} \in \{X/Xn, Y/Yn, Z/Zn\})$

4.1.2 Quantization

The second step in preprocessing is quantization. A wide range of application areas including any sort of color based content-based image indexing methods utilize color quantization of one form or another. The number of colors present in an image is minimized with the aid of color quantization. Since global feature extraction becomes easy with less color space, the images are quantized. In my system, this paper proposed reduction of the colors by grouping the converted *L* * *a* **b* * values to the closest predefined *L* * *a* **b* * value. Luminance (*L**) varies from 0 to 100 and represents blackness and whiteness while *a* * and *b* *represent tint or tone of the color.

4.1.3. Denoising Using Convolution Kernel Filter

The third step is the elimination of the noise that emerges after quantization. This paper uses convolution kernel filter to eliminate the noises from the quantized image. The resultant pixel of a convolution is the weighted sum of neighboring pixels. A matrix that assigns a particular weight to each of the neighbor pixels acts as the basis of convolution. This matrix is known as convolution kernel [12].

4.1.4. CIE Lab to RGB Color Space Conversion

The final step in preprocessing is the conversion of the images from CIELab to RGB color space The pixels are converted from *L* * *a* **b* * color space to RGB using the following formulas [13].

CIELAB to CIEXYZ conversion

$$X=\begin{cases} X_n f_n^3, f_x>\delta \\ (f_x-16/116)^3\delta^2 X_n, \textit{ otherwise}\end{cases}$$

$$Y=\begin{cases} Y_n f_y^3, f_y>\delta \\ (f_y-16/116)^3\,\delta^2 Y_n, \textit{ otherwise}\end{cases}$$

$$Z=\begin{cases} Z_n f_z^3, f_z>\delta \\ (f_z-16/116)^3\,\delta^2 Z_n, \textit{ otherwise}\end{cases}$$

Where δ =

$f_x = f_y + a^*/500,\ f_z = f_y - b^*/200$

CIELAB to RGB conversion:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{pmatrix} 0.412435 & 0.35780 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{pmatrix}^{-1} = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

4.2 Global Features Calculation

4.2.1 Color Average

CBIR systems extensively utilize the color feature. Color is considered to be a convenient and valuable feature employed in similarity searches [14, 15]. In color average measure found that the average number of color layers in an image. It deal with three color layers namely red green and blue since it utilize the RGB color space for this feature. All the pixels of a particular layer are added and divided by the total number of pixels or (width x height) of the image and this is performed for each of the layers.

$$A = 1/m \sum_{n=0}^{n=m} (Pn)$$

Where, A is the average value, m is the total number of pixels, P_n is the nth pixel value. It obtain three values corresponding to red, green and blue average color values as a result of this feature.

4.2.2. Color Sigma

The intensity variations in an image are denoted by the color sigma. The standard deviation of the intensity values of the pixels are employed in the calculation of color sigma. Three values of standard deviation for each of the color layers would exist since, It utilize the RGB color space. Intensity mean and variance form the components of standard deviation. Initially it determines the average value of each of the color layer followed by the corresponding variance. Sigma or standard deviation is obtained by determining the square root of variance. Sigma can be found with the aid of the following formula:

$$\overline{x} = 1/N \sum_{i=1}^{N} xi = x_1 + x_2 + \ldots + x_n$$

Where, x is the average value, N is the total number of pixels; xi is the i^{th} pixel value.

4.2.3. Edge Detection Using Canny Operator

The Canny method finds edges by looking for local maxima of the gradient of the system. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is therefore less likely than the others to be fooled by noise, and more likely to detect true weak edges.

4.2.4. Edge Density

The mean pixel value of the improved image is denoted by the edge intensity feature. This is determined by improving the pixels belonging to edges and boundaries with the aid of a standard edge detector.

4.2.5. Boolean Edge Density

The edge density feature calculation will give us an enhanced image. The Boolean edge density feature is calculated from this edge enhanced image. In this feature, the number of pixels that are considered as an edge is counted. The edge detected images are imposed a certain threshold in order to classify the edge pixels as white (1) and non edge pixels as black(0). The quantity of white (edge) pixels in the region is returned by the measure. The employing either relevance feedback or trial and error to obtain the threshold. The initial threshold is considered the mean value of the image.

5. Region Features Extraction

The region features play a significant role in CBIR systems since a majority of images constitute some objects and a user frequently concentrates on an object or a region whilst specifying an image for retrieval. The images are initially segmented to extract regions present in it. The region features extracted includes: Region area, Grey level and Moment invariants. These features are calculated for all the regions in an image.

5.1 Image Segmentation

Segmentation of image into homogeneous regions based on visual features is an important process in CBIR system for the retrieval of images using region features. Image segmentation forms as elementary process of the image, video and computer vision applications. The elementary components of an image that correspond to real-world objects are decomposed by image segmentation. An image segmentation where in an image is segregated into related regions by combining neighboring pixels of identical features followed by the merger of adjacent regions on basis of a certain criterion such as homogeneity of features in neighboring regions, [5] is necessary for the computation of region features.

5.2 Region Features Calculation

The region features has three factors are:-

1. Region Area

Region area feature represents the number of pixels in a region. The segmentation algorithm segments the image into regions. Region area feature is calculated for all the regions in an image. It is a number that represents the count of pixels in a region.

2. Grey Level

The grey level feature represents the mean intensity value of an image. Each region will have different value for grey level feature. The grey level of a region is a number that represent the mean intensity value of that region.

3. Moment Invariants

The normalized central moments can be integrated to define a set of seven moment invariants. The formula to determine the invariants have been discussed in detail in [16] and are given as follows:

Moment:

$$\boldsymbol{m_{pq}} = \sum_{xy} x^{\boldsymbol{p}}\, y^{q}\, f(x,y)$$

where, pq the $(p+q)^{th}$ order of moment; $f(x,y)$is the pixel value at coordinate (x,y).

6. Indexing Using Tree Structures

Effective indexing and fast searching of images on basis of visual features pose a significant issue in Content based image retrieval. Commonly a tree structure is utilized to store image information since it has high dimensional metric space. R-tree [17], R*-tree [18], VP-tree structure [19] and Hybrid Tree [20] are some of the widely used tree structures. A majority of these multi-dimensional indexing methods perform significantly well for dimensions (up to 20). In my system, it will be used R*-Tree structure to achieve better performance and efficiency. A variant of R-tree employed in the indexing of spatial information is known as R*-tree. Both point and spatial data are supported at the same instant by an R*-tree but they are slightly expensive compared to R-trees. The computed global and region features are stored in data structures. The data structure used is split into two: global data structures and region data structures. The global and region features are stored in global and region data structures respectively. All region data structures are inserted into tree structure (R*-Tree) and each region's spatial information is represented by a rectangle used by the tree structure at searching stage. Each region data structure in R*-tree will point to its corresponding global data structure.

7. Retrieval Using Fractional Distance Measures

The visual similarities between a query image and images in an image database are determined as an alternative to exact image matching in case of content based image retrieval. Consequently a list of images ranked in order of their resemblance with the query image is enlisted as a result of retrieval. Lately, numerous similarity measures have been developed for image retrieval that works on basis of approximations of the distribution of features. The retrieval performance of an image retrieval system is greatly influenced by different similarities or distance measures. L-Family Distance, which includes L1 distance (also known as Manahattan distance) and L2 distance (also known as Euclidean distance); Earth Mover Distance (EMD) and Kullback-Leibler (KL) distance are some of the frequently utilized similarities. This system will use Fractional Distance Measures proposed by Aggarwal et al. [20]. The L-norm metrics which include Manhattan and Euclidean distance measures have been extended to form the aforesaid measures. The measure distinctly outperformed the commonly utilized *lp* norms [20] when applied to high-dimensional database vectors [20]. Generally the Lp norm is induced by the distance,

$$dist_d^p(x,y) = \left[\sum_{i=1}^{d} \left\| x^i - y^i \right\|^p \right]^{1/p}$$

Where d is the dimensionality of the space and p is a free parameter, $p \geq 1$.This definition was augmented by Aggarwal et al. [20] allow $p \in (0,1)$. Since the triangle inequality has been violated by the fractional measures defined by $dist^p$ with $p \in (0,1)$. these are no longer considerd as distances in the mathematical sense. The indexing and partitioning methods that depend on the metric properties may be affected as a result. The mean average precision retrieval is remarkably enhanced with the aid of Fractional distance measures in comparison with that of the widely used L1 and L2 norms [21]. The retrieval system splits the process of finding similarity into two sections: global and region section. In global section, the similarity between global features is calculated, while in the region section similarity between region features is calculated. The average value of similarity between region and global section is determined for comparing query image and dataset image. The similarity values computed against images in the dataset are sorted in ascending order. The result will be a collection of images where in those with smaller similarity values come up first, meaning those images are similar with the query image in theory.

8. Results

This work has been implemented in Delphi7. The proposed image retrieval system has been tested with a database set of images. The global and region features of the images in the image database are calculated and stored. For a given query image, the global and region features are estimated and similar images are retrieved from the data set based on the Fractional distance measures. The given query images are shown in figure 3, 5, and 7, and the corresponding retrieved images are shown in figure 4, 6, and 8 respectively.

Fig3.query image

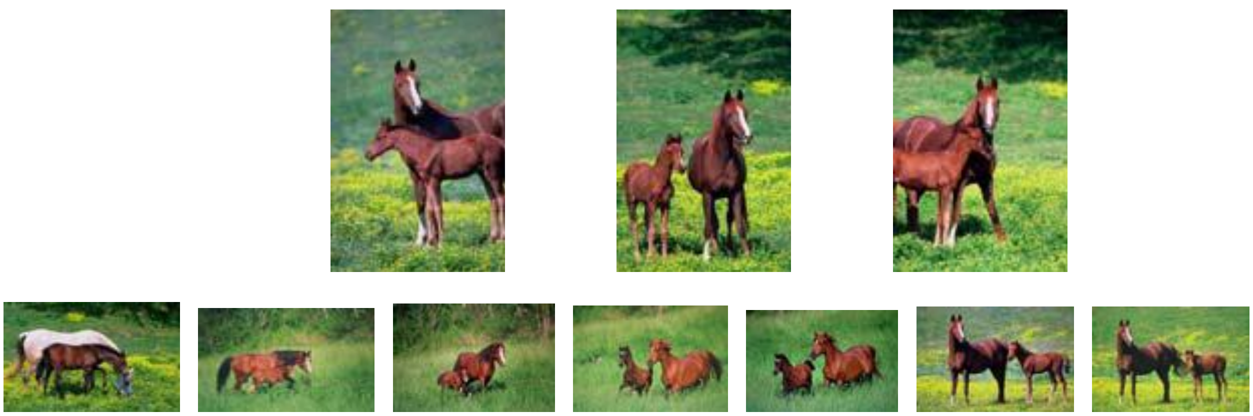

Fig.4. Retrieved similar images corresponding to Query image

Fig5. query image

Fig.6. Retrieved similar images corresponding to Query image

Fig7. query image

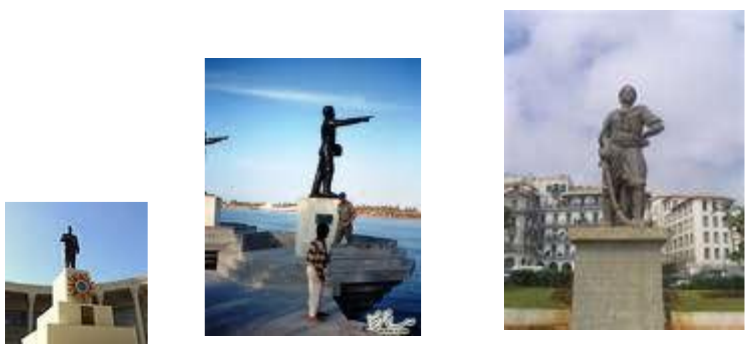

Fig.8. Retrieved similar images corresponding to Query image

9. Conclusion

The rapid growth in the number and size of image databases has prompted the need for accurate and efficient system for retrieval of images on the basis of their content. There has been a significant growth in the utilization of image databases in numerous areas such as medical image management, multimedia libraries, document archives, art collections, geographical information system, law enforcement agencies, and journalism leading to momentous growth in research related to the Content based image retrieval (CBIR). This research presents an elegant system for content-based image indexing and retrieval. The system has combined the global and regional features for the indexing of images. The proposed system has employed the image processing techniques like color space conversion, Quantization, denoising, Edge detection and segmentation. R*-Tree data structure is used in indexing the region features. The fractional distance measures employed in the retrieval have outperformed both the similarity measures: L1 and L2 norms. The experimental results have demonstrated that the proposed system can efficiently retrieve similar images from a collection of images based on a query image besides improving retrieval accuracy. The research in this field has come a long way during the last decade, but it has still a long way to go to provide the users with tools to retrieve images from the multimedia or image databases in a very efficient way through input in the form of text, image or drawing. Problems involving meaningful image segmentation or to find semantic meanings of an image from low-level features or to find correct symmetry between input image and image of the database using color, texture, shape and spatial relationships still remain to be resolved although some progress has been achieved. XML-based image annotation of the images at the time of creation of the images, in an automatic way has been suggested but not yet implemented. This method has the potentiality to solve the problem of computer perception being faced by researchers in this field. But this method is still in its infant stage and needs to be developed further to attain maturity. In short, there are plenty of difficult research issues still unresolved in the area which call for more coordinated research efforts in the coming years.

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