# A Novel Approach for Content-Based Image Indexing and Retrieval System using Global and Region Features

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**Summary**
Recently, digital content has become a significant and inevitable asset for any enterprise and the need for visual content management is on the rise as well. There has been an increase in attention towards the automated management and retrieval of digital images owing to the drastic development in the number and size of image databases. A significant and increasingly popular approach that aids in the retrieval of image data from a huge collection is called Content-based image retrieval (CBIR). Content-based image retrieval has attracted voluminous research in the last decade paving way for development of numerous techniques and systems besides creating interest on fields that support these systems. CBIR indexes the images based on the features obtained from visual content so as to facilitate speedy retrieval. In this paper, we have presented an elegant and effective system for content-based image indexing and retrieval. The system exploits the global and regional features of the images for indexing and fractional distance measure as similarity measure for retrieval. The images are quantized before extracting the global features. We have also presented a novel approach for image segmentation to extract the region features effectively. R*-Tree data structure is used in indexing the region features. The experimental results show that the proposed system can improve the retrieval accuracy as well as reduce the time for retrieval.

***Key words:***
*Content Based Image Indexing (CBII), Content-Based Image Retrieval (CBIR), Global Features, Region Features, Lab Color space, Edge detection, Segmentation, R*-Tree Structure, Fractional Distance Measure.*

## 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 [9]. The drastic increase in the rate of generation of images in myriad fields ranging from entertainment to profession and science has attracted voluminous research in the field of Visual information retrieval [2],[3],[4].Multimedia [5], video [6] and audio [7], [8] searching, have attracted particular interest as well. Content based image retrieval (CBIR), having its roots from image processing, computer vision, very large databases and human computer interaction [10], [11], [12] is one of the significant research topics. CBIR is potential technology that intends to enhance the functionality of Picture Archiving and Communication Systems (PACS) [13].

The problem of searching identical images from large image repositories on basis of their visual contents is called Content-Based image retrieval [17] [18]. 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 [15]. 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 [37]. 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].

The large collections of images and video frames have made scalability, speed and efficiency the key requirements for the success of an image retrieval system. Image indexing and retrieval systems are classified into two broad categories: one on basis of the content of the images such as color, texture, shape, and objects (the content based ones) and the other on basis of the depiction of the images such as keywords, size and caption (the description based ones) [40]. The description based image retrieval systems face similar problems like the ones faced by the information retrieval systems, in text databases or web search engines, besides requiring lesser effort to implement and design the user interface for. Commonly, the CBIR systems make use of the visual features in order to index the systems. The mode in which the visual

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features are extracted and indexed and the manner in which the queries are done in this system varies greatly with that of the others [40]. A huge number of works on CBIR that are in existence focus mainly on the indexing of images to a storage system and the retrieval of the same for a particular query.

Even though CBIR has been in existence before the 1990 the number of publications on it were very low then. The escalating interest in the field of CBIR research led to the gradual increase in the number of publications since 1997. Numerous CBIR algorithms were developed as a result of those researches [22 - 25]. QBIC [14], Virage [38] and Excalibur's RetrievalWare are a notable few among the commercial systems. Photobook [20], VisualSEEK [18], WEBSEEK [17] and Netra are a few significant research systems. Comprehensive surveys on CBIR systems are available in [14, 27 - 29]. Many researchers of the computer science community have turned their attention towards image indexing and retrieval recently [2], [14], [17], [27]. Numerous multimedia database systems like the IBM QBIC System developed at the IBM Almaden Research Center, the Virage System [38] of Virage, Inc., and the Photobook [20] System of the MIT Media Lab [39, 20] have developed and applied the image feature vector indexing technique. Nevertheless there are copious research problems that continuously draw attention from various disciplines.

The determination of the image feature or combination of image features that are to be utilized for image indexing and retrieval purposes is the first crucial decision to be taken in the development of a visual content-based image retrieval system. Image feature selection has a profound influence on diverse aspects of the system design besides determining the image retrieval capabilities of the ultimate system [9]. CBIR systems utilize three stages of image content description. Features such as color, shape and texture form the basis for the low level description. Object background and object spatial relation form an integral part of the middle level description. A concept that is tedious to capture with the aid of a mathematical model (for instance scene, event and emotion) serves as the basis of high level description [19]. A majority of image retrieval systems do not consider the regions present in an image. Commonly the user is interested solely on an object or a region in the image when he specifies an image that consists of some objects and thus ignoring the regions would cause problems.

The primary intent of our research 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 our research.. In this paper, we have presented 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.

The images in the datasets are preprocessed before the extraction of the global features. Edge detection is performed to compute the global features like edge density and edge direction. In order to extract the region features, the images are segmented using the proposed segmentation algorithm. The extracted global and region features are stored in global and region data structures respectively. The region data structures are inserted into the R*-Tree structure which in turn points to its corresponding global data structure. Fractional distance measures are applied to obtain a degree of similarity between the query image's features and the database image's features thereby facilitating retrieval. We have also employed feature weighting scheme since different features have different amount of discriminatory characteristics. Thus our approach aspires to speed up the image retrieval process and intends to facilitate effective usage of storage space, internal memory without compromising the accuracy of the retrieval.

The remainder of the paper is organized as follows; Section 2 gives a brief review of relevant researched on content based image retrieval. The architecture of the proposed content-based image indexing and retrieval system is presented in Section 3. Section 4 details the global index features extraction. The proposed segmentation algorithm is presented along with the calculation of region features in Section 5. The data structures for indexing the features are detailed in Section 6. Section 7 describes the retrieval process using fractional distance measures and feature weighting scheme. In Section 8, the experimental evaluation and the results are presented. Conclusions are summed up in Section 9.

## 2. Related Works

M. Flicker et al. [14] have introduced QBIC (Query by Image and Video Content) system, in which content-based queries such as query by example image, query by sketch and drawing, and query by selected color and texture patterns were supported. The visual features used in the system include color, texture, and shape. In their system, color was represented using a k-bin color histogram and the texture was described by an improved Tamura texture representation. The shape information used includes area, circularity, eccentricity, major axis orientation, and moment invariants. KLT (Karhunen-Loeve transform) was used to reduce the dimension of the feature vectors and R*-Tree was the indexing structure.

A. Pentland et al. [20] have presented the Photobook system which was composed of a set of interactive tools for browsing and searching images. It supports retrieval on the basis of query by example image. The images were organized in three subbooks from which shape, texture, and face appearance features were extracted respectively and used in the retrieval process.

J.R. Smith et al. [18] have presented the VisualSEEK system, in which both content-based query (query by example image and spatial relation pattern) and text-based query were supported. The system uses the following visual features: color represented by color set, texture based on wavelet transform, and spatial relationship between image regions. A binary tree was used to index the feature vectors.

Jeremy S. De Bonet et al. [22] have presented an algorithm which approximates the perceived visual similarity between images. In their algorithm, the images are initially transformed into a feature space which captures visual structure, texture and color using a tree of filters. Similarity is the inverse of the distance in the perceptual feature space. By using the algorithm they have constructed an image database system which can perform example based retrieval on large image databases.

Ze-Nian Li et al. [40] have presented the prototype system C-BIRD for content-based image retrieval from large image and video databases. Issues in both database design and image content based retrieval were addressed. They have also presented two methods for image content based retrieval, i.e., Search by Illumination Invariance and Search by Object Model.

Jing Huang, et al. [24] have defined an image feature called the color correlogram and uses it for image indexing and comparison. The image feature distills the spatial correlation of colors and when computed efficiently, turns out to be both effective and inexpensive for content-based image retrieval. Experimental evidence showed that the feature outperforms not only the traditional color histogram method but also the recently proposed histogram refinement methods for image indexing/retrieval.

Yihong Gong et al. [9] have proposed a novel system that strives to achieve advanced content-based image retrieval using seamless combination of two complementary approaches: on one hand, they proposed a color clustering method to better capture color properties of the original images; on the other hand, expecting that image regions acquired from the original images inevitably contain many errors. They also proposed an effective image indexing scheme to facilitate fast and efficient image matching and retrieval. The experimental evaluation showed that the image retrieval system surpasses other methods under the comparison in terms of not only quantitative measures, but also image retrieval capabilities.

James Z. Wang et al.[12] have presented SIMPLIcity (Semanticssensitive Integrated Matching for Picture LIbraries), an image retrieval system, which uses semantics classification methods, a wavelet-based approach for feature extraction, and integrated region matching based upon image segmentation. They have experimented with the idea that images can be classified into global semantic classes, such as textured or non-textured, graph or photograph, and that much can be gained if the feature extraction scheme was tailored to best suit each class.

Marjo Markkula et al. [37] have introduced a test collection for the evaluation of CBIR algorithms. In the test collection, the performance testing was based on photograph similarity perceived by end-users in the context of realistic illustration tasks and environment. The results showed that the clear correlation between the subjects' similarity assessments and the functioning of feature parameters of the tested algorithms.

Nobuo Suematsu et al. [26] have proposed a region-based image retrieval method which performs image segmentation and indexing using texture features computed from wavelet coefficients. The retrieval method has advantages in texture feature extraction and hierarchical image segmentation over the previous region-based techniques using wavelet transform.

Kyoung-Mi Lee et al. [4] have introduced a refinement method for retrieval based on the learning of the user's specific preferences. The system indexes objects based on shape and group them into a set of clusters, with each cluster represented by a prototype. The approach to learn the users' preference was to refine corresponding clusters from objects provided by the users in the foreground, and to simultaneously adapt the database index in the background. The quality of the returned results was superior to that of a color-based query, and continued to improve with further use.

Paisarn Muneesawang et al. [3] have proposed a machine learning approach for CBIR task, which allows users to directly modify query characteristics by specifying their attributes in the form of training examples. Specifically, they have applied a radial-basis function (RBF) network for implementing an adaptive metric which progressively models the notion of image similarity through continual relevance feedback from users. Experimental results showed that the methods not only outperform conventional CBIR systems in terms of both accuracy and robustness, but also previously proposed interactive systems.

Peter Howarth et al. [36] have applied the concept of fractional distance measures, proposed by Aggarwal et al. [21], to content-based image retrieval. Their experiments showed that the fractional distance measures give a significant improvement in mean average precision retrieval over the commonly used L1 and L2 norms and the retrieval performances of these measures consistently outperform the more usual Manhattan and Euclidean distance metrics when used with a wide range of high-dimensional visual features.

Christian Hartvedt [19] has presented the findings from a project that investigated if combining text and image retrieval algorithms with the use of image context can help to reduce the problem of merging and ranking distributed results. The evaluation of his approach, was implemented in a system called CAIRANK (Context-Aware Image Ranking), showed that it returns significantly better results than a more traditional ranking approach based on using DBMS-normalized image similarity scores alone.

Heba Aboulmagd Ahmed et al. [1] made use of fuzzy logic to improve CBIR by allowing users to express their requirements in words, the natural way of human communication. The image was represented by a Fuzzy Attributed Relational Graph (FARG) that describes each object in the image, its attributes and spatial relation. The texture and color attributes were computed in a way that model the Human Vision System (HSV). They have proposed an approach for graph matching that resemble the human thinking process. The system was evaluated by different users with different perspectives and gives satisfactory results.

Thomas M. Deserno et al. [13] have suggested a more systematic and comprehensive view of the concept of "gaps" in medical CBIR research. In particular, they defined an ontology of 14 gaps that addresses the image content and features, as well as system performance and usability. In addition to the gaps, they have identified seven system characteristics that impact CBIR applicability and performance. The created framework can be used as a posteriori to compare medical CBIR systems and approaches for specific biomedical image domains and goals and a priori during the design phase of a medical CBIR application, as the systematic analysis of gaps provides detailed insight in system comparison and helps to direct future research.

## 3. The System Architecture

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

### 3.1 Content-Based Image Indexing System

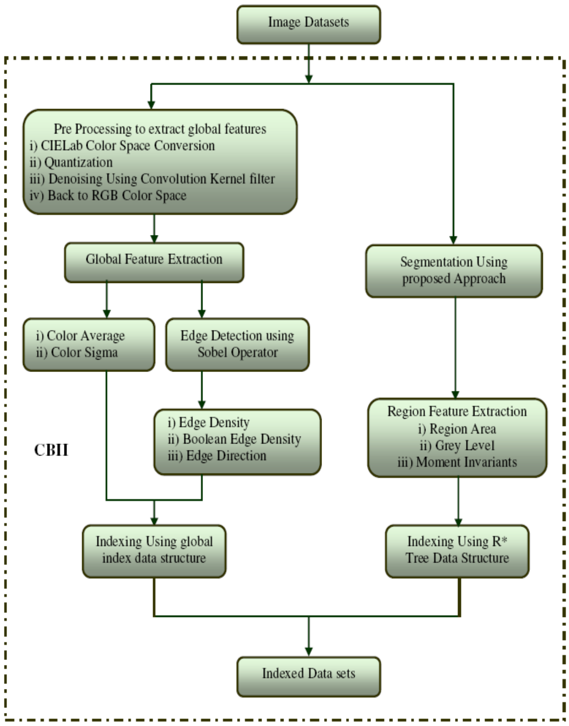


Fig. 1. The architecture of Content-Based Image Indexing System

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 sobel operator. The images are segmented using the proposed segmentation algorithm so as to extract region features. The detailed explanation of all the steps involved in the proposed indexing system is presented in the remainder sections of the paper.

### 3.2 Content-Based Image Retrieval System

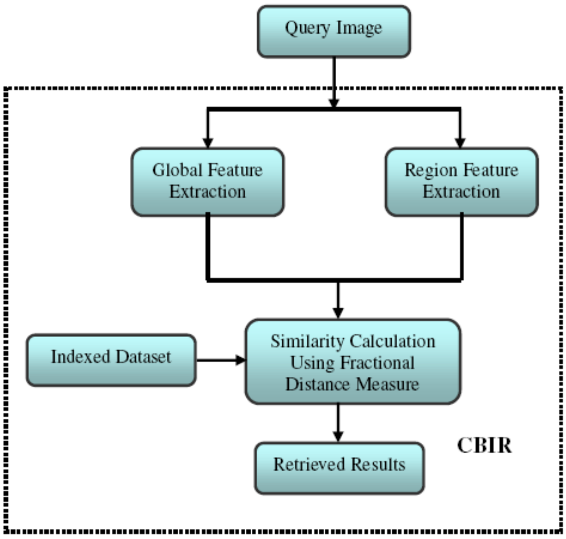


Fig. 2. The architecture of Content-Based Image Retrieval System

Figure 2 shows the architecture of the proposed content-based 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, Boolean edge density and Edge direction. Edge detection is performed using sobel operator for the calculation of edge related features. The following subsections discuss in detail the preprocessing and the calculation of the global features from the images.

### 4.1 Preprocessing of Images

The preprocessing of images for the global features extraction is presented in this sub-section. 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 [41], which is a color-opponent space with dimension 'L' for lightness and 'a' and 'b' for the color-opponent dimensions. The luminance is denoted by $L*$ and it varies uniformly from 0 for black to 100 for white. The $a*$ and $b*$ values are expressed such that $+a/-a$ denotes red/green coordinate and $+b/-b$ denotes blue/yellow coordinate. The non-linear relations for $L*$, $a*$ and $b*$ are as follows [42]:

RGB to CIEXYZ conversion

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412435 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

CIEXYZ to CIELab conversion:

$$L* = \begin{cases} 116(Y/Y_n)^{1/3} - 16, if \quad Y/Y_n > 0.008856 \\ 903.3(Y/Y_n), \quad if \quad Y/Y_n \le 0.008856 \end{cases}$$

$$a* = 500 * (f(X/X_n) - f(Y - Y_n))$$

$$b* = 200 * (f(Y/Y_n) - f(Z - Z_n))$$

Where $f(t) = \begin{cases} t^{1/3}, & if \quad t > 0.008856 \\ 7.787 * t + 16/116, & if \quad t \le 0.008856 \end{cases}$

Here $X_n$, $Y_n$ and $Z_n$ are the CIEXYZ tristimulus values of the reference white point (the subscript n suggests "normalized").

### 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 our system, we have reduced 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. We have used 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 [43]. The matrix is a square one having 3x3, 5x5 or 7x7 or higher dimensions depending on the filters. Other name of the convolution kernel is linear filter. Various digital image processing applications such as the noise reduction through spatial averaging utilize convolution kernels [44]. Each pixel in a color layer is substituted by a convolution kernel of the color levels in a neighborhood of that particular pixel [30].

### 4.1.4. CIELab 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 [45].

CIELab to CIEXYZ conversion

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

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

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

Where $\delta = 6/29$ , $f_y = (L^* + 16))/116$ , $f_x = f_y + a^*/500$, $f_z = f_y - b^*/200$

CIEXYZ to RGB conversion:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 0.412435 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix}^{-1} * \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

## 4.2 Global Features Calculation

The calculation of the global features: Color Average, Color sigma, edge density, Boolean edge density, and edge direction is presented in this subsection.

### 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 [46, 47]. In color average measure we find an average number of color layers in an image. We deal with three color layers namely red green and blue since we 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.

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

Where, $A$ is the average value, $m$ is the total number of pixels, $P_n$ is the $n^{th}$ pixel value. We 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 we utilize the RGB color space. Intensity mean and variance form the components of standard deviation. Initially we determine 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:

$$\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i = \frac{x_1 + x_2 + \cdots + x_N}{N}$$

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

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2}$$

Where, $\sigma$ is the standard deviation, $\bar{x}$ is the average value, $N$ is the total number of pixels, $x_i$ is the $i^{th}$ pixel value.

### 4.2.3. Edge Detection Using Sobel Operator

Edge detection of the images is carried out for the calculation of edge related features. The proposed system employs sobel operator for edge detection. Image processing algorithms precisely the edge detection algorithms utilize the sobel operator. In technical terms it is a discrete differentiation operator that calculates an approximation of the gradient of the image intensity function. Determination of the maximum and minimum in the first derivative of the image aids in edge detection. The regions of elevated spatial frequency analogous to edges are intensified by the sobel operator since it carries out a 2-D spatial gradient measurement on an image. Traditionally, the approximate absolute gradient magnitude at each point in an input grayscale image is determined with the aid of a sobel operator [31].

Theoretically the sobel operator comprises a pair of 3×3 convolution kernels as given in figure 3. Rotation of one of the kernels by 90° forms the other. This is identical to Roberts Cross operator.

| | | |
|---|---|---|
| -1 | 0 | +1 |
| -2 | 0 | +2 |
| -1 | 0 | +1 |

$G_x$

| | | |
|---|---|---|
| +1 | +2 | +1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

$G_y$

Fig. 3. Sobel convolution kernels

These kernels are designed in such a way so that they provide maximum reaction to the edges that run horizontally and vertically in relation with the pixel grid, one kernel for each of the two perpendicular orientations. Distinct measurements of the gradient component in each orientation (denote as $G_x$ and $G_y$ ) can be facilitated by applying the kernels discretely to the input image. These in turn can be integrated to determine the absolute magnitude of the gradient at each of the points besides its orientation. Gradient magnitude is denoted as $|G| = \sqrt{G_x^{\,2} + G_y^{\,2}}$ . The angle of orientation of the edge (relative to the pixel grid) forming the spatial gradient is denoted as $\theta = \arctan\left( {G_y}/{G_x} \right)$.

### 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. We have used Sobel operator [31] for edge detection in the proposed system whose result is a set of pixels whose values corresponding to their residence on an edge with the values of pixels far from the edges reducing to 0 and those near the edges having the maximum value. Edge density is calculated using the formula used for color average calculation.

### 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. The quantity of white (edge) pixels in the region is returned by the measure. We employ 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 computation of the region features from the images is presented in this section. 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. We have proposed a novel approach for the segmentation of images. The region features extracted includes: Region area, Grey level and Moment invariants. These features are calculated for all the regions in an image. The proposed image segmentation algorithm and the calculation of region features are detailed in the following subsections.

### 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, [37] is necessary for the computation of region features. In our system, we have proposed a novel approach to segment image into regions for the effective extraction of the region features. The segmentation algorithm proposed is for grey scale images. Therefore, the color images are initially converted into grey scale images and then segmentation is performed. The segmented output is mapped into the original color image for further process. The proposed segmentation algorithm is described as follows:

The pixels of a given grey scale image are represented as a 2-D matrix as follows:

$$IP_V = \begin{bmatrix} a_{11} & \mathrm{a}_{12} & \cdots & \mathrm{a}_{1\mathrm{j}} & \cdots & \mathrm{a}_{1\mathrm{n}} \\ a_{21} & \mathrm{a}_{22} & \cdots & \mathrm{a}_{2\mathrm{j}} & \cdots & \mathrm{a}_{2\mathrm{n}} \\ \vdots \\ a_{i1} & \mathrm{a}_{\mathrm{i}2} & \cdots & \mathrm{a}_{\mathrm{ij}} & \cdots & \mathrm{a}_{\mathrm{in}} \\ \vdots \\ a_{m1} & \mathrm{a}_{\mathrm{m}12} & \cdots & \mathrm{a}_{\mathrm{mj}} & \cdots & \mathrm{a}_{\mathrm{mn}} \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_i \\ \vdots \\ y_m \end{bmatrix}$$

The 2-D representation of the pixel values are converted into 1-D representation so as to facilitate further processing. The index of all the pixel values is stored in a vector $IMP_V$ .

$$MP_V = [y_1 \;\; y_2 \;\; \cdots y_i \;\; \cdots y_m]$$

$$IMP_V = \Delta MP_V[i] \;\; ; i = 1 \;\; to \;\; n$$

i.e, $IMP_V = [Iy_1 \;\; \mathrm{I}y_2 \;\; \cdots Iy_i \;\; \cdots Iy_m]$

This is followed by the calculation of significant value for all the pixels. The difference between a pixel and the remaining pixels in the vector $MP_V$ gives the significant value of that pixel.

$$\{P_{VM}\} = \left(MP_{V(i)} - MP_{V(j)}\right)^2 \;\; ; \quad j = 1 \;\; to \;\; n$$

If the resultant significant value is less than a predefined threshold, then those values are replaced by one and the rest by zero.

$$[P_{VI}] = \begin{cases} P(i), \;\; if \;\; \{P_{VM}\} < Threshold \\ 0, \;\; else \end{cases} \qquad i = 1 \;\; to \;\; n$$

i.e., $[P_{VI}] = [1 \;\; 0 \;\; 1 \;\; 1 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; \cdots \;\; 0 \;\; 1]$

The values corresponding to zero are obtained from the $MP_V$ for further processing.

$$P_Z = [\Omega P_{VI}]$$

Where $\Omega P_{VI}$ is the set of zeros from $P_{VI}$ . Following this, the indexes of all the values are obtained from $P_{VI}$.

$$P_{ZI} = [\Delta P_Z]_{P_{VI}}$$

Where $\Delta P_Z$ is the index of the zero elements. Finally values corresponding to those elements are acquired from $MP_V$ for segmentation.

$$P_V = [Val(P_{ZI})]_{MP_V}$$

The process discussed above needs to be repeated until the whole image is segmented. The significant values less than the threshold in the subsequent iterations are replaced by two, three and so on and these values are moved to their respective segments. Eventually the segmented values are converted back to 2-D representation so as to represent the distinct regions in the image.

## 5.2 Region Features Calculation

The calculation of the region features from the segmented regions is given in this sub-section.

### 5.2.1. Region Area

Region area feature represents the number of pixels in a region. The proposed 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.

### 5.2.2. 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.

### 5.2.3. 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 [30] and are given as follows:

**Moments:**

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

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

**Centroid (balance point):**

$$\bar{x} = \frac{1}{m_{00}} \sum x f(x,y) = \frac{m_{10}}{m_{00}}$$

$$\bar{y} = \frac{1}{m_{00}} \sum y f(x,y) = \frac{m_{01}}{m_{00}}$$

Where, $\bar{x}$ is the balance in $x$ coordinates; $\bar{y}$ is the balance in $y$ coordinates; $xf(x,y)$ is the $x$ coordinates in the region

**Central Moments:**

$$\mu_{pq} = \sum_{xy} \left(x-\bar{x}\right)^{p} \left(y-\bar{y}\right)^{\ell} f(x,y)$$

Where, $\mu_{pq}$ is the central moment; $x$, $y$ are the coordinates; $\bar{x}$ is the balance in $x$ coordinates; $\bar{y}$ is the balance in $y$ coordinates

**Normalized Central Moments:**

$$\gamma = 1 + \frac{p+q}{2}$$

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}}$$

Where, $\eta$ is the normalized central moments; $p\ q$ the $(p+q)^{th}$ order of moment.

**Invariant Moments:**

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})\right]$$
$$\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]$$

$$\phi_6 = (\eta_{20} - \eta_{02})\left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$\phi_7 = (3\eta_{21} - \eta_{30})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})$$
$$\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]$$

Where, $\phi_n$ is the $n^{\text{th}}$ moment invariant $n = 17$.

## 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 [32], R*-tree [33], VP-tree structure [34] and Hybrid Tree [35] 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 our system, we have 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. Norbert Beckmann, Hans-Peter Kriegel, Ralf Schneider and Bernhard Seeger put forth the concept of R*-Tree in 1990 [51]. Though R*-Tree displays significant improvements over the R-Tree variants its reinsertion method poses a considerable overhead. Database systems organizing both multidimensional points and spatial data can benefit from the R*-Trees. Reduction of the area, margin and overlap of the directory rectangles are the basis for an R*-Tree. The r*-Tree utilizes an algorithm analogous to that of the R-Tree's for query and delete operations. The primary difference lies in the insert algorithm. To be precise the mode of selection of which branch to insert the new node into and the methodology for splitting a full node in an R*-Tree differs from that of the R-Tree [33]. The R*-Tree distinctly outperforms Greene's R-tree, the quadratic R-tree and the popular linear R-tree upon performance comparison.

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. In our system, we have used Fractional Distance Measures proposed by Aggarwal et al. [48]. 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 $l_p$ norms [48] when applied to high-dimensional database vectors [48]. 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. [48] 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 [49].

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. Experimental Results

This section provides the experimental evaluation of our image retrieval system. This work has been implemented in java. 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 image is shown in figure 4 and the corresponding retrieved images are shown in figure 5.

Fig. 4. Query image

Fig. 5. 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). In this paper, we have presented 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. The novel image segmentation technique proposed has been found to segment the images in very effective manner. 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: $L_1$ and $L_2$ 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.

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