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Image Retrieval Based on Content Using Color Feature

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First, I thank Allah who inspired me and gave me favors to complete this thesis. My heartiest gratitude to my beloved family: my martyr father, my mother, my wife, my children Mohammed and Sarah, and my brothers and sisters; whom without I would have never been able to accomplish this work.

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Ahmed J. Afifi

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List of Abbreviations

AMORE	:	Advanced Multimedia Oriented Retrieval Engine (A World Wide Web Image Retrieval Engine)
CBIR	:	Content Based Image Retrieval
CCM	:	Color Co-occurrence Matrix
CHKM	:	Color Histogram for K-Means
CIE	:	International Commission of Illumination
CMY	:	Cyan, Magenta, and Yellow Color Space
CSH	:	Color Shape Histogram
DBPSP	:	Different Between Pixels of Scan Pattern
GCH	:	Global Color Histogram
GLCM	:	Gray Level Co-occurrence Matrix
HSV	:	Hue, Saturation, and Value Color Space
KIWI	:	Key-point Indexing Web Interface
LCH	:	Local Color Histogram
MARS	:	Multimedia Analysis and Retrieval System
MIT	:	Massachusetts Institute of Technology
QBIC	:	Query By Image Content
RGB	:	Red, Green, and Blue Color Space
SSE	:	Sum of Squared-Error
SVM	:	Support Vector Machine
VIR	:	Visual Information Retrieval
WBIIS	:	Wavelet-Based Image Indexing and Searching

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Abstract

In various application domains such as education, crime prevention, commerce, and biomedicine, the volume of digital data is increasing rapidly. The problem appears when retrieving the information from the storage media. Content-based image retrieval systems aim to retrieve images from large image databases similar to the query image based on the similarity between image features.

In this thesis we present a CBIR system that uses the color feature as a visual feature to represent the images. We use the images from the WANG database that is widely used for CBIR performance evaluation. The database contains color images, so we use the RGB color space to represent the images. We use the Ranklet Transform to make the image invariant to rotation and any image enhancement operations. This is a preprocessing step performed on every image. For the resulting ranklet images we extract the color feature by calculating the color moments. The color moments are invariant to rotation and scaling. This is a benefit of our system. To speed up the retrieval time, images are clustered according to their features using k-means clustering algorithm.

Finally, we compared with other existing systems that use the same features to represent the images. We show the outperforming of our system against the other systems.

استرجاع الصورة استنادا إلى المحتوى باستخدام ميزة اللون

مقدم من

أحمد جمال عفيفي

ملخص الرسالة

يزداد حجم البيانات الرقمية في مجالات التطبيق المختلفة مثل التعليم و منع الجريمة و التجارة و الطب الحيوي بشكل سريع، ظهر المشكلة عند استرجاع المعلومات من وسائط التخزين، يهدف نظام استرجاع الصور استنادا إلى المحتوى إلى استرداد الصور من قواعد البيانات والتي تشابه الصورة المدخلة، يستند التشابه بين الصور إلى ملامح الصورة نفسها.

في هذة الأطروحة نقدم نظاما لاسترجاع الصور استنادا إلى المحتوى باستخدام ميزة اللون كميزة لوصف الصورة، لقد قمنا باستخدام قاعدة البيانات وانغ للصور والتي تستخدم كثيرا لتقييم أداء مثل هذا النظام، تحتوي قاعدة البيانات هذه على مجموعة من الصور الملونة، لذلك سنستخدم نظام RGB لتمثيل الصور، لقد قمنا باستخدام نظام التحويل الرتيبة لجعل الصورة غير متأثرة للدوران، هذه خطوة تحضيرية يتم تنفيذها على جميع الصور، يتم استخدام الصور الناتجة من الخطوة التحضير ية لحساب بعض القيم الإحصائية (Color Moments)، ولتقليل الوقت في عملية استرجاع الصور نقوم بعملية تصنيفية للصورة، يتم تصنيف الصور تبعا لمميزاتها. قمنا باستخدام الخوارزمية k-means لتصنيف الصور الموجودة في قاعدة البيانات.

أخيرا قمنا بمقار نة النتائج التي حصلنا عليها من نظامنا المقترح بأنظمة استرجاع للصور أخرى تعمل بنفس آلية عمل نظامنا، أظهرت النتائج تفوق نظامنا.

Chapter 1 - Introduction

1.1 The growth of digital imaging

Imaging has played an important role in our life. Our ancestors used the walls of their caves to paint some pictures telling us some information about their life. With the beginning of the twenty century, imaging has grown with an unparalleled way in all our walks of life. Now, images play an important role in many fields such as medicine, journalism, education and entertainment. By the revolution of computers, a wide range of techniques helps us for image capturing, processing, storage, and transmitting. The emergence of the World-Wide Web enables users to access data from any place and provides the exploitation of digital images in any fields [1].

Naturally, when the amount of data becomes larger and larger, it will be useless unless there are effective methods to access. Problems with effective search and navigation through the data can be solved by information retrieval.

1.2 The need of image data management

Until now, information collected all over the world about any branch of science is increasing day by day. This information is categorized and stored on computers. To retrieve any information, we have to search for it among all the information collected and stored in that computer. Nowadays, using the internet to search for any information is easy. Unfortunately, the search engine will retrieve millions of results related to the search topic. Therefore, smart and fast techniques of search are needed to facilitate the search and retrieve issue.

In fact, storing and managing images are not as easy as we consider. Some methods of cataloguing and indexing are needed. The main problem arises when storing images is the difficulty of locating the desired image in large and varied collections of images. Searching for an image by text such as a name or description is not good enough in a large database. While it is desirable to search for an image in a small database by browsing, more effective retrieval techniques are needed with databases containing thousands of items. These methods save time and facilitate getting the required image [1].

1.3 Information retrieval Problems

From the past and until now, images from different fields are stored in groups as image databases. For each field, thousands of images have some common features. If we want to search for a certain image, the primitive methods, like search by text or image description, are not accurate and time consuming. These images are used in all fields such as medical, engineering, educational, sports, criminal, and many of them. For example, images in medical fields such as X- rays are used for diagnoses and research purpose. For criminal field, face recognition is used for retrieving the suspicious people. As we mentioned before, to search for an image in a huge image database, it is not efficient to use text or image descriptors. To overcome this problem, a new technique called content based image retrieval is used to search and retrieve an image from the database [2].

1.4 What is Content Based Image Retrieval (CBIR)

Content Based Image Retrieval (CBIR) is the retrieval of images based on their visual features such as color, texture, and shape [3]. The first use of the concept content based image retrieval was by Kato to describe his experiments for retrieving images from a database using color and shape features. After that this term (CBIR) has been used widely for the process of retrieving images from a large collection of images based on features (color, shape, and texture) that is the signature of the image.

CBIR systems have become a reliable tool for many image database applications. There are several advantages of CBIR techniques over other simple image retrieval approaches such as text-based retrieval techniques. CBIR provided solution for many types of image information management systems such as medical imagery, criminology, and satellite imagery.

CBIR differs from classical information retrieval in that image databases are essentially unstructured, since digitized images consist purely of arrays of pixel intensities, with no inherent meaning. One of the key issues with any kind of image processing is the need to extract useful information from the raw data (such as recognizing the presence of particular shapes or textures) before any kind of reasoning about the image's contents is possible [4].

Research and development issues in CBIR cover a range of topics, many shared with mainstream image processing and information retrieval. Some of the most important issues are [1]:

- Understanding image users' needs and information-seeking behavior.
- Identification of suitable ways of describing image content.
- Extracting such features from raw images.
- Providing compact storage for large image databases.
- Matching query and stored images in a way that reflects human similarity judgments.
- Efficiently accessing stored images by content.
- Providing usable human interfaces to CBIR systems.

CBIR are used in many fields like image processing and computer vision. It is not a subset of these fields as some say. It differs from these fields at the techniques used for image retrieval with some desired characteristics from large databases. However, image processing covers a wider field such as image enhancement, compression, restoration, and transmission. For example, if the police forces want to recognize some faces for suspects, they may compare the image individually with each single image in the database to verify the identity. In this case, only two images are matched. If they use the database to be searched to find the most closely matching images, this is CBIR.

A typical CBIR uses the contents of an image to represent and access. CBIR systems extract features (color, texture, and shape) from images in the database based on the value of the image pixels. These features are smaller than the image size and stored in a database called feature database. Thus the feature database contains an abstraction (compact form) of the images in the image database; each image is represented by a compact representation of its contents (color, texture, shape and spatial information) in the form of a fixed length real-valued multi-component feature vectors or signature. This is called off-line feature extraction [5].

When the user submits a query image to the CBIR system, the system automatically extracts the features of the query image in the same way as it does for the image database. The distance (similarity) between the feature vector of the query image and the feature vectors stored in the feature database are computed. The system will sort and retrieve the best similar images according to their similarity values. This is called on-line image retrieval [5].

The main advantage of using CBIR system is that the system uses image features instead of using the image itself. So, CBIR is cheap, fast and efficient over image search methods.

1.5 The Importance of Content Based Image Retrieval

To search for an image, we use some text or a keyword that describes the image to retrieve it. This method is not good for image retrieving, because in that case, every image must have a powerful complete description and then must match the words we use to search. Unfortunately, we have huge image databases, and it is illogical to describe every image in the database with a good complete description and when we retrieve the images, the system will often miss some images and will retrieve images that don't relate to what we need. From this point, we want to find a new technique and use it to retrieve images depending on its content not its description [2].

To solve the problem of searching for an image using text, we will use the content of the image to search and retrieve it. CBIR is a technique to search and retrieve images. A content-based retrieval system processes the information contained in image data and creates an abstraction of its content in terms of visual attributes. These attributes are color, shape, and texture. Any query operations deal with this abstraction rather than with the image itself. Thus, every image inserted into the database is analyzed, and a compact representation of its content is stored in a feature vector, or signature [5].

To retrieve an image, the query image must compare with other images in the database for similarity. Similarity comparison uses the image representation. Representation of an image includes extracting some features. Features extracted from an image can be color, texture, or shape. The similarity is to calculate the difference between the images' features. For this point, CBIR has several advantages comparing with other approaches such we have mentioned such as text-based retrieval.

1.6 Practical Application

CBIR concepts have been used widely in many real applications. Most of our fields need image processing and retrieving such as medical, architectural, criminal, and in the web. For the medical field, CBIR is used for diagnosis by identifying similar past cases. In critical buildings, this technique is used for finger print or retina scanning for privileges. The most important application that uses CBIR is the web. Many web applications provide searching and retrieving images based on their contents. In general, retrieving images based on their content becomes serious and important techniques in most of the human applications [1]. Potentially fruitful areas include:

- **Crime Prevention**

Nowadays, police forces keep large archives of evidence for past suspects, including facial photographs and fingerprints. When a crime is happened, they take the evidence from the scene of the crime and compare it with the records in their archives. They use CBIR systems to get their results. The most import thing when designing these systems is the ability to search an entire database to find the closest matching records instead of matching against only a single stored record.

- **Medical Diagnosis**

Modern medicine depends on diagnostic methods such as radiology, histopathology, and computerized tomography. These diagnostic methods have resulted in a large number of important medical images that most hospitals stored. Now, there is a great interest to use of CBIR methods to aid diagnosis by identifying similar past cases.

- **Home Entertainment**

Most home entertainment is images such as holiday images, festivals and videos such as favorite programs and movies. CBIR methods can be used for image management. Now, number of large organizations devotes large development effort to design simple software for retrieval with affordable price.

- **Web Searching**

One of the most CBIR applications is the web searching. Uses face problems when they search for certain images by some image description. Many search engines use the text-based search and for many times the results are not stratified by the user. Some content-based search engines are developed so that the user submits the query image and the search engine retrieve the most similar images. Some content-based search engines provide a relevance feedback facility to refine search results. Numerous commercial and experimental CBIR systems are now available, and many web search engines are now equipped with CBIR facilities, as for example Alta Vista, Yahoo and Google.

1.7 Motivation of This Work

Research in CBIR is a hot topic nowadays. It is important to realize that image retrieval does not entail solving the general image understanding problems. The retrieval system presents similar images. The user should define what the similarity between images has to be. For example, segmentation and complete feature descriptors may not be necessary for image similarity. So, when we want to develop an efficient algorithm for CBIR, some problems have to be solved. The first problem is to select the image features that will represent the image. Naturally, images endowed with information and features that can be used for image retrieval. Some of the features can be visual features (color, texture, shape) and some can be the human description of the image like impressions and emotions. The second problem is the computational steps to extract features of an image and to deal with large image databases. We have to keep in our mind that large image databases are used for testing and retrieving.

This thesis aims to provide an efficient content based image retrieval system. It is expected to overcome the problem of image feature selection to represent the image and to reduce the computation load. The major contributions of this thesis can be summarized as follows:

1. Most CBIR systems use gray-scale images. If the image database or the query image is a color image, they convert it to gray-scale image. However, when some systems use the color of the image as its feature, they derive the histogram from the color space of the image. In this work, the color moments will be used for extracting the image features because the distribution of color in an image can be interpreted as a probability distribution. Probability distributions are characterized by a number of unique moments. So, the moments of the color image can be used as features to identify that image based on color.
2. To make the system invariant to noise, image transformation (contrast enhancement, gamma correction, and histogram equalization) and pixels values, a preprocessing step will be done for the query image. Ranklet Transform makes the image invariant to noise and image transformation. In previous work, Ranklet Transform was used for gray-scale images to extract texture features. In our work, Ranklet Transform will be used for colored images to extract color features. The

image will be in RGB color space. Ranklet Transform will be performed on each layer of the image to extract the features.

3. When CBIR system is ready for testing, the query image is compared with every target image in the database to find the best matching images. This is a linear search method, which will take long times if the database is large. In fact, this is not necessary to repeat the comparison between the query image and the database every time. Each image database contains number of classes that each image belongs to one class. The system can select some images from different classes and use them to be compared with the query image. This can be done by divide the database into categories. A clustering algorithm, definitely the k-means, is used to cluster the database into classes. Images with similar features are clustered to one class. This step is done one time. Each class will be associated with class ID. To retrieve images similar to the query image, the system will compute the distance between the query image and the centroid image of each class. The smallest distance (most similar) will determine to which the image belongs. The class with the smallest distance is returned and the images in this class will be compared with the query image. The most matching images will be retrieved. This method saves time and computation load.

1.8 Outline of This Thesis

This thesis is divided into seven chapters. Chapter 2 reviews some related work, especially about the research issues. Ranklet Transform and its main role as a preprocessing step are discussed in Chapter 3. We also discuss how we can use Ranklet Transform on colored images. In Chapter 4, we discuss some background for CBIR principle, image features such as color, texture, and shape and how can be extracted. We introduce some image similarity measures, image indexing, and finally we focus one color features. In Chapter 5, we introduce the proposed system for CBIR and talk about some methods for image indexing and clustering. System implementation, simulation results, and evaluation are discussed in Chapter 6 in details. Chapter 7 summarizes our proposed system and contributions. Some recommendations and future work are also suggested there.

Chapter 2 - Review of Related Works

2.1 Introduction

CBIR describes the process of finding images from a large data collection that match to a given query image. One highly problem when designing CBIR system is to make a system general-purpose. This problem appears because of the size of the database, the difficulty of understanding images by users and computers, the difficulty of system evaluation, and results retrieval. Many general-purpose systems have been developed. QBIC [6], VIR [7], and AMORE [8] are examples of commercial general purpose systems. Recently, academic systems have been developed such as MIT Photobook [9]. Berkeley Blobworld [10], Columbia Visualseek and Webseek [11], Netra [12], and Stanford WBIIS [13] are some of the recent well known systems.

When a user intends to access a large image database, a linear browsing is not practical for finding the target image. Depending on the query format, image retrieval algorithms are divided into two categories: keyword-based approaches and content-based methods. In keyword-based approach, images are indexed using a keyword stored for the image describing the image content. Keyword-based retrieval is not standardized because different users describe images using different keywords. Using this approach, humans are required to personally describe every image in the database, so for a large image database the technique is cumbersome, expensive and labor-intensive.

In content-based methods, the content of the image is used for search and retrieve images. This method was introduced to overcome the problem of keyword-based approach and support effective searching and browsing of large digital image libraries based on automatically derived image features.

All CBIR systems view the query image and the target images as a collection of features. These features, or image signatures, characterize the content of the image. The advantages of using image features instead of the original image pixels appear in image representation and comparison for retrieving. When we use the image features for matching, we almost do compression for the image and use the most important content of the image. This also bridges the gaps between the semantic meaning of the image and the pixel representation.

In general, features fall into two categories. The first category is global features. Global features include color and texture histograms and color layout of the whole image. The second category is local features. Local features include color, texture, and shape features for subimages, segmented regions, and interest points. These features extracted from images are then used for image matching and retrieving. The formulation of the similarity measure varies greatly. The similarity measure quantifies the resemblance in contents between a pair of images.

2.2 General Purpose Systems

Several general-purpose systems have been developed for content based information and image retrieval. For each system, we will focus on the features are used to extract information from the image and matching between the query image and the database. We will mention some of them below:

2.2.1 QBIC

QBIC (Query by Image Content) system was the first commercial system for CBIR developed by IBM Almaden Research Center, San Jose in 1995. This system uses color, texture, shape, and sketches for image representation. The QBIC system allows queries on large image and video databases based on example images, user-constructed sketches and drawings, color and texture patterns, and camera and object motion. The color features are the average of the image color histograms in different color space (RGB, YIQ, Lab, and Munsell). The texture features are the modified version of coarseness, contrast, and the directionality features proposed by Tamura. The shape features used to extract the image features are the area, circularity, eccentricity, and some invariant moments.

2.2.2 NETRA

NETRA [12] system has been developed by Department of Electrical and Computer Engineering at University of California, Santa Barbara in 1997. It uses three feature vectors to represent the image. The first vector is computed from color histogram to represent the image color feature. The second vector is the normalized mean and standard deviation, derived from the Gabor Wavelet Transform of the image, to represent the image texture feature. The third vector is the curvature function of the contour to represent the shape feature. Similarity matching is done by the Euclidean distance.

2.2.3 KIWI

KIWI (Key-point Indexing Web Interface) [14] has been developed in France by INSA Lyon in 2001. This system extracts the key points in the query image rather than the entire image using some wavelet-based salient point detector. Color histograms, are computed from each color component (R, G, and B), and the shape descriptors, computed from Gabor Filter, are used as image features. Euclidean distance is used for similarity matching.

2.2.4 ImageMiner

ImageMiner [15] has been developed by Technologie-Zentrum Informatik at Univerity of Bremen in Germany in 1997. It uses color, texture, and shape to describe the image. Color histogram is used to describe image color features. Grey level co-occurrence matrix is used for texture feature. Image contour size, centroids, and boundary coordinates are used for shape features. For similarity, special module is developed within the system.

2.2.5 Photobook

Photobook [9, 16] was developed by Vision and Modeling Group at MIT Media Lab in 1997. It implements three different methods for image representation according to image content type (face, 2D shape, and texture). Photobook consists of three sub-books. There are the Appearance Photobook, Shape Photobook and Texture Photobook, which can extract the face, shape and texture, respectively. To query an image, users can select one of image features that the system supports or a combination of different features besides a text-based description.

2.3 Color Based Approaches

One of the most straightforward visual features of an image is the color because human eye is sensitive to colors. Color features are the basic characteristic of the content of images. Using color features, human can recognize most images and objects included in the image. Images added to the database have to analyze first. Images can be represented by color histograms that show the proportion of pixels of each color within the image. The most common form of the histogram is obtained by splitting the range of the data into equally sized bins. The numbers of pixels that have the same color value is computed for each bin. Therefore, it is common to use color features for image retrieval.

Several methods for retrieving images on the basis of color similarity have been proposed, but most are variations on the same basic idea. Each image added to the database is analyzed to compute its feature. Two traditional approaches have been used. Global Color Histogram (GCH) is used for representing images by their histograms and the similarity between two images will be determined by the distance between their color histogram. This approach does not represent the image adequately. Furthermore, this approach is sensitive to intensity variations, color distortions, and cropping. Local Color Histograms (LCH) divide images into blocks and obtain the histogram for each block individually. So, an image will be represented by these histograms. To compare between two images, each block from one image will be compared with another block from the second image in the same location. The distance between these two images will be the sum of all distances. This approach represents the image more deeply and enables the comparison between image regions.

In 1996, Stricker and Dimai [17] proposed CBIR system that partitioned the image into five overlapped blocks and computed the Color Moments for each block. The computation was done using the HSV color space for each channel. These weights are to make the effect of one moment in a certain color channel less or greater that other moments in the same color channel. The reason to include weights in the formula is to make the effect of pixels close to the boarder less than the pixels close to the center of a certain block.

In 2000, Stehling et al [18] developed a method based on color histograms. He used a variable number of histograms called color-shape histograms (CSHs) instead of using a fixed number of cells or a single histogram. This variable histogram depends on the actual number of image colors. This method is used to represent the spatial distribution of the color for each image cell and non-existing color will not be presented.

In 2006, Mahdy, Shaaban, and Abd El-Rahim [19] proposed to extract the features from the image using its color histogram. The image is segmented into four blocks and converted from RGB color space to CIE XYZ color space then to LUV color space. The histogram is then calculated from the last color space for each of the four blocks. A histogram similarity measure is used to compare images.

In 2009, Lin, Chen, and Chan [20] proposed a smart method for image retrieval. Three image features and a feature selection technique are used for that. The first and the second image features are for color and texture features that are respectively called color co-occurrence matrix (CCM) and difference between pixels of scan pattern (DBPSP). The third image feature is for color distribution called color histogram for k-mean (CHKM). The feature selection technique is used to select the most optimal features for maximizing the detection rate and simplifying the computation of image retrieval. The three image features are not affected by image displacement and rotation and also able to resist noise-induced variations.

In 2002, Shin and Chen [21] proposed the partition-based color-spatial method. The query image is divided into 100 blocks and for each block the three color moments are computed for each color layer. The mean vector of each block is considered as the primitive of the image. This method is not suitable for image databases containing large images. However, Chan and Chen [22] proposed a similar method of considering the mean value of the color component at each block. They divided the image into 3 x 3 blocks instead of 100 blocks. The mean value is computed for each block color layer (R, G, and B) separately. Although this method reduces the effect of noise and variations in size, it is affected by the shift of objects in the image.

In 2008, another system is proposed by Mustaffa, Ahmad, Rahmat, and Mahmod based on color-spatial features [23]. Images in the database used for evaluation are set to the same size (192 x 128), image format (JPEG), and color space (RGB). These constraints needed for the application and during the retrieval time. Through feature extraction, the color features are extracted using the Dominant Color Region Segmentation that maps the color in the image with the 25 color categories that can be found in the image. The region's location feature is extracted using the Improved Sub-Block method. The extracted features are used to create the index table for all possible for that image.

Some proposed systems combined color and texture features to improve the system performance. In 2004, D. Zhang [24] computed color and texture features from the image database. So, for each image, color and textures features are computed. When a query image is submitted, the color and texture features are computed. Firstly, the images in the database are ranked according to the color features. The top ranked images from color features are reranked according to the texture features.

In 2010, Kekre and Mishra [25] presented a new algorithm for digital search and retrieval. They used Fast Fourier Transform for each image color components (R, G, and B). The frequency plane for each component is divided into 12 sectors. The real and the imaginary parts for each sector are computed and their average is taken as one parameter for the feature vector that will represent the image.

In March 2011, Sharma, Rawat, and Singh [26] proposed an efficient CBIR using color histogram processing. The proposed method used color moments and color histograms. They computed the color moments from the images. The color features are used for matching between the query image and images in the database. They also computed the color histograms from the color components of the query image and compare them with a number of top ranked images from the first step.

As a summary, dealing with color images and extracting features have some drawbacks. First, color images have large dimensions, and the computations are quite time consuming. Second, color images are sensitive to noise interference as illumination. Furthermore, most CBIR systems cannot handle rotation and translation. Our contribution is to overcome most of the previous problems. We propose a color-based retrieval system for comparing similarities between images. Our proposed system will reduce the computation of the distance to find the similarity between images. We will address the issue of indexing for the image database we will use. The system will be able to overcome the translation and rotation.

Chapter 3 - Ranklet Transform

3.1 Introduction

Fourier Transform has been the mainstay of signal transform. Fourier Transform converts a signal from the time-domain into the frequency-domain to measure the frequency components of the signal. For CBIR, Fourier Transform was used to extract texture features from high frequency components of the image. Unfortunately, Fourier Transform failed to capture the information about objects locations in an image and could not provide local image features. After its revolution, Wavelet Transform was used for image processing methods due to its efficiency and effectiveness in dealing with most important image processing tasks such as image analysis and compression. The main difference between Fourier Transform and Wavelet Transform is how to represent the signals to be analyzed. Fourier Transform represents the signal as weighted sum of the sinusoidal trigonometric functions. On the other hand, Wavelet Transform uses completely supported functions of limited duration in time and frequency domains [28].

3.2 Basic Image Concepts

Images can be thought as a two-dimensional function, f(x, y), with x and y are spatial coordinates and the value at the coordinate (x, y) is called the intensity. In an image, if x, y, and the intensity values are all finite and discrete quantities, we call the image a *digital image*. One of the most important steps in digital image processing is the image enhancement. Image enhancement is the process of manipulating an image to make the results more suitable than the original image for applications. Image enhancement methods are so varied and use so many different image processing approaches. For this reason, there is no general theory of image enhancement. Human is the ultimate judge of how well a specific method works. Systems that acquire images generate images with continuous voltage waveform. In order to digitize them, they have to be sampled in both coordinates and intensity. Digitizing the coordinate values is called sampling. Digitizing the intensity values is called quantization. Sampling and quantization allow representing images as matrices. A digital image of the size M x N can be represented in the form of matrix as the following:

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \cdots & f(0,N-1) \\ f(1,0) & f(1,1) & \ldots & f(1,N-1) \\ \vdots & \vdots & & \vdots \\ f(M-1,0) & f(M-1,1) & \cdots & f(M-1,N-1) \end{bmatrix} \tag{3.1}$$

In Equation 3.1, the right side is the digital image. Each element of the matrix is called image element of pixel [27].

3.3 Ranklet Transform

Ranklet Transform belongs to a family of non-parametric, orientation selective, and multi-resolution features has the wavelet style. It has been used for pattern recognition and in particular to face detection. Later on, it has been used for testing and estimating 3D structure and motion of objects. From 2004, Ranklet Transform has been used in medical fields. It has been applied to the problems of tumoral masses detection in digital mammograms. Some tests show that Ranklet Transform performs better than some methods such as pixel-based and wavelet based image representations. Ranklet Transform has three main properties. First, it is non-parametric that it is based on non-parametric statistics that deal with a relative order of pixels instead of their intensity values. Second, it is orientation selective that it is modeled on Haar wavelets. This means that for an image, vertical, horizontal, and diagonal ranklet coefficients are computed. Finally, it is multi-resolution that the ranklet Transform can be calculated at different resolutions using Haar wavelet supports. Now, Ranklet Transform properties are discussed in details [29].

3.3.1 Non-Parametric Statistics

The expression non-parametric denotes statistical methods that are distribution free from the data of a given probability distribution. Non-parametric methods are useful when the applications are interested in ranking rather than numerical interpretation. The robustness of non-parametric methods makes scientists to apply them in several learning methods such as Support Vector Machine (SVM) [30].

Rank statistics are widely used in medical search for treatment or drug tests. In order to test a new innovated drug, participants suffering from the same disorder are divided into groups namely Treatment and Control. Randomly, the Treatment group receives the new drug and the Control group is given a placebo with letting them know who is having what in order to reduce the psychological effects. After that, the participants are ranked according to their severity of their condition; most severe is ranked first. The new drug will be considered if the Treatment group participants rank high. This example is related to the idea for the Ranklet Transform. To complete, some statistical methods have to be illustrated [30].

3.3.1.1 Rank Transform

Suppose a set of P_1, P_2, …, P_N pixels and we want to perform a rank transform [31] on the set. We refer to the rank transform with the symbol π. The rank transform will order the elements in the set in an ascending order and substitute each pixel value with its rank among all other pixels. For example, if we have the matrix S of size 4 x 4:

$$S = \begin{bmatrix} 55 & 99 & 25 & 153 \\ 26 & 75 & 92 & 200 \\ 21 & 64 & 88 & 154 \\ 101 & 190 & 199 & 222 \end{bmatrix}$$

If we apply the rank transform on S we get:

$$\pi(S) = \begin{bmatrix} 4 & 9 & 2 & 11 \\ 3 & 6 & 8 & 15 \\ 1 & 5 & 7 & 12 \\ 10 & 13 & 14 & 16 \end{bmatrix}$$

If any two pixels have the same value, a mid-rank transform is used to assign each group of pixels with equal values the average of ranks they occupy. For example, the matrix S has some elements with the same values:

$$S = \begin{bmatrix} 55 & 99 & \mathbf{25} & 153 \\ \mathbf{25} & \mathbf{64} & 92 & 200 \\ 21 & \mathbf{64} & \mathbf{64} & 154 \\ 101 & 190 & 199 & 222 \end{bmatrix}$$

The mid-rank transform will substitute each group with equal values that is the average of the ranks they occupy. Element 25 occupies the ranks 2 and 3. The average rank will be 2.5 ((2 + 3) / 2). After applying the mid-rank transform on S we get:

$$\pi(S) = \begin{bmatrix} 4 & 9 & \mathbf{2.5} & 11 \\ \mathbf{2.5} & \mathbf{6} & 8 & 15 \\ 1 & \mathbf{6} & \mathbf{6} & 12 \\ 10 & 13 & 14 & 16 \end{bmatrix}$$

3.3.1.2 Wilcoxon Test

The Rank Transform and Wilcoxon Test [30] are related. Consider a set of ***N*** pixels that divides into two sub-sets. The first sub-set is called Treatment (T) that contains ***m*** pixels and the second sub-set is called Control (C) that contains ***n*** pixels, so that ***m* + *n* = *N***. We have to test whether the T set is significantly higher or lower than the C set. We first rank the elements in each sub-set (T and C). Let W_S be the Wilcoxon statistic defined by:

$$W_S = \sum_{i=0}^{N} \pi_i V_i \quad where\ \pi_i = Rank\ of\ element\ i\ \ and \quad V_i = \begin{cases} 0, & \pi_i \in C \\ 1, & \pi_i \in T \end{cases} \tag{3.2}$$

From Equation 3.2, we are just interested in the sum of ranks for the set T. We say that a set T is higher than a set C if $\boldsymbol{W_S}$ is greater than critical value $\boldsymbol{\tau}$, in other words if $\boldsymbol{W_S} > \boldsymbol{\tau}$.

3.3.1.3 Mann Whitney Test

Mann Whitney Test is a non-parametric statistical hypothesis test for assessing whether two independent samples of observations have equally large values. Mann Whitney test [30] was introduced because it has an immediate interpretation in terms of pixels comparison. Mann Whitney test (W_{XY}) is computed by the following equation:

$$W_{XY} = W_S - \frac{m(m+1)}{2} \tag{3.3}$$

Equation 3.3 is equal to the number of pixel pairs ($\mathbf{p_m}$, $\mathbf{p_n}$) with $\mathbf{p_m} \in$ T and $\mathbf{p_n} \in$ C, such that the intensity value of $\mathbf{p_m}$ is higher than the intensity value of $\mathbf{p_n}$. The value of W_{XY} ranges from 0 to the number of pairs ($\mathbf{p_m}$, $\mathbf{p_n}$) $\in$ T × C, namely $\boldsymbol{m} \times \boldsymbol{n}$. Notice that to compute the value of W_{XY}, it takes a huge computational time approximately $O(N^2)$. To reduce this computational time, the value is obtained by the rank transform that ranks the pixels and sum the ranks of the Treatment set T.

An example will make all previous equations more clear. Consider a set of pixel values such that S = {20, 5, 4, 9, 7, 1, 13, 10, 19, 15, 11}. Let the set T = {5, 9, 1, 10, 15} and the set C = {20, 4, 7, 13, 19, 11}. So, $\boldsymbol{N}$ = 11, $\boldsymbol{m}$ = 5, and $\boldsymbol{n}$ = 6. Then, we have to rank the elements in the set S in ascending order and mark them to the either set T or set C.

Sample	T	C	T	C	T	T	C	C	T	C	C
Value	1	4	5	7	9	10	11	13	15	19	20
Rank	1	2	3	4	5	6	7	8	9	10	11

From the table, we sum the ranks of elements belong to the set T using Wilcoxon Test W_S (Equation 3.2).

$\boldsymbol{W_S} = 1 + 3 + 5 + 6 + 9 = 24.$

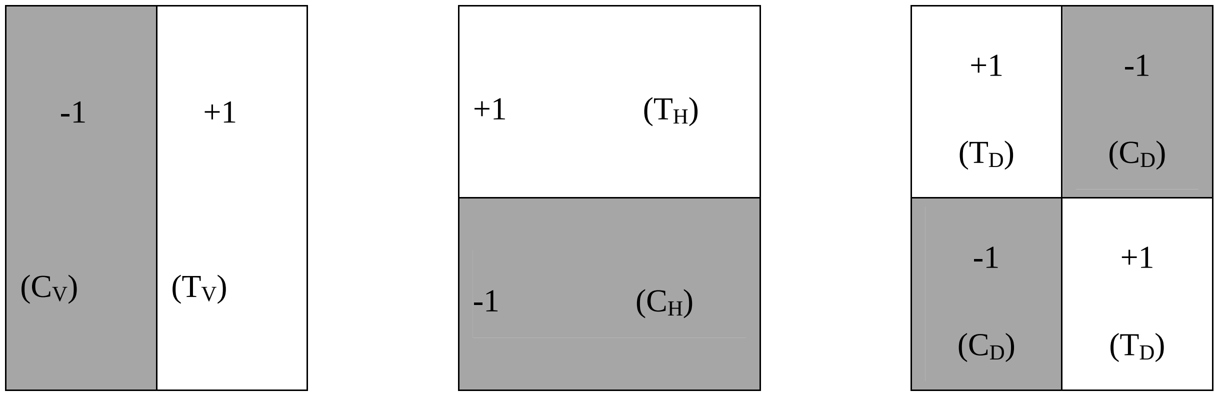
From Equation 3.3, we compute the Mann Whitney Test $\boldsymbol{W_{XY}}$.

$\boldsymbol{W_{XY}} = 24 – [5(5 + 1) / 2] = 9$

After that, the value of Mann Whitney Test will be used to compute the Ranklet coefficient that will be in the range [-1, +1].

3.3.2 Orientation Selectivity

We have discussed the non-parametric property of the Ranklet Transform that is derived from the Rank Transform and non-parametric statistic methods such as the Mann Whitney Test. The second property of Ranklet Transform is orientation selective. This property is derived from the fact that it is modeled based on bi-dimensional Haar wavelets [32]. Haar wavelets supports divide a 2D set into two equally sub-sets. They divide the set in different orientation. Suppose an image containing N pixels. To compute the Mann Whitney Test, the N pixels is divided into two sub-sets T and C of size m = n = N/2. Thus, half of pixels are assigned to the set T and the second half of pixels are assigned to the set C. As we said, we can divide the set into different orientations. We are basically interested in dividing the set in vertical, horizontal, and diagonal orientation. This is similar to the Haar wavelet supports that divide the set into vertical Haar (h_V), horizontal Haar (h_H), and diagonal Haar (h_D). Figure 3.1 [29] illustrates the three Haar wavelet supports that any two sub-sets can be described using them.



Vertical (h_V) Horizontal (h_H) Diagonal (h_D)

Figure 3.1: Ranklet Transform orientation-selective analysis.

An important note is that the arbitrariness distribution of the two sub-sets T and C is the basic in order to be able to choose the two sub-sets based on the Haar wavelet supports. In other words, the arbitrariness with which we choose the sub-sets is the orientation selective property of the Ranklet Transform.

3.3.2.1 Ranklet Coefficients

Once we have introduced the Haar wavelet supports, the definition of the Ranklet Transform is straightforward. For an image constituted by a set of ***N*** pixels, we first derive the Haar wavelet supports in the three orientations (vertical, horizontal, and diagonal). For each orientation we divide the set into sub-sets T and C. We compute the rank transform and then the Mann Whitney Test for each orientation. The Ranklet coefficient R_j then can be computed by the following equation:

$$R_j = \frac{W_{XY}^{j}}{mn/2} - 1 \qquad whrer\ j = V, H, D \tag{3.4}$$

Notice that W_{XY}^{j} is computed for each vertical, horizontal, and diagonal Haar wavelet supports by splitting the N pixels into sub-sets T_j and C_j. Ranklet coefficients have a geometric interpretation. Figure 3.2 shows a synthetic image that has a vertical edge with the darker side on the left (left part), where C_V is located, and the brighter side on the right, where T_V is located [33]. The Ranklet coefficient will be close to +1 if many pixels in T_V have higher intensity values than the pixels in C_V. Conversely, the Ranklet coefficient will be close to the value -1 if the dark and bright sides are reversed. The same idea can be drawn for the other Ranklet coefficients in alternative orientation (horizontal and diagonal).

As we mentioned before, to compute the Ranklet coefficient, we have to compute the rank transform and the Mann Whitney Test to get the W_{XY}. The computation of the Ranklet coefficient using the Mann Whitney Test clarifies the non-parametric property of the Ranklet Transform. From the Haar wavelet supports, we can get different orientations for the image, namely vertical, horizontal, and diagonal. Putting the image in different orientations by means of Haar wavelet supports clarifies the orientation selective property of the Ranklet Transform.

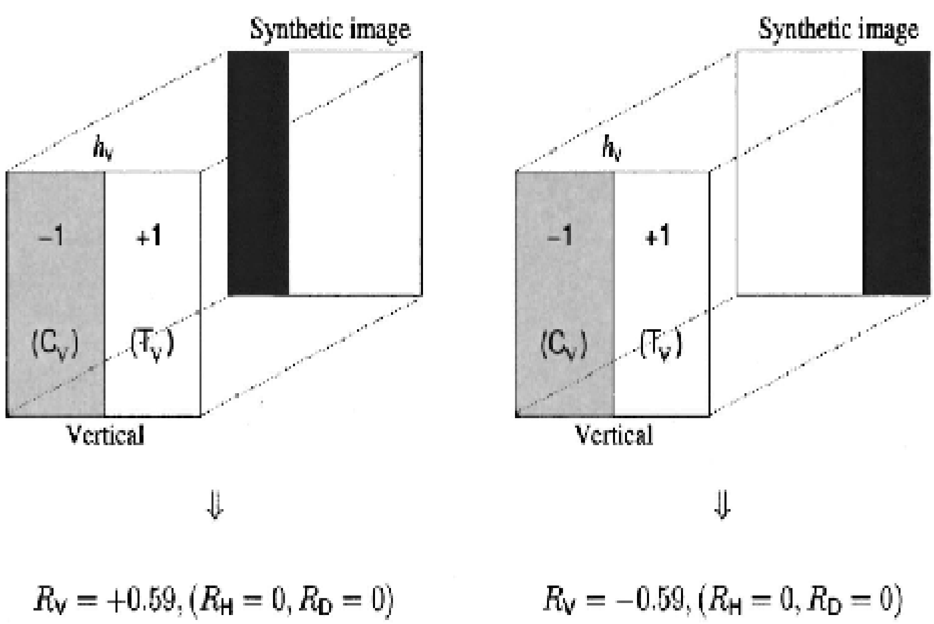


Figure 3.2: Ranklet Transform applied to some synthetic images.

3.3.3 The Multi-Resolution

Because the Ranklet Transform is modeled on the Haar wavelet, this leads to extend the multi-resolution property to the Ranklet Transform [33]. Ranklet coefficients can be computed at different resolutions by stretching and shifting the Haar wavelet supports. For example, suppose that we have to perform the Ranklet Transform on an image of size 8 x 8. The Ranklet Transform will be performed at different resolutions as {8, 4, and 2}. Figure 3.3 [33] shows the image with size 8 x 8 and the Haar wavelet supports with pixels 8 x 8, 4 x 4, and 2 x 2 to perform the Ranklet Transform. We also consider that the vertical and horizontal shifts of the Haar wavelet supports along the horizontal and vertical dimensions are of 1 pixel. After performing the Ranklet Transform, we find that the image will be composed by 1 triplet $R_{V,H,D}$ of Ranklet coefficients derived from the Ranklet Transform at resolution 8, 25 triplets at resolution 4, and 49 triplets at resolution 2.

In general, we can calculate the number of triplets (the size of the generated vertical, horizontal, and diagonal Ranklet Images) that can be generated after performing the Ranklet Transform on an image of size I x I at a resolution S x S using Equation 3.5:

$$nT = (I + 1 - S)^2 \tag{3.5}$$

As a summary, when we perform Ranklet Transform on an image, it results a set of three Ranklet images (vertical, horizontal, and diagonal) for each resolution. Ranklet coefficients are calculated using some non-parametric statistical methods based on the relative order of pixels instead of their intensity values. We have shown the Ranklet Transform has the property of orientation selectivity derived from the Haar wavelet that generates images in three orientations. Multi-Resolution property makes the Ranklet

Transform to deal with different resolutions by stretching and shifting the Haar wavelet supports.

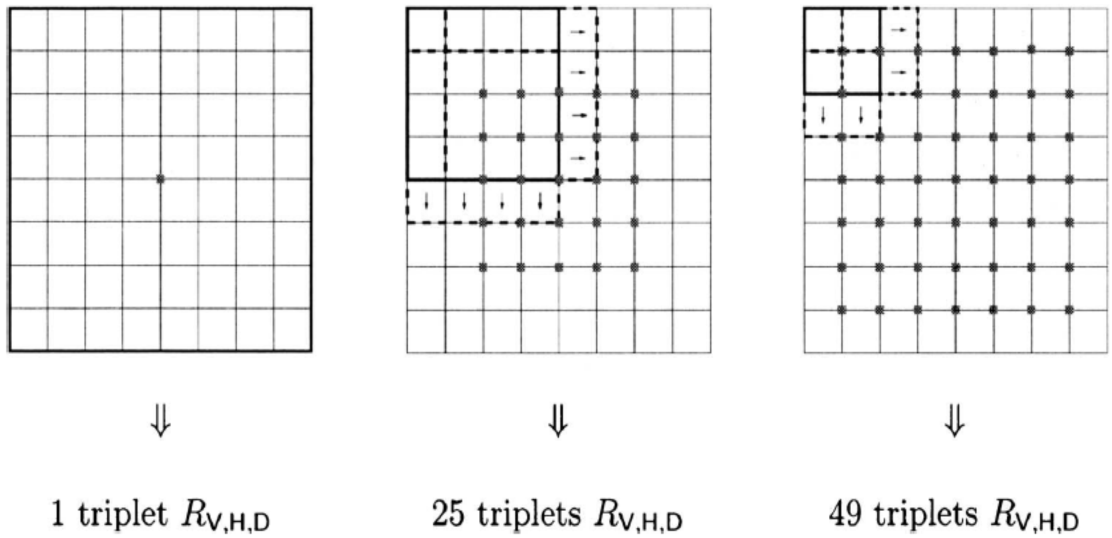


Figure 3.3: Multi-Resolution Ranklet Transform at different resolutions.

In our CBIR proposed system, we will use the Ranklet Transform as a preprocessing step. After performing the Ranklet Transform on the image, three ranklet images are generated with different orientations. This makes the image invariant to rotation.

Chapter 4 - Fundamentals of Image Retrieval

4.1 Introduction

The main idea behind CBIR systems is to allow users to find images that are visually similar to the query image. Similar may have different meanings. Some users may be interested in some image regions. Others are interested in some shapes and the color of them. Therefore, different needs mean different methods for similarity. To allow different methods for similarity, different image descriptors are needed. Image descriptors may account for different properties of images. Image descriptors mean image features. A feature means anything that is localized, meaningful and detectable. If we talk about image features, we mean objects in that image such as corners, lines, shapes, textures, and motions. Features extracted from an image describe and define the content of that image.

Intuitively, the most direct method to compare two images is to compare the pixels in one image to the corresponding pixels in the other image. Clearly, this method is not feasible, because images may have different size that applications cannot determine which pixels from one image correspond to which pixels in the other image. Another reason is the computational complexity. When a system wants to match two images by comparing pixel by pixel, it will take a long time. This is just for two images. Nowadays, we talk about thousands of images stored in databases that are used for image retrieving. Comparing images using their pixels is time consuming. More powerful method is to use image features instead of using the original pixel values because of the significant simplification of image representation, and the easy way to compare images using their features.

A wide variety of features had been considered for image retrieval. Color, texture, and shape are some image features that can be used to describe an image. However, no particular feature is most suitable for retrieving all types of images. Color images need color features that are most suitable to describe them. Images containing visual patterns, surface properties, and scene need texture features to describe them. In reality, no one particular feature can describe an image completely. Many images have to be described by more than one feature. For example, color and texture features are best features to describe natural scenes.

Features extracted from the image are used for computing the similarity between images. Some measurement methods are used to calculate the similarity between images. In this chapter, we will define image features, explaining their properties. We introduce some methods for similarity measures.

4.2 Feature Extraction

Feature extraction means obtaining useful information that can describe the image with its content. We mean by image features the characteristic properties. For example, the image of a forest can be described by its green color and some texture of trees. Objects in the image can be considered as shapes that can be a feature for the image. To describe an image, we have to consider its main features. Selecting image features is an important step so that it can represent the content of the image very well. Color, texture, and shape are some features considered for content image description. In this section, we will introduce the three main features.

4.2.1 Color

Color is the sensation caused by the light as it interacts with our eyes and brain. Color features are the fundamental characteristics of the content of images. Human eyes are sensitive to colors, and color features enable human to distinguish between objects in the images. Colors are used in image processing because they provide powerful descriptors that can be used to identify and extract objects from a scene. Color features provide sometimes powerful information about images, and they are very useful for image retrieval.

4.2.1.1 Color Fundamentals

In 1666, Sir Isaac Newton discovered that a beam of sunlight consists of a continuous spectrum of colors when that beam passes through a glass prism. The colors are violet, indigo, blue, green, yellow, orange, and red (Figure 4.1 [27]).

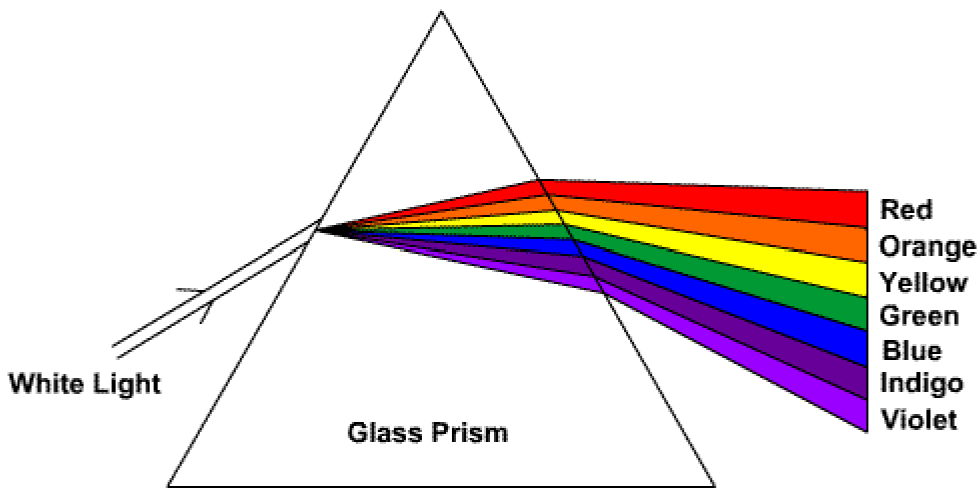


Figure 4.1: Color spectrum seen by passing white light through a prism.

To facilitate the specification of colors in some standard, color spaces (also called color models or color systems) are proposed. A color space is a specification of a coordinate system and a subspace within the system where each color is represented by a single point. Today, most color spaces in use are oriented toward hardware (such as for color monitors and printers) or toward software for applications where color manipulation is the target. In most digital image processing, RGB (red, green, blue) color space is used in practice for color monitors and CMY (cyan, magenta, yellow) color space is used for color printing. In our work, we are focusing on the RGB color space [27].

- **Color Space**

To extract the color features from the content of an image, we need to select a color space and use its properties in the extraction. In common, colors are defined in three-dimensional color space. The purpose of the color space is to facilitate the specification of colors in some standard, accepted way. Several color spaces are used to represent images for different purposes. The RGB [34] color space is the most widely used color space. RGB stands for Red, Green, and Blue. RGB color space combines the three colors in different ratio to create other colors. In digital image purposes, RGB color space is the most prevalent choice. The main drawback of the RGB color space is that it is perceptually non-uniform. We can imagine the RGB color space as a unit cube with red, green, and blue axes (Figure 4.2 [27]). Any color in the RGB color space can be represented by a vector of three coordinates. To overcome the drawback of the RGB color space, different color spaces are proposed.

The HSx color space is commonly used in digital image processing that converts the color space of the image from RGB color space to one of the HSx color spaces. HSx color space contains the HSI, HSV, HSB color spaces. They are common to human color perception. HS stands for Hue and Saturation. I, V, and B stand for Intensity, Value, and Brightness, respectively. The different difference between them is their transformation method from the RGB color space. Hue describes the actual wavelength of the color. Saturation is the measure of the purity of the color. For example, red is 100% saturated color, but pink is not 100% saturated color because it contains an amount of white. Intensity describes the lightness of the color. HSV color space is the most widely used when converting the color space from RGB color space [34].

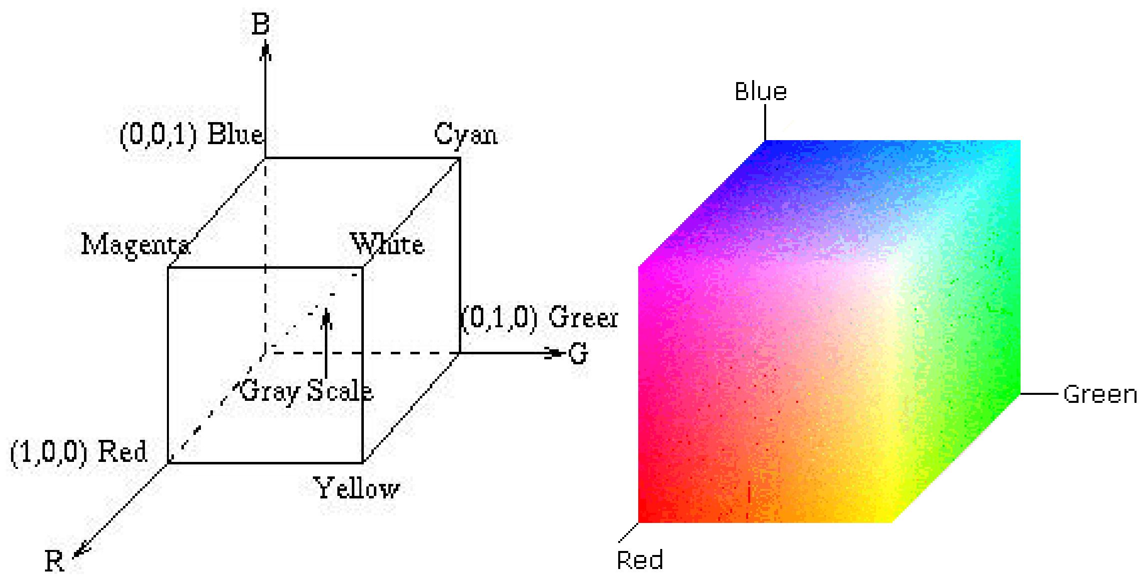


Figure 4.2: RGB Color Space.

Other color spaces are YUV and YIQ. They were developed for television broadcasting. The Y channel represents the luminance of the pixel and is the only channel used in the black and white television. The other channels (U, V, I, and Q) are the chromatic components. The CIE L*u*v and CIE L*a*b color spaces are both perceptually uniform systems and device-independent, which provide easy use of similarity metrics for comparing color [35].

To complete extracting color features from an image and after choosing the proper color space, we have to choose some effective color descriptors to represent the color of the image contents. Color histograms, color moments, and color texture are some of the color descriptors that have been developed for color image representation. Next, we introduce the RGB color space and color histograms in details.

- **The RGB Color Model**

RGB color model is the most common color model in use. The primary colors are red, green, and blue. Figure 4.2 shows the color subspace of interest [27]. From the figure, the RGB model is based on a Cartesian coordinate system. The three coordinates of the system are the primary colors of the model. The color black is at the origin of the plane, and the color white is at the farthest corner from black. The different colors in this model are on or inside the cube, and are defined by vectors extending from the origin.

Images represented in the RGB color model consist of three component images, one for each primary color. When a monitor displays the image, the three images are combined to produce the original image. The number of bits used to represent each pixel is called the pixel depth. For example, if we represent each primary color in the RGB model by 8 bits, then each pixel in an RGB color image is represented using 24 bits (8 bits for each primary color). In general, the total number of colors in a 24-bit RGB image is $(2^8)^3$ that is equal to 16,777,216 colors. Figure 4.3 shows an RGB image and its three components.

The original Image

Red Component Green Component Blue Component

Figure 4.3: An RGB Image and its components.

- **Color histograms**

As mentioned, the most widely used features to describe the image are color features. Many CBIR systems use color histograms as a color feature to represent the image. A color histogram is a graphical representation that shows the distribution of colors in an image. For digital images, a color histogram represents bars that the height of each bar represents the number of pixels in the image that have the same color. The x-axis of the histogram represents the number of colors being used in the image, while the y-axis represents the number of pixels. For each color, the height of a vertical line represents the number of pixels of that color. [27].

In color histograms, it is common to normalize the histograms. Normalizing histograms is to reduce the number of bins by taking colors that are similar to each other and putting them in the same bin. Reducing the number of colors will decrease the possibility that similar colors are assigned to different bins, but it will increase the possibility that distinct colors may be assigned to the same bins. This step will decrease the information can be gained from the image about its content. On the other hand, the storage media and the time of calculating histograms and the distance between color histograms will be saved. Therefore, there is a trade-off between the number of bins in the histogram and the information gained from the histogram. The trade-off is also between the processing time, storage space, and the accuracy of the results.

Color histograms can be obtained by different methods. Traditionally, two known methods are used to calculate color histograms. They are the global color histogram (GCH) and the local color histogram (LCH). GCH method is the most popular method. GCH takes the histogram of all the image and the distance between two images are determined by the distance between their color histograms. The drawback of this method is that it does not include information about all image regions. This makes the distance between images cannot show the real difference. Furthermore, it is possible to make two different images to be similar using their GCH (short distance between their color histograms).

LCH method takes into account the color distribution of regions. This method divides the image into fixed blocks and calculates the color histogram for each block individually. The image will be represented by these color histograms. To compare two images, using their histograms, we calculate the distance between a block from one image and another block from the second image in the same location. This method improves the efficiency of retrieving images more than using GCH. However, this method needs more computation, and it does not work well when images are translated or rotated. Figure 4.4 shows an example of color histogram for an image in RGB color space [36].

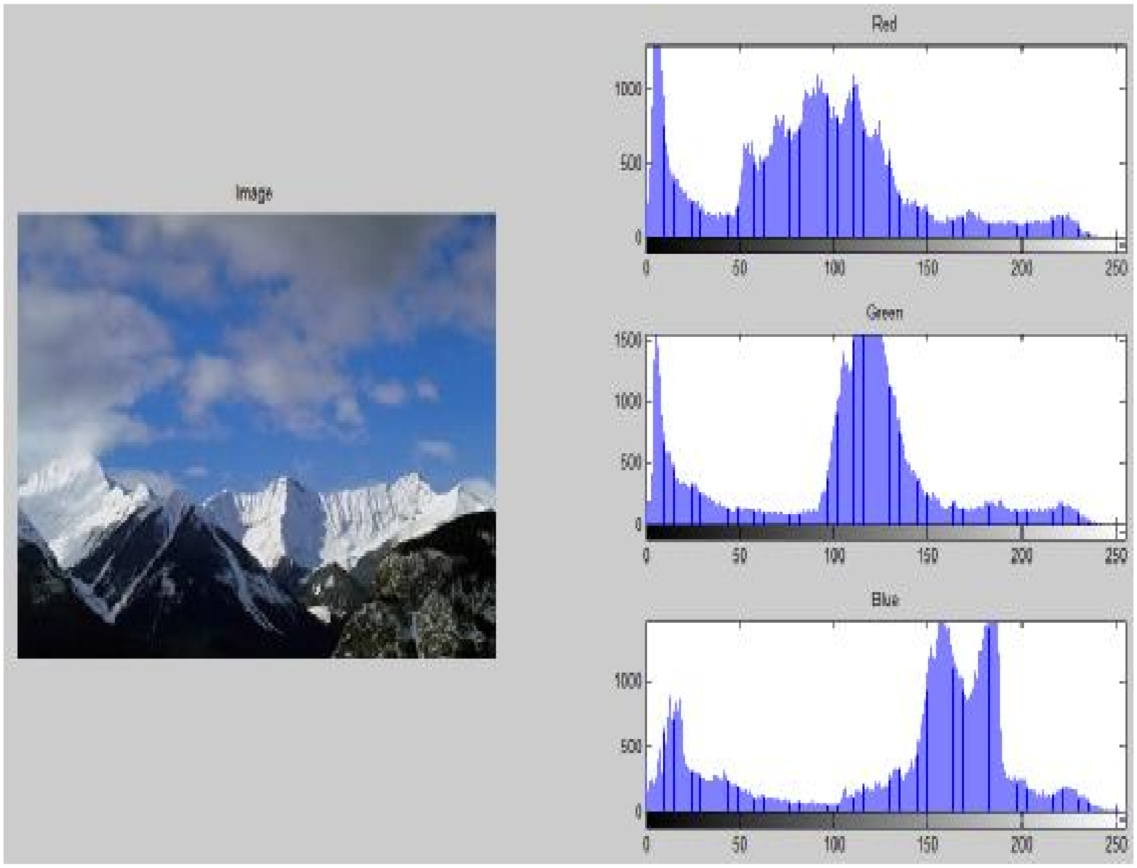
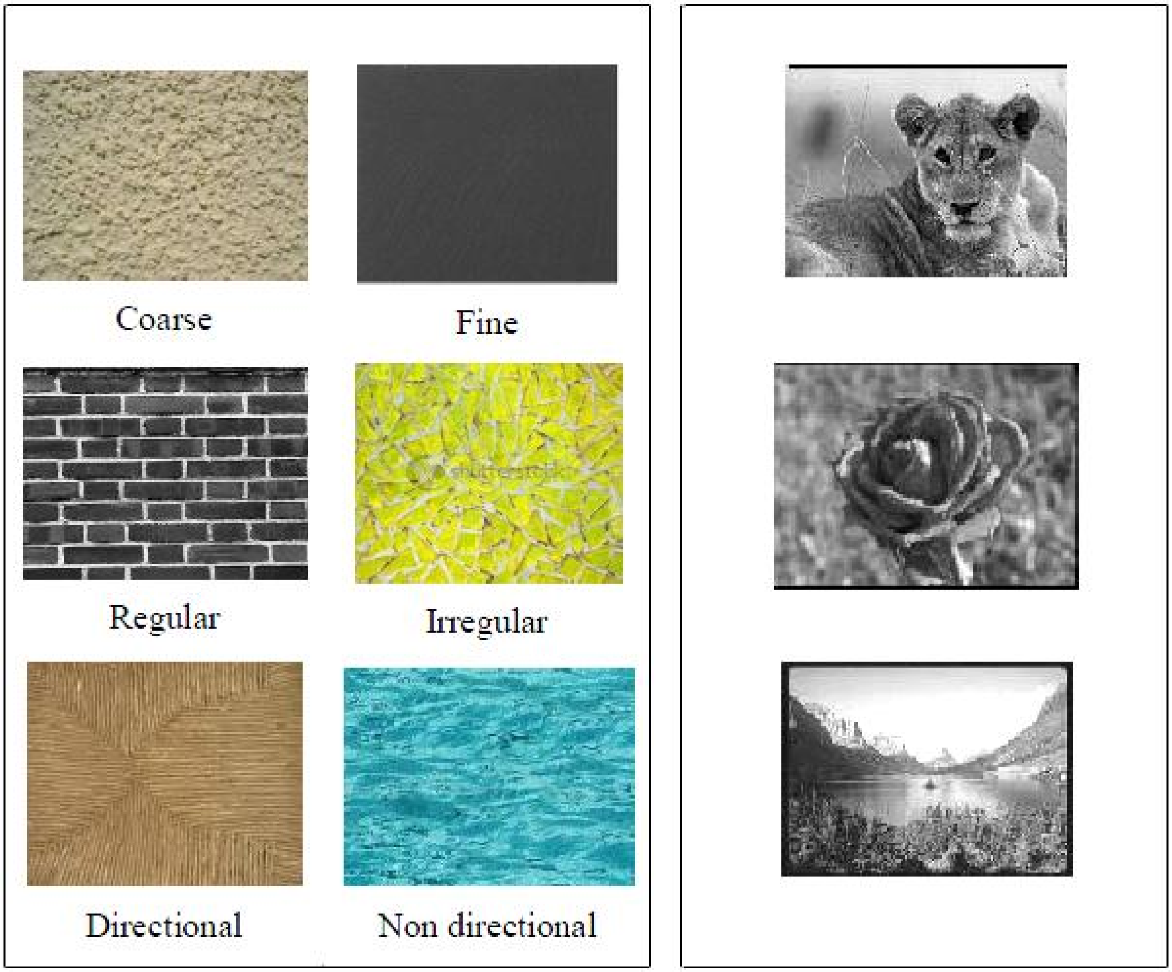


Figure 4.4: Sample Image and Its Color Histograms.

4.2.2 Texture

Quantifying texture content of an image is the most important method to image region description. No formal definition for texture, but we can say that it provides the measures of properties such as smoothness, coarseness, and regularity. Furthermore, texture can be thought as repeated patterns of pixels over a spatial domain. If the texture has exposed to some noise, the patterns and their repetition in the texture can be random and unstructured. Some scenes in our world have complex texture (Figure 4.5 [40]). The various brightness intensities give rise to a blend of different human perception of texture.



Simple Texture **Complex Texture**

Figure 4.5: Examples of Simple and Complex Texture Images.

Many applications in image processing and computer vision depend on texture images. They use them for recognition of image regions and extracting image shapes using texture properties, recognition of texture boundaries using texture properties, and generation of texture images from texture models.

Since there is no accepted mathematical definition for texture, many different methods are proposed for computing texture. Among these methods, no single method works best with all types of texture. Some common methods are used for texture feature extraction such as statistical, model-based, and transform-based methods.

Model-based methods try to generate a model for the process that generates the texture. To create a model, part of image model parameters are assumed according to some hypotheses, and other model parameters are estimated so that the model works in the best way. Currently, there are popular models as Markov models, fractals, and the multi-resolution autoregressive features.

Transform-based models use the frequency content of the image to determine texture features. These methods aim to represent images in mathematical models. For example, Fourier transform is used to describe the global frequency content of the image. It converts the signal into sine waves of various frequencies. Multi-resolution transforms such as wavelet and Gabor use a window function to transform a signal to a shifted and scaled version of the original signal [37].

- **Statistical Methods**

One of the simplest methods for describing texture is the statistical methods. Statistical methods analyse the spatial distribution of the gray values by computing local features at each point in the image, and deriving a set of statistical distribution of the local features. Co-occurrence matrix representation and statistical moments are the most common methods used for texture representation.

It is important to take into account the relative position of pixels with respect to each other. One way to incorporate this information into texture analysis is to consider the distribution of intensities and the relative positions of pixels in an image. This can be achieved by the Gary-level Co-occurrence Matrix (GLCM). It measures the relative frequencies of occurrence of gray level contributions among pairs of pixels with a specific spatial relationship. It is a two-dimensional joint probability matrix between pairs of pixels. It is popular in texture representation and used in many applications as recognizing fabric defects. A set of descriptors is derived for characterizing the GLCM such as energy, entropy, maximum probability, correlation, and invariant different moments.

Figure 4.6 shows an example of how to construct the gray-level co-occurrence matrix [27, 38]. Image I is a gray scale image of size 4 x 5. To create the gray-level co-occurrence matrix, we have to create a square matrix and its dimension is equal to the largest pixel value in the image. In the GLCM, element (1, 1) contains the value 1 because there is only one instance in the image where two, horizontally adjacent pixels have the values 1 and 1. Element (1, 2) contains the value 2 because there are two instances in the image where two, horizontally adjacent pixels have the values 1 and 2. We repeat this for every two adjacent pixels and count the number of times this pair of values are appeared in the image.

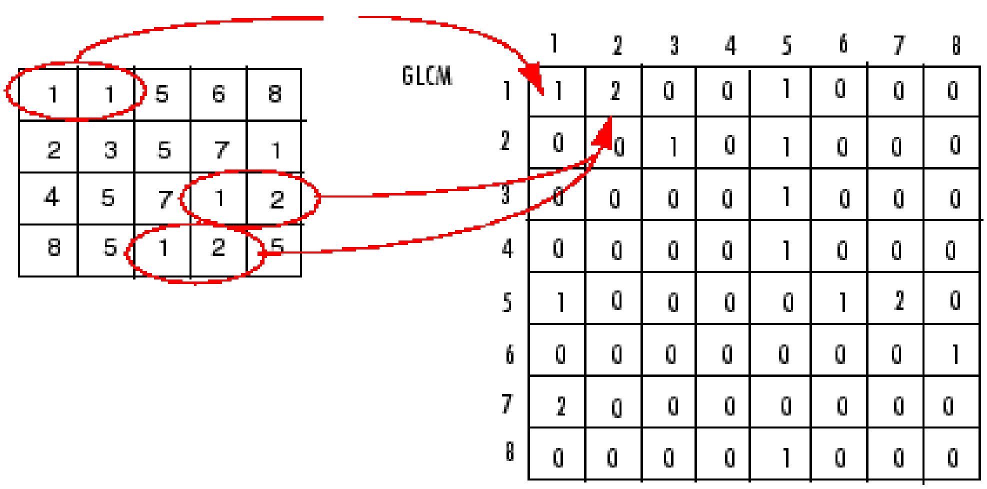


Figure 4.6: How to create GLCM.

4.2.3 Shape

Shape is one of the common image features that used to represent the image. Shape of an object is the characteristic surface configuration as represented by the outline or the contour. Human can recognize the surrounding environment through recognizing the shapes. Shapes are used in CBIR systems to identify region of interest in images. Basically, representing a region involves two choices. One choice is to represent the region in terms of its external characteristics (its boundary). The other choice is to represent the region in terms of its internal characteristics (the pixels comprising the region). If we focus on the shape characteristics, the external representation is chosen. Otherwise, the internal representation is chosen to characterize the regional properties. They are related to region-based and boundary-based methods. In some situations, it may be necessary to use both representations [27].

There are several boundary-based shape descriptors. Area, perimeter, compactness, and eccentricity are some of these descriptors. Complex boundaries are represented using Fourier descriptors, chain codes, and statistical methods.

Region-based methods take all pixels into account to represent the shape. Moment descriptors are most common used to extract features from shapes. They combine information gained from the entire pixels with information extracted from the boundary points. Therefore, they provide some global properties rather than the boundary or contour properties [27].

In our work, we are not interested in shape features. Our work depends mainly on color features. We will use color moments in our work to represent image features. In our future work, we will take into account the shape features to represent image regions.

4.3 Similarity Measures

One fundamental step in CBIR system is the similarity measures. Similarity between two images is to find the distance between them. The distance between two images can be calculated using feature vectors that are extracted from the images. Therefore, the retrieval result is not a single image, but many images will be retrieved similar to the query image. Different similarity measures have been proposed based on the empirical estimates of the distribution of features, so the kind of features extracted from the image and the arrangement of these features in a vector will determine the kind of similarity measures to be used. Different similarity measures will affect the retrieval performance of image retrieval significantly. Some of similarity measures are introduced next [5].

- **Minkowski-Form Distance**

Minkowski distance is one of the most popular similarity measures used in CBIR. If we have two images and the feature vectors of them are ***A*** and ***B***, then the distance between the two images is calculated by Equation 4.1:

$$D(A,B) = \left(\sum_{i=1}^{N} |(a_i - b_i)|^k\right)^{1/k} \quad (4.1)$$

In equation 4.1, ***N*** is the dimension of the feature vector. A special form from equation 4.1 is when k = 2. The new form is called Euclidian Distance that is widely used to measure the similarity between images. Many systems use the Euclidean Distance such as Netra, MARS, and Blobworld. The distance between two images with N-dimensional feature vectors using Euclidean Distance is shown in Equation 4.2.:

$$D(A,B) = \left(\sum_{i=1}^{N} |(a_i - b_i)|^2\right)^{1/2} \quad (4.2)$$

For some kind of features such as color histograms, similarity measures like Euclidean Distance may not be ideal to measure the similarity between images [5]. Similarity between color images with histogram features is proposed by Swain and Ballard. Let $\boldsymbol{I}$ and $\boldsymbol{J}$ are two images and $\boldsymbol{f_i(I)}$ is the number of pixels in pin $\boldsymbol{i}$ of the image $\boldsymbol{I}$, then the histogram intersection is defined by Equation 4.3:

$$S(I,J) = \frac{\sum_{i=1}^{N} \min\left(f_i(I), f_i(J)\right)}{\sum_{i=1}^{N} f_i(J)} \tag{4.3}$$

4.4 Indexing Schema

Our world contains many digital images of different categories. Images are stored in digital libraries or databases. As we said before, searching for a certain image is a difficult task, because the databases contain huge number of images. Using some text descriptions to describe images and store them is not a meaningful method. This is because no one has the same description for the same image, and the description may be not powerful that it describes the image correctly. To overcome these problems, indexing method is needed.

Indexing schema is important in CBIR systems. Indexing methods are proposed to accelerate searching and retrieving steps. Indexing methods categorize images in the database to groups. Each group contains similar images. This can be a preprocessing step for CBIR system. Features extracted from images in the database are used for indexing. A number of methods have been proposed for indexing. R*-tree is a popular multi-dimensional indexing method [5, 39].

In our work we will use k-means algorithm as a clustering algorithm for indexing. K-means algorithm will be used to cluster the database into clusters. With these clusters, the search step will be performed by means of nearest neighbor search. When the user submits a query image, it will be compared with each cluster’s centroid. According to the similarity with the query image, the clusters will be ranked. The query image will be compared with the images in the top ranked cluster. This method will reduce the number of comparisons. Number of comparisons depends only on the number of clusters and the number of images in the top ranked cluster.

Chapter 5 - Image Retrieval Based On Content

In this chapter, we introduce our proposed CBIR system. In our proposed system, we will extract some color features to represent the image and use these features to compare between the images.

5.1 Color Feature Extraction

The color composition of an image can be viewed as a color distribution in the sense of the probability theory. The discrete probability distribution can be viewed as a histogram. The color histogram is one of the most well-known color features used for image feature extraction. It denotes the joint probability of the intensities of the image. The quantization step for color histogram is necessary, but it is hard to find an optimal quantization. Furthermore, if we find an optimal quantization for the histogram, it may produce unwanted quantization effects.

From the probability theory, a probability distribution can be uniquely characterized by its moments. Thus, if we interpret the color distribution of an image as a probability distribution, moments can be used to characterize the color distribution. In our work, the moments of the color distribution are the features extracted from the images, and we will use them to describe the image and for image matching and retrieval [41].

The first order (*mean*), the second (*standard deviation*) and the third order (*skewness*) color moments have been proved to be efficient and effective in representing color distributions of images. If the value of the *i*-th color channel at the *j*-th image pixel is p_{ij}, then the color moments are as the following:

Moment 1: Mean

$$E_i = \frac{1}{N} \sum_{j=1}^{N} p_{ij} \tag{5.1}$$

Moment 2: Standard Deviation

$$\sigma_i = \sqrt{\left(\frac{1}{N} \sum_{j=1}^{N} \left(p_{ij} - E_i\right)^2\right)} \tag{5.2}$$

Moment 3: Skewness

$$s_i = \sqrt[3]{\left(\frac{1}{N} \sum_{j=1}^{N} \left(p_{ij} - E_i\right)^3\right)} \tag{5.3}$$

For color image, color moments are very compact representation features compared with other color features since only 9 (3 values for each layer) numerical values are used to represent the color content of each image channel.

5.2 K-Means for Database Clustering

Time is one of the most important factors to CBIR. It mainly depends on the number of images in the database. Many systems use every image in the database to be compared with the query image to find the top matching images. This method is highly computationally inefficient when the database contains large number of images. However, it is a benefit to use all images in the database for similarity matching, so that the results will be good enough. To overcome this problem, image clustering or categorization has often been treated as a preprocessing step to speed-up image retrieval in large databases and to improve the accuracy. Clustering algorithms are used as a preprocessing step to cluster the database into N different categories [42].

A cluster is a group of objects that are similar to each other within the same group and are dissimilar to the objects in other groups. Clustering has been widely used in different applications, including pattern recognition, data analysis, machine learning, and image processing. K-means is one of the simplest clustering algorithms.

In k-means algorithm, the clustering results are measured by the sum of within-cluster distances between every vector and its cluster centroid. This criterion ensures that the clusters generated are tight. K-means algorithm takes k, the number of clusters to be generated, as the input parameter and partitions a set of N objects into k clusters so that the resulting intracluster similarity is high but the intercluster similarity is low. If the number of clusters is not specified, a simple method is done. The algorithm initializes the number of clusters to a certain number less than the total number of the dataset. The algorithm increases that number gradually until the average distance between a vector and its cluster centroid is below a given threshold [43, 37].

The k-means algorithm works as the following. The number of clusters, k, is entered as an input parameter. The algorithm randomly selects k of the objects, each of which initially represents a cluster centroid. For each of the remaining objects, an object is assigned to the cluster to which it is most similar. Similarity between the cluster centroid and the object is determined by a distance. For example, if we use the Euclidean Distance to measure the similarity and the result is smaller than a threshold, this means that this object belongs to the cluster. It then computes the new mean for each cluster. This process is iterated until the criterion function converges. The criterion function used for convergence is the sum of squared-error (SSE). The SSE is defined by:

$$E = \sum_{i=1}^{k} \sum_{p \in c_i} |p - m_i|^2 \tag{5.4}$$

In equation 5.4, E is the sum of squared error for all objects in the database, p is feature vector representing the image and m_i is the mean of cluster c_i. This criterion attempts to make the resulting k clusters as separate as possible.

The algorithm tries to determine the k clusters that minimize the squared error function. It will work well when the clusters are compact and well separated from one another. This algorithm is relatively scalable and efficient in processing large data sets, but it often terminates at a local optimum. The k-means algorithm is given in Table 5.1 [43].

We use the k-means algorithm to classify the feature vectors of the input images. We select the k-means algorithm because it is suitable to cluster large amount of data. Each feature vector is treated as an object having a location in space. The cluster generates in which objects within this cluster are close to each other and far from objects in other clusters as possible. Selecting the distance measure is an important step in clustering. The distance measure determines the similarity of two images.

To begin clustering, k objects are selected randomly to initialize the centroids of the clusters. The centroid for each cluster is a point to which the sum of distances from all objects in that cluster is minimized. The clusters are generated by calculating the distance between the centroid and the objects for each cluster.

In our proposed CBIR system, we will prepare the database as a preprocessing step. First, features are extracted from the images in the database. Using k-means, the feature vectors are then used to generate the clusters so that all images in the database are classified. When a query image is submitted, the features are extracted. Instead of comparing the query image with all images in the database, a similarity distance is calculated between the query image and each centroid of all clusters. The smallest distance means that the query image belongs to that cluster. After that, the similarity distance is calculated between the query image and the images only in that cluster to retrieve the top most similar images. This will improve the speed and will make the retrieval processing much faster.

Table 5.1: The k-means Algorithm

Purpose: The k-means algorithm for partitioning based on the mean value of the objects in the cluster.

Input: A database of N objects, number of clusters k.

Output: A set of k clusters.

Method:

1. Arbitrarily choose k objects as the initial cluster centers.
2. (Re)Assign each object to the cluster to which the object is the most similar based on the mean value of objects in the cluster.
3. Update the cluster means, i.e., calculate the mean value of the objects for each cluster.
4. Repeat steps 2 and 3 until no changes.

5.3 The proposed CBIR System

In this section we are introducing our proposed system for CBIR. In our system, we will use images represented in the RGB color space. Although the RGB color space is perceptually non-uniform and device-dependent, it is widely used for representing color images. We do not worry about that because the image will have a preprocessing step. Also, images in the database to be used for system testing and evaluation seem to be captured and treated by the same way (the same capturing device and environmental conditions). WANG database [44] is widely used for CBIR, and we will use it for our system. Ranklet Transform is used as a preprocessing step. The advantage of using Ranklet Transform is that it generates three images with different orientation that are vertical, horizontal, and diagonal images. Because we use RGB color image, we perform the Ranklet Transform for each image layer (the red, green, and blue layers). The Ranklet Transform generates three images for each layer, three ranklet images for the red layer, three ranklet images for the green layer, and three ranklet images for the blue layer. This step is shown in Figure 5.1.

Figure 5.1 shows the preprocessing step. The original image is an RGB image that contains the three layers or components. Ranklet Transform is applied for each image layer. For each image layer, three ranklet images are generated in three different orientations. They are the vertical, the horizontal, and the diagonal ranklet images. So, for each input image we have nine images that have different information. We have to exploit these images to extract features that represent the original image, and can be used for similarity and retrieval. The preprocessing step will be applied for every image in the database so that it will be ready for the next step that is extracting the features.

After applying the Ranklet Transform for the image, we have to extract its features that represent the image. In our system, we select the color feature that represents the image, to be extracted. Color moments are widely used to represent the color images, and we will use them to extract the features from the images. We have nine images generated from the preprocessing step. We calculate the three color moments for each image using equation 5.1 for the mean, 5.2 for the standard deviation, and 5.3 for the skewness. After calculating the three values, we concatenate them in one vector called image feature vector. This vector has 27 values that represent the image, and we use it to measure the similarity between the images.

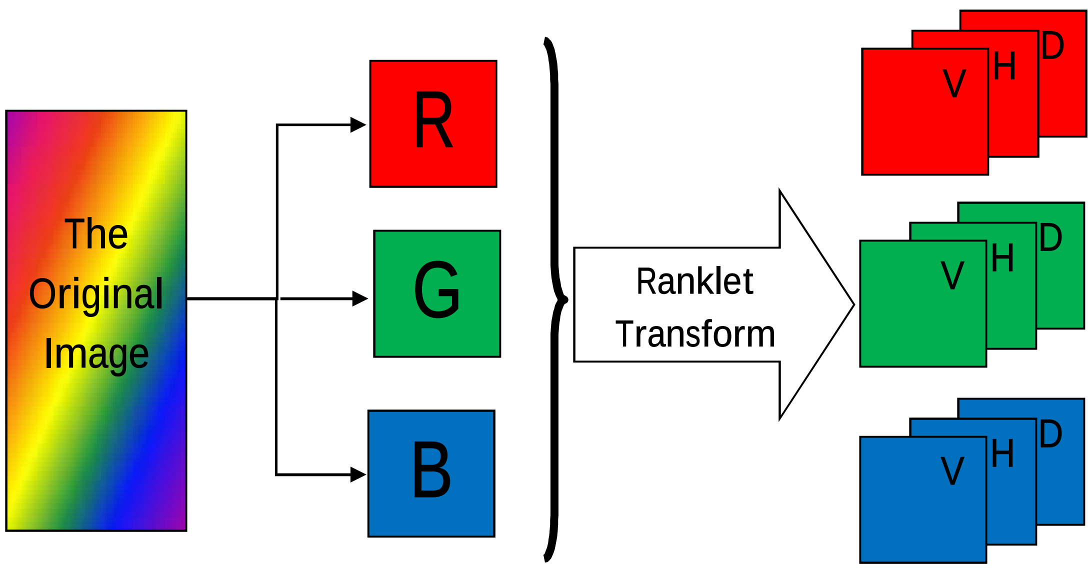


Figure 5.1: The preprocessing step.

We calculate the feature vector for every image in the database. We use the k-means clustering algorithm to cluster the images into different categories. This step will decrease the time of retrieval. When the user submits an image, it will not be compared with each image in the database. Instead, the feature vector of the image will be compared with the centroid of each category by computing the distance between them. The smallest distance means that the input image is similar to the category holds that centroid. The input image then is compared with the images in that category and system will retrieve the most similar images to the input image.

Because we deal with image components instead of a single image, we will use a similarity function that gives some weights for some image components. Equation 5.5 will be used to measure the similarity between two images, which is [41]:

$$d_{mom}(H,I) = \sum_{i=1}^{r} w_{i1}\left|E_i^1 - E_i^2\right| + w_{i2}\left|\sigma_i^1 - \sigma_i^2\right| + w_{i1}\left|s_i^1 - s_i^2\right| \qquad (5.5)$$

In equation 5.5:

H and ***I*** are the two images to be compared,

i is the current image component index that is 1= R, 2 = G, and 3 = B,

r is the number of image layers that is 3,

$\boldsymbol{E_i^1}, \boldsymbol{E_i^2}$ are the means of the two images in the *ith* component,

$\boldsymbol{\sigma_i^1}, \boldsymbol{\sigma_i^2}$ are the standard deviations of the two images in the *ith* component,

$\boldsymbol{s_i^1}, \boldsymbol{s_i^2}$ are the skewness of the two images in the *ith* component, and

$\boldsymbol{w^i}$ is the weight for each moment.

In equation 5.5, $\boldsymbol{d_{mom}}$ value is a similarity function and not a metric because we deal with multidimensional images (images have 3 layers). Using this equation for similarity measurement, it is possible to lead to false positive results. For image retrieval system, this drawback is negligible. Fortunately, this function proved that it is more robust that other methods or metrics used for similarity measures. The most important parameter in the equation is the weight value w_i. This parameter is user defined. In our proposed system, we deal with three moments and three image layers. Some moments have some preferences than the others. We use the weight parameter to give preferences to different features of an image. For example, the mean is the most important moment and the other two moments are derived from it. We want to give it the highest priority so that it is the main feature. Also we can give any image layer the preference so that it is the main image layer. In the implementation phase, we will tune the weights until we get the best results. This is like the training for the system. We find that the best results are when $w_{i1} = 2$, $w_{i2} = 1$, and $w_{i3} = 1$. After the system is ready for testing, the user just has to submit the query image and the system will retrieve images similar to the query image.

The retrieved images will be ranked and the user will specify the number of images to appear. The proposed algorithm is stated in Table 5.2.

Table 5.2: The proposed CBIR algorithm

Purpose: The algorithm is to retrieve images similar to the input image.

Input: An RGB image, number of retrieved images ***n***.

Output: n images similar to the input image.

Method:

Step 1: The input image is a color image in RGB color space.

Step 2: Apply the Ranklet Transform for each image layer(R, G, and B). The output images will be in three orientations (vertical, horizontal, and diagonal).

Step 3: For each ranklet image (vertical, horizontal, and diagonal) in a specified layer, calculate the color moments using equations 5.1, 5.2, and 5.3.

Step 4: Construct the feature vector that will represent the image containing 27 numerical values.

Step 5: Cluster the images in the database using k-means algorithm (Table 5.1) into different categories.

Step 6: Calculate the distance between the input image and the centroid of each cluster using equation 5.5, and find the smallest distance.

Step 7: Calculate the distance between the input image and the images in the cluster that has the smallest distance with the input image.

Step 8: Retrieve the first n images that is similar to the input image.

Chapter 6 - System Results and Evaluation

6.1 Introduction

In this chapter, we will present the evaluation of our proposed system that was introduced in the previous chapter. We introduce the database we select to test our system, and we will compare our system results with other already existing CBIR systems that most of them use the same image database.

6.2 WANG Database

WANG database [44] is an image database that the images are manually selected from the Corel database. In WANG database, the images are divided into 10 classes. Each class contains 100 images. It is widely used for testing CBIR systems. Classification of the images in the database into 10 classes makes the evaluation of the system easy. Figure 6.1 shows one example image for each class.

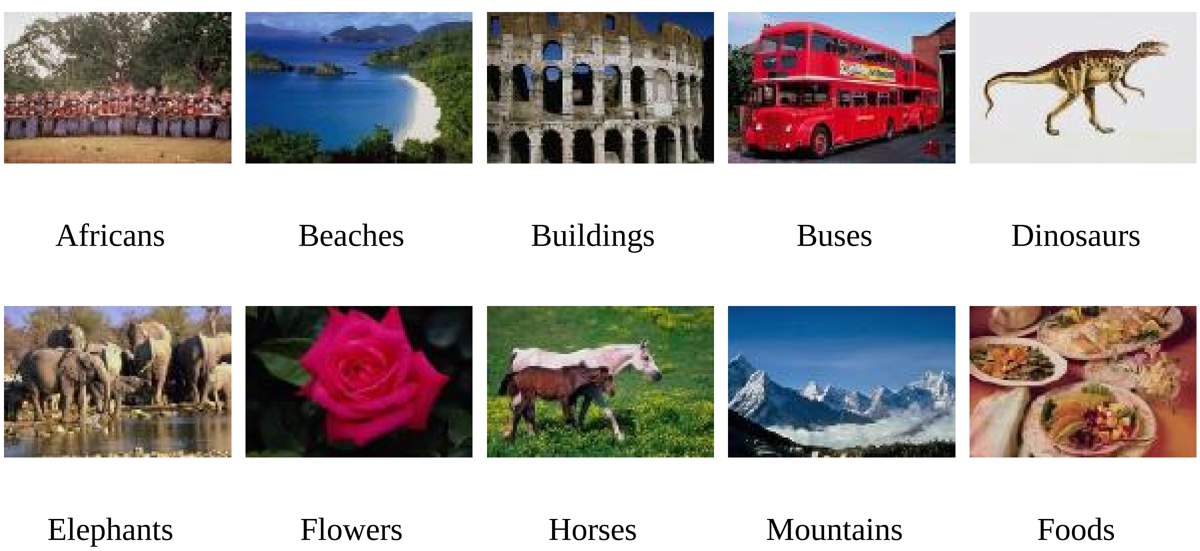


Figure 6.1: One example image from each of the 10 classes of the WANG database.

This database was created by the group of Professor James Wang from the Pennsylvania State University. This database is free and available to download. It was used extensively to test many CBIR systems. This popularity is because the size of the database and the availability of class information allows for performance evaluation. Since this database is a subset of the Corel database, the images are of size 384 × 256 or 256 × 384 pixels as well.

As we said before, we choose this database for many reasons. Many CBIR systems use this database, so we can easily compare our results with these systems. This database contains large images in different classes (100 images per class). Diversity in the images helps us to get more results and enhance our system. Also, we can explain the results we get according to the database that the number of images we get from testing and compare them with the images in the database. The most interesting point is that the images are familiar to human, and they are very friendly to us.

6.3 Implementation Environment

Our proposed system is implemented using Matlab image processing program of version 7.8.0.347 (R2009a). We use a platform of Intel Core 2 Due Processing power of 2.13 GHz CPU with 3 GB RAM during the implementation. From the 1000 images, we randomly select 300 images from the database. From each class we randomly select 30 images. The selected images went through the implemented system to extract the features and stored them. The extracted features are used for classification using the k-means clustering algorithm. This step is made offline for the 300 images selected from the database. The database now is ready for testing and evaluating our CBIR proposed system.

6.4 Performance Evaluation Metrics for CBIR Systems

When we want to evaluate a CBIR system, we may face some problems. One major problem we face for CBIR system performance evaluation is that neither a standard database nor a unique performance measure is available. There are many image databases that are used to represent results for CBIR system. So, no standard image databases are available for CBIR systems. Therefore, it is impossible to compare the performance of different systems using different image databases. Furthermore, the early CBIR systems were restricted their results. They presented one or more example queries, which are used to give a positive impression about the efficiency of the system. This is neither a quantitative nor an objective measure that can be used for system performance evaluation.

In CBIR, the most commonly used performance measures are Precision and Recall. **Precision** is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images [45]. We denote to the precision by **P**. The equation of precision is:

$$P = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ retrieved} \tag{6.1}$$

Recall is defined as the ratio of the number of retrieved relevant images to the total number of relevant images in the database [45]. We denote to the recall by **R**. The equation of recall is:

$$R = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ relevant\ images\ in\ the\ database} \tag{6.2}$$

In CBIR, if the precision score is 1.0, this means that every image retrieved by a search is relevant, but we do not know if the search retrieves all the images relevant to the query. If the recall score is 1.0, this means that all relevant images are retrieved by the search, be we do not know the number of irrelevant images were also retrieved.

In classification task, a precision of score 1.0 for a class ***X*** means that every object labeled as belonging to class X does indeed belong to class X, but we do not know the number of objects from class ***X*** that were not labeled correctly. Also, a recall of score 1.0 for a class ***X*** means that every object from class ***X*** was labeled as belonging to ***X***, but we do not know the number of objects were also labeled as belonging to class ***X*** incorrectly. There is a trade-off between precision and recall. In search engine, for example, the user prefers to increase the number of results relevant to the query by retrieving more documents. This will increase the recall. On the other hand, the results will have quite large number of irrelevant documents retrieved. This will decrease the precision [46].

In general, when we want to evaluate the performance of a CBIR system, we use both the two metrics. The precision/recall graph is widely used. It provides meaningful results when the database is known and has been used in some earlier systems. Because we know every image in the database and also know the relevant images for each image, we can use any image from the database to be the query.

6.5 The proposed System Evaluation

This section is the most important section in the thesis. Here, we test our proposed system and show the results. We explain the results, comment on them, and compare our system with other existing systems.

In order to check retrieval effectiveness of the proposed system, we have to test it by selecting some images randomly and retrieve some images. Also, we have to calculate the two performance evaluation metrics that are Precision and Recall. Finally, we compare our proposed system with other existing systems and show the efficiency of the proposed system. To test the system, we select 300 different images from WANG database and from different classes (30 images from each class). For initial test to our proposed system, we select four images from different classes randomly and retrieve 10 images similar to the query image.

The first test is selecting a random image from the Beaches class. We submit the image to the system and retrieve the top 10 images that are similar to the query image.

As can be seen from Figure 6.2, we select the query image from the Beaches class randomly and retrieve the most top 10 images that are similar to the query image. All images retrieved by the system are relevant to the query image. Notice that the retrieved images are belonging to the same class of the query image, and all the images are similar in the color feature. So, the system retrieves them correctly.

Figure 6.3 shows another query image and its result. This is the second test for the system. We select an image randomly from the Buildings class and retrieve 10 images similar to the query image. Again, all images from the results are belonging to the same class of the query image. Also, the images retrieved have similar color to the query image. Almost images in the same class are similar to each other in their color, and our proposed system depends mainly on the color feature.

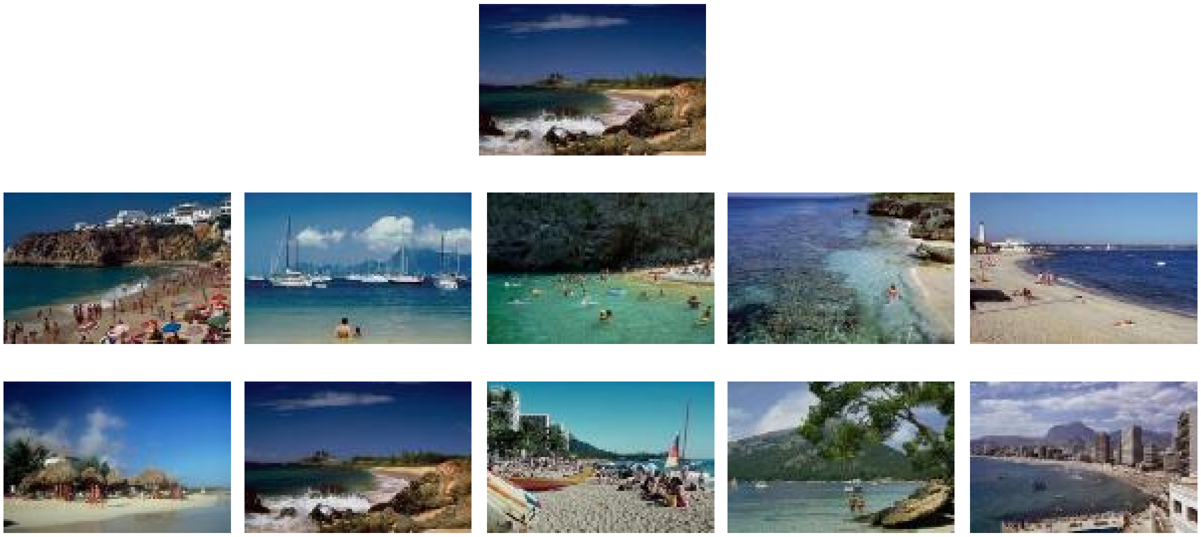


Figure 6.2: Beach Query, The Top 10 Retrieved Images.

If we look to Figure 6.3 deeply, we notice that the last image retrieved by the system has an object with different color (the yellow flower). Although the image contains flowers with a strange color from other images, the system retrieves it and assigns it to the Building class. This is true because the major color for the image is similar to the query image, so the system retrieves it.

Figure 6.3: Building Query, The Top 10 Retrieved Images.

We also select a random image from the Horses class. We submit the image and retrieve 10 images similar to the query image. Figure 6.4 shows the result of retrieving images similar to the query image. As we can see from Figure 6.4, all the images are similar to the query image and belong to the same class.

Figure 6.4: Horse Query, The Top 10 Retrieved Images.

The last test is for the Flowers class. We select the query image randomly and retrieve 10 images similar to the query image. Figure 6.5 shows the result. From Figure 6.5, we notice that all retrieved images are similar to the query image and have the same class. Furthermore, we have some flower images in the database with color is not red; the system does not retrieve them. The reason is that our system is mainly depends on the color feature and when retrieving images, it just interests in the color feature and retrieve images similar to each other in their color.

From the above testing, we can notice that the system works well and it retrieves good results over the randomly selected images as queries. This gives us a good impression that the system will also retrieve good results for most of the other images in the database if we use them to retrieve images.

Figure 6.5: Flower Query, The Top 10 Retrieved Images.

One limitation of the system is that it only uses the color feature to represent the image. During some testing, we notice that some retrieved images are similar to the query image in the color, but they do not belong to the same class. This makes the retrieval task incorrect. For example, if we submit a query image and the dominant color is gray, then the system will retrieve images similar to the query image and maybe also retrieve some images that contain gray color as a dominant color in it.

Figure 6.6 shows the limitation we have explained before. As we can see in the figure, the query image belongs to the Elephants class. The system retrieves the images similar to the query image. Some images do indeed belong to the Elephants class, but the other images are not. The system retrieves the incorrect images because they are similar to the query image in their color. In Figure 6.6, the incorrect images are from the Building class. These images are similar to the query image if we use the color feature to represent images. This leads the system to retrieve some incorrect images. So, in some cases, the system may retrieve some incorrect images.

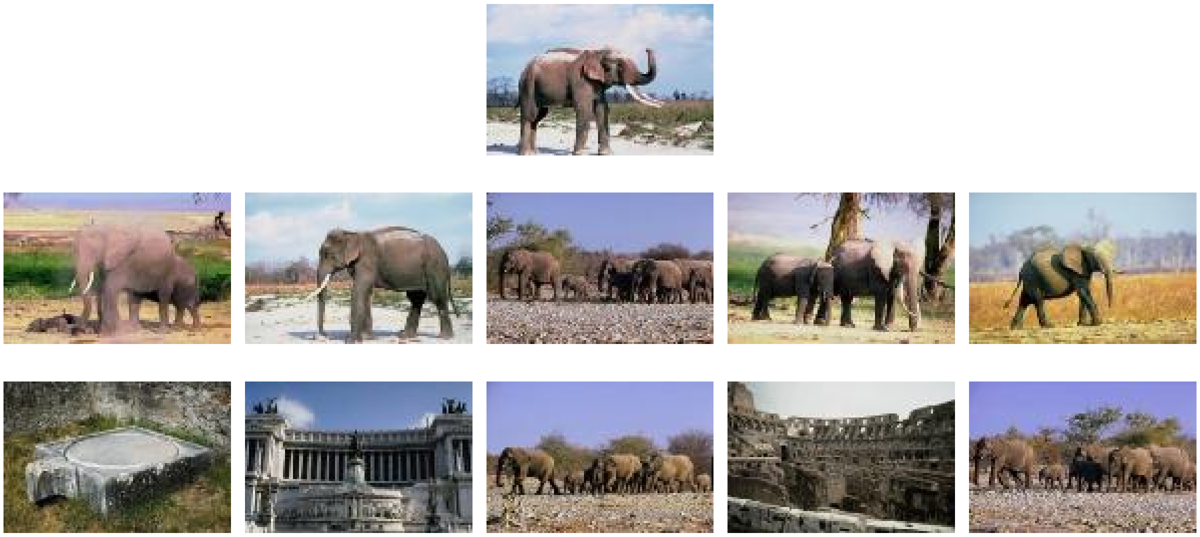


Figure 6.6: Elephant Query, The Top 10 Retrieved Images.

In general, the performance evaluation of the system is satisfactory and we will present the performance metrics in the next section to evaluate the system. Also, we will compare our system with other existing CBIR systems and shows that our proposed system outperforms other CBIR existing system although it uses just the color feature to represent the image.

One traditional graph that describes the performance of the system is the Precision-Recall graph. It provides a meaningful result when the database is known and has been used be some earlier systems. To evaluate our proposed system, we use the Precision-Recall graph. We select 30 images randomly from each class in the database to use them as queries to calculate the precision and recall. For each image, the precision of the retrieval result is obtained by increasing the number of retrieved images. Figure 6.7 shows the Precision-Recall graph.

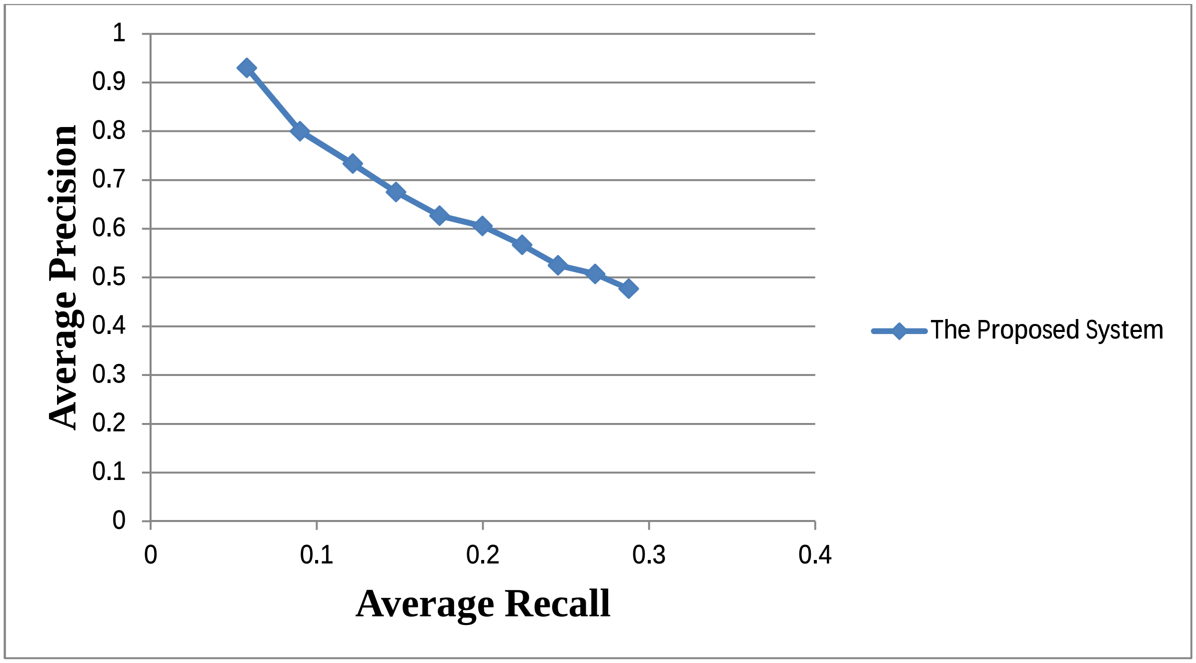


Figure 6.7: The Average Precision/Recall Chart of The Proposed System.

Form Figure 6.7, we notice that the system has good precision results over the different values of recall. The maximum average precision of 0.93 at recall value of 0.05, and the precision value decreases to 0.47 at 0.28 of recall. For example, if a user submit a query image and he want just 10 relevant images from 100 images retrieved by the system, the graph shows us that the user will get 70 relevant images to the query image instead of 10 images. In other words, for an average recall value of 10%, we have an average precision 70%. This means that we intent to get 10% of the relevant images in the database and we will get 70% of the retrieved images that are relevant to the query image. This clarifies that our system works well.

We have improved the efficiency of our proposed system by clustering the image database using k-means clustering algorithm (Table 5.1). We perform the clustering algorithm on the database as an offline step, and then we use the clusters to retrieve images relevant to the query image. This is done by calculating the distance between the query image and the centroid of each cluster. The smallest distance between the query image and a centroid means that the query image is relevant to the centroid's cluster. Then, we calculate the distance between the query image and the images in that cluster to retrieve the most similar images. To apply this, we chose some images randomly from each class as queries and applied them twice. In the first time, we use the k-means algorithm to cluster the database before image retrieval. In the second time, we retrieve images without clustering the database as a preprocessing step. The average precision for each class for the top 30 relevant images is shown in Figure 6.8.

Figure 6.8: Comparison of Precision of The Proposed System Applied With Clustering and Without Clustering.

From Figure 6.8, we note that the system works well when using the k-means clustering algorithm and the results are better without using the clustering algorithm. Furthermore, we test the time that the system takes to retrieve the relevant images. We again apply the query images twice; one with clustering before retrieving and the second without clustering. We notice that the system takes less time when using the k-means clustering algorithm that without using it. If we look carefully on Figure 6.8, we can note that the precision of classes Dinosaurs and Foods without using k-means is better that the precision when using the k-means. This is because some images from each class are incorrectly clustered. However, the difference between the two precisions is small and negligible.

Applying a clustering algorithm on image database as a preprocessing step before the retrieving step reduces the time consuming for retrieving images. The clustering step avoids the system the computation complexity. The system does not need to search the entire database to retrieve relevant images.

6.6 Comparison of the Proposed System with Other Systems

In this section, we present some earlier CBIR systems' results and compare them with our proposed system. The existing systems we chose for comparison use color features to represent images, and they also use the WANG database to evaluate their proposed systems. To evaluate our proposed system, we use each image in our database to be a query image and submit it to the system. We calculate the Precisions for each query in all classes. Then for each class we take the average of all calculated Precisions as shown in Table 6.1.

The result of this study is compared against the performance of Jhanwar et al.'s method [47], Hung and Dai's method [48], CTDCBIRS [49], and SCBIRS [20].

Table 6.1 shows that our proposed system performs significantly better than other systems for all classes except for classes 4, 8, and 9 which are Buses, Horses, and Mountains respectively. The reason behind this limitation is that the dominant color of the images in these classes is red, green, and blue respectively, and from the results we get , the system retrieves images have with mixed colors and the dominant color of any image is not one of the basic colors of the RGB color space.

Figure 6.9 shows the comparison of the proposed system with other systems. We represent the precision value of each system for each class using the value from Table 6.1 by a vertical bar. We can see that our proposed system outperforms other existing systems, over most classes, that use the color features to represent the images and also they use the same database for evaluation.

Table 6.1: Comparison of Precision of the Proposed System with Previously Existed Systems.

Semantic Group	Jhanwar et al.	Hung and Dai's	CTDCIRS	SCBIRS	Proposed System
Africans	0.4525	0.4240	0.5620	0.6830	**0.7143**
Beaches	0.3975	0.4455	0.5360	0.5400	**0.8560**
Buildings	0.3735	0.4105	0.6100	0.5615	**0.8341**
Buses	0.7410	0.8515	**0.8930**	0.8880	0.8571
Dinosaurs	0.9145	0.5865	0.9840	0.9925	**0.9975**
Elephants	0.3040	0.4255	0.5780	0.6580	**0.7143**
Flowers	0.8515	0.8975	0.8990	0.8910	**0.9374**
Horses	0.5680	0.5890	0.7800	**0.8025**	0.5714
Mountains	0.2925	0.2680	0.5120	**0.5215**	0.4286
Foods	0.3695	0.4265	0.6940	0.7325	**0.9752**

As a conclusion, the results show that our proposed system works well comparing with other existing systems. The limitation we have mentioned is because we are using one feature to represent the image.

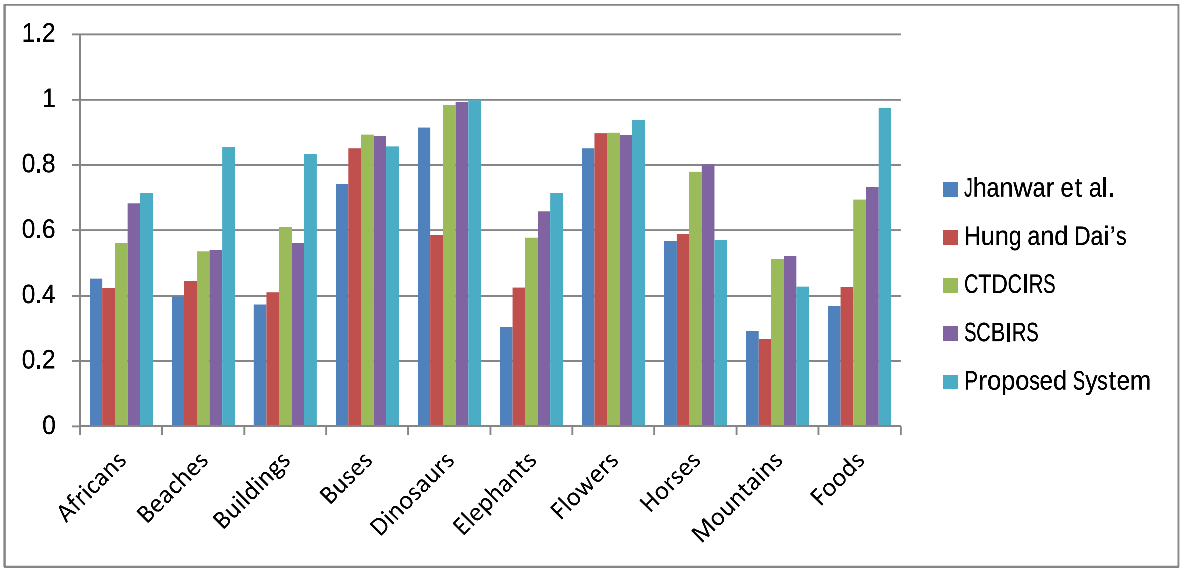


Figure 6.9: Comparison of Precision of The Proposed System with Previously Existed Systems.

Chapter 7 - Conclusion and Future Work

In this Chapter, we will present a summary of our work, talking about the contributions we have achieved and a conclusion for the work. We also present some recommendation and future works.

7.1 Conclusion

Nowadays, content-based image retrieval is a hot topic research. Many researches have been done to develop some algorithms that solve some problems and achieve the accuracy when retrieving images and distinguishing between them. Many proposed algorithms use images to extract features and use their features for similarity matching. However, most of the algorithms use the gray scales images. In our work, we use the color image to extract the color feature and use it for similarity matching. We do this because most images in our world are color images. So, color feature is one of the most features that can be taken into account when developing a CBIR system.

In our work, we used WANG database that is widely used for CBIR. This database contains 1000 images divided into 10 classes where 100 images for each class. Images in the database are friendly and used for evaluating many CBIR systems. We used it to evaluate the performance of our system by calculating the Precision and Recall metrics. We used the RGB color space to represent the images. We used the Ranklet Transform to be as a preprocessing step. This preprocessing step is important to prepare the image for the next step. In the preprocessing step, we make the image invariant to rotation and image enhancements. For example, if the query image is rotated or enhanced by any image enhancement methods, the proposed system will be invariant and retrieve images correctly. This step gives our proposed system satisfactory results. We used the color feature to represent the images in the database. We calculated the moments for the image to be the descriptor of the image. Color moments are easy to calculate and they do not add any overhead on the system in the computation. We also compared our proposed system with other existing CBIR systems that use the same database we have used for system evaluation. The comparison shows that our system outperforms the other systems and the results are satisfactory.

7.2 Limitations

One limitation in our work is that the color feature is not enough to represent the image and use it for similarity matching. From the results, we notice that some retrieved images are not similar to the query image (see Figure 6.6). The proposed system matches the images if the dominant color is similar. We can overcome this limitation by using more than one feature to represent the image. In the next section, we state some ideas to enhance the system.

7.3 Recommendations and Future Works

The recommendation and the future work appear from the limitations and the difficulties when we develop our system. The recommendations and the future works are as the following:

- To represent an image, more than one feature is needed. Our system uses the color feature. We recommend the combination of the texture, shape, and spatial features with the color feature to represent the image. This will give good results. (to overcome our system limitation).
- To further improve the retrieval results, segmentation is a method to extract regions and objects from the image. The segmented regions are used for similarity matching.

- To enhance the results, the system has to take the feedback from the user. The user checks the results and comments on them by some way. Then, the system recalculates the results with the advantage of the feedback.

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