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Content-Based Image Retrieval (CBIR) System Based on the Clustering and Genetic Algorithm

By

Eng. Ahmed K. Mikhraq

Supervisor

Prof. Mohammad Mikki

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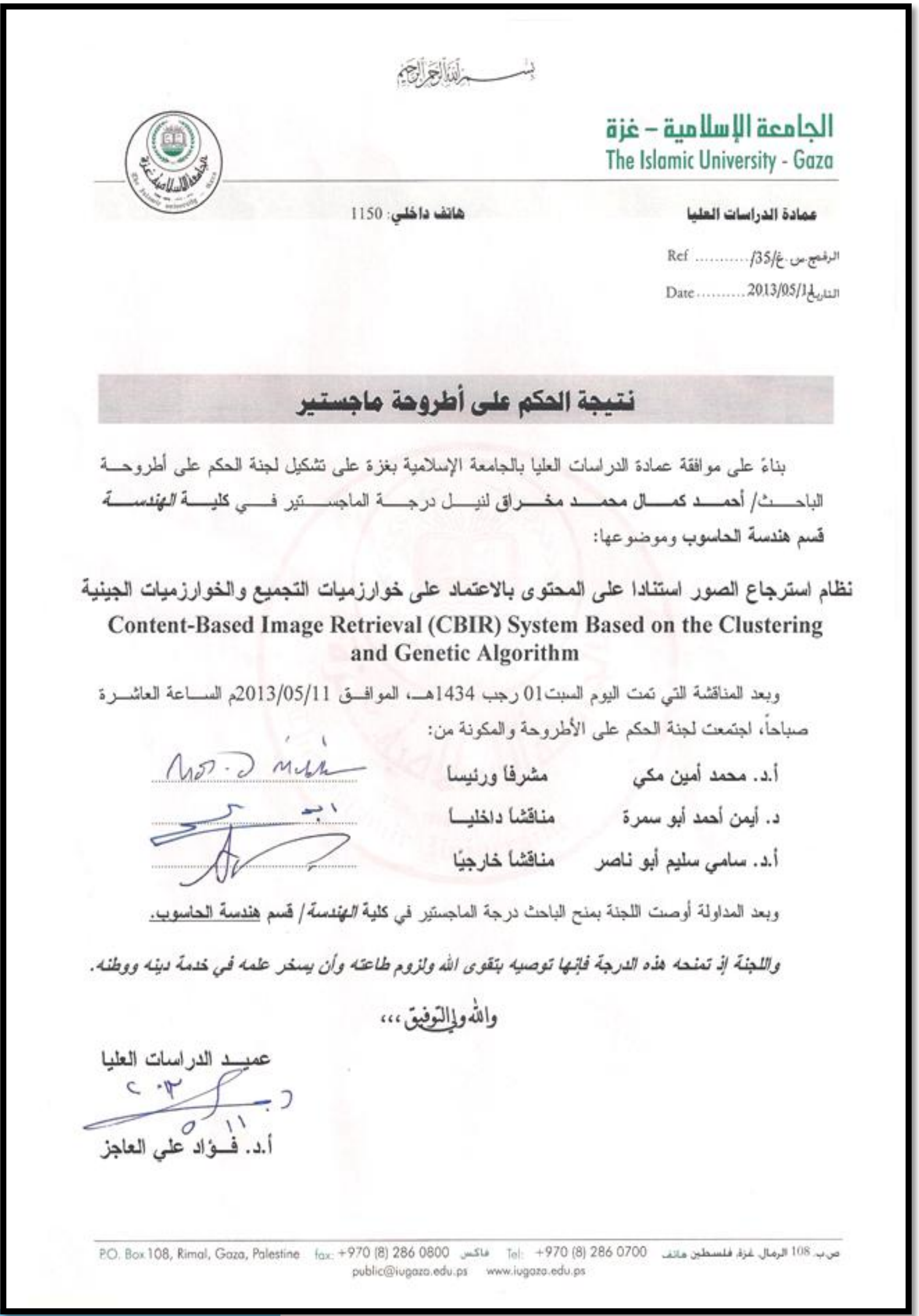

بســـم الله الرحمن الرحيم

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نتيجة الحكم على أطروحة ماجستير

بناءً على موافقة عمادة الدراسات العليا بالجامعة الإسلامية بغزة على تشكيل لجنة الحكم على أطروحة الباحـــث/ أحمـــد كمـــال محمـــد مخـــراق لنيـــل درجـــة الماجســـتير فـــي كليـــة *الهندســـة* قسم هندسة الحاسوب وموضوعها:

نظام استرجاع الصور استنادا على المحتوى بالاعتماد على خوارزميات التجميع والخوارزميات الجينية

Content-Based Image Retrieval (CBIR) System Based on the Clustering and Genetic Algorithm

وبعد المناقشة التي تمت اليوم السبت 01 رجب 1434هـ، الموافـق 2013/05/11م السـاعة العاشـرة صباحاً، اجتمعت لجنة الحكم على الأطروحة والمكونة من:

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د. أيمن أحمد أبو سمرة	مناقشا داخليا	[illegible]
أ.د. سامي سليم أبو ناصر	مناقشا خارجيًا	[illegible]

وبعد المداولة أوصت اللجنة بمنح الباحث درجة الماجستير في كلية *الهندسة* / قسم <u>هندسة الحاسوب</u>.

واللجنة إذ تمنحه هذه الدرجة فإنها توصيه بتقوى الله ولزوم طاعته وأن يسخر علمه في خدمة دينه ووطنه.

والله ولي التوفيق ،،،

عميـد الدراسات العليا

[illegible]

أ.د. فـؤاد علي العاجز

P.O. Box 108, Rimal, Gaza, Palestine fax: +970 (8) 286 0800 فاكس Tel: +970 (8) 286 0700 ص.ب. 108 الرمال. غزة. فلسطين هاتف
public@iugaza.edu.ps www.iugaza.edu.ps

DEDICATION

To the spirit of my brother martyr Nabil, that his departure increased my insistence on the face of life, I miss you a lot in the meantime.

To my beloved brother and friend, Mohammed, who has never dawdle in my support in various ways.

To My beloved Family, My Father, My Mother, My Brothers and Sisters who are the main reason that gives me the power to complete this work.

To the rose of my life, my wife Amani, who fills my life with love, happiness, warmth and tenderness,.

To my Sons, Mohammed and Nabil, and my daughters, Zaina and Samira, who are the candles that bring the light into my heart and my mind.

To My second family, My wife's Father and Mother, her Brothers and Sisters who gave me special kind of love and incubation.

To all, I dedicate this work.

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First of all, All praise and glory are due to Allah for blessing me with the much needed strength and stamina to successfully accomplish this work.

This thesis would have been an impossible task without the assistance, guidance,, valuable advice and encouragement of my supervisor Prof. Mohammad Mikki throughout the course of my research. I deeply thank him for all of his efforts to support me during my work.

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I owe my largest debt to my family, and I wish to express my heartfelt gratitude to all of them for their encouragement, constant prayers, and continued support. My dear parents who have given me all their love and support over the years; I thank them for their unwavering commitment through good times and hard times.

Finally, I thank all of those whose names are not mentioned here but have helped and supported me in any way to accomplish this work.

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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
CIE	: International Commission on Illumination
CLUE	: Cluster-based Retrieval Images by Unsupervised Learning
CMY	: Cyan, Magenta, and Yellow Color Space
DB	: DataBase
EHD	: Edge Histogram Descriptor
GA	: Genetic Algorithm
GFBIR	: Global Feature Based Image Retrieval
GCH	: Global Color Histogram
GLCM	: Gray-Level Co-occurrence Matrix
HSV	: Hue, Saturation, Value color space
KIWI	: Key-point Indexing Web Interface
LCH	: Local Color Histogram
MARS	: Multimedia Analysis and Retrieval System
QBIC	: Query By Image and video Content
RBIR	: Region Based Image Retrieval
RF	: Relevance Feedback
RGB	: Red, Green, Blue color space
SSE	: Sum of Squared-Error
VIR	: Visual Information Retrieval
WALRUS	: Wavelet-based Retrieval of User-specified Scenes
WBIIS	: Wavelet Based Image Indexing and Searching

نظام استرجاع الصور استنادا على المحتوى بالاعتماد على خوارزميات التجميع والخوارزميات الجينية

مقدم من

أحمد كمال محمد مخراق

الملخص

في أيامنا هذه، كل مجالات الحياة البشرية تقريبا بما في ذلك التجارة، والحكومة، والتعليم، والمستشفيات، ومنع الجريمة، المراقبة، والهندسة، والبحوث التاريخية تستخدم المعلومات كصور، وبالتالي فإن حجم البيانات الرقمية في تزايد مستمر وسريع. كما تصنف هذه الصور والبيانات الخاصة بها وتخزن في أجهزة الحاسوب وتظهر المشكلة عند استرجاع هذه الصور من وسائط التخزين. وهكذا أصبح نظام استرجاع الصور باستخدام المحتوى يحظى بمساحة كبيرة من الاهتمام في السنوات الأخيرة وخاصة في العقد الأخير.

في أطروحة الماجستير هذه نقدم نظاما فعالا لاسترجاع الصور استنادا على محتواها وهذا النظام يستخدم اللون والنسيج والشكل كخصائص بصرية لوصف محتوى الصورة.وتكمن المساهمة الرئيسة في هذا البحث في ثلاثة اتجاهات:

الاتجاه الأول : نحن نستخرج ميزة اللون للصورة عن طريق حساب بعض القيم الإحصائية للون والتي هي خاصية فريدة للصورة وثابتة ضد الدوران و التحجيم.

الاتجاه الثاني : نحن نستخدم تقنية مرشحات جابور لاستخراج ميزات النسيج من مناطق عشوائية الشكل تم فصلها من الصور بعد عملية التجزئة لزيادة فعالية النظام.

الاتجاه الثالث : لزيادة فعالية النظام أيضا نحن نستخدم وصف الرسم البياني للحدود والتي تشمل خمس فئات كخاصية لوصف شكل الصورة وهذه الخاصية هي ثابتة ضد الدوران و التحجيم أيضا.

الاتجاه الرابع : لتحسين كفاءة النظام المقترح قمنا بتعيين أوزان مختلفة للخصائص البصرية المختلفة ، هذه الأوزان يتم تحسينها حتى يتم الوصول للاوزان المثلى باستخدام الخوارزميات الجينية المعتمدة على دقة خوارزمية التجميع.وعلاوة على ذلك ولتسريع عملية حساب التشابه واسترجاع الصور المتشابهة ، نقوم بتقسيم الصور الموجودة في قاعدة البيانات إلى مجموعات بناء على الخصائص المستخرجة منها والموزونة مسبقا وذلك باستخدام خوارزمية التجميع. يتم تطبيق الخوارزمية الجينية وخوارزمية التجميع في مرحلة أولية سابقة لعملية الاستعلام. وبالتالي للرد على استعلام معين فإن هذا النظام لا يحتاج للبحث في صور قاعدة البيانات بأكملها، بدلا من ذلك فإنه يبحث فقط في عدد من الصور المرشحة المطلوبة ليتم البحث فيها عن التشابه مع الصورة المطلوبة.

النتائج العملية التجريبية لنظامنا تمت باستخدام قاعدة بيانات وانج للصور الملونة والتي تستخدم على نطاق واسع لتقييم أداء أنظمة استرجاع الصور استنادا على المحتوى. وأظهرت النتائج التجريبية أن نظامنا المقترح تجاوز عددا من نظرائه من الأنظمة الأخرى من حيث دقة الاسترجاع و كمية الاسترجاع ووقت الاسترجاع ، حيث تم زيادة متوسط دقة الاسترجاع من 78.1% إلى 88.2% ، وزيادة متوسط كمية الاسترجاع من 50.4% إلى 69.9% وكما حصلنا على متوسط انخفاض في وقت استرجاع الصور بلغ 6.21 ثانية. لقد أثبتت النتائج التجريبية أن نظامنا المقترح هو النظام الأمثل لاسترجاع الصور استنادا على المحتوى. علاوة على ذلك فان نموذجنا يعتبر واحدا من النماذج الأولى التي تجمع بين مفاهيم وتقنيات مختلفة لبناء نظام لاسترجاع الصور استنادا على محتواها.

الكلمات المفتاحية: استرجاع الصور استنادا على المحتوى، اللون ، النسيج ، الشكل ، مرشحات جابور، وصف الرسم البياني للحدود، خوارزميات التجميع، الخوارزميات الجينية، دقة الاسترجاع، كمية الاسترجاع.

Content-Based Image Retrieval (CBIR) System Based on the Clustering and Genetic Algorithm

By
Ahmed K. M. Mikhraq

ABSTRACT

Nowadays, virtually all spheres of human life including commerce, government, academics, hospitals, crime prevention, surveillance, engineering and historical research use information as images, so the volume of digital data is increasing rapidly. These images and their data are categorized and stored on computers and the problem appears when retrieving these images from storage media. Thus, Content based image retrieval from large resources has become an area of wide interest in recent years especially in the last decade.

In this thesis we present an efficient general-purpose CBIR system that uses color, texture and shape as visual features to describe the content of an image. The main contribution of this thesis is of *four directions*. **First**, we extract the color feature of the image by calculating the color moments which they are unique and invariant to rotation and scaling. **Second**, we use Gabor filters to extract texture features from arbitrary shaped regions separated from an image after segmentation to increase the system effectiveness. **Third**, to further increase the efficiency of the proposed system, edge histogram features that include five categories are used as shape descriptor which are invariant to rotation and scaling. **Fourth**, to improve the efficiency of the proposed system we assign different weights to each feature. These weights are optimized using genetic algorithm (GA) with a k-means accuracy as a fitness function to select optimum weights for features. Furthermore, to speed up retrieval and similarity computation of the proposed system, the database images are clustered using k-means clustering algorithm according to their weighted feature vectors. We perform GA and clustering algorithm on the database as an offline step before query processing, therefore to answer a query, the system does not need to search the entire database images; instead just a number of candidate images are required to be searched for image similarity.

The experimental evaluation of the proposed system is based on the WANG color image database that is widely used for CBIR performance evaluation. From the experimental results, it is evident that the proposed system surpassed its counterpart, other existing systems, in terms of precision, recall and retrieval time. The average precision increased from 78.1% to **88.2%**, the average recall increased from 50.4% to **69.9%** and an average reduction in time that equal to **6.21** seconds. Thus, the experimental results confirm that the proposed CBIR system architecture attains better solution for image retrieval. Furthermore, at our knowledge, the proposed model represents one of the first models in which combine different concepts and techniques to build general purpose CBIR system.

Keywords: Content Based Image Retrieval (CBIR), Color, Texture, Shape, Gabor Filters, edge histogram descriptor (EHD), Clustering, Genetic Algorithm (GA), Precision, Recall.

Chapter 1
Introduction

1.1 Information Retrieval

In recent years especially in the last decade, the rapid development in computers, storage media and digital image capturing devices enable to collect a large number of digital information and store them in computer readable formats. The large numbers of images has posed increasing challenges to computer systems to store and manage data effectively and efficiently. In the meanwhile, the advances of software and hardware technology have eased the problem of maintaining large information collections including books, journals, newspapers, videos, audios, images and satellite pictures accessible for computer users [1]. Although the advent in internet makes it possible for the human to access this huge amount of information easily, but the rule is that the more information available about a given topic, the more difficult to locate accurate and relevant information easily. For this reason the need and the demand for an efficient and accurate information retrieval system has increased and attracted much interest among the researchers in recent years.

1.2 Information Retrieval Problem as Image Retrieval Problem

Nowadays, virtually all spheres of human life including commerce, government, academics, hospitals, crime prevention, surveillance, engineering, architecture, journalism, fashion and graphic design, and historical research use information as images [2]. These images and their data are categorized and stored on computers as a large collection referred to as image database. Image data include the raw images and information extracted from images by automated or computer assisted image analysis.

To retrieve any image, we have to search for it among the database using some search engine. Then, this search engine will retrieve many of images related to the searched one. The main problem encounters user here is the difficulty of locating his relevant image in this large and varied collection of resulted images. This problem referred to as *image retrieval problem*. A general view for this problem is shown in Figure 1.1 below. To solve this problem, *text-based* and *content-based* are the two techniques adopted for search and retrieval in an image database [3].

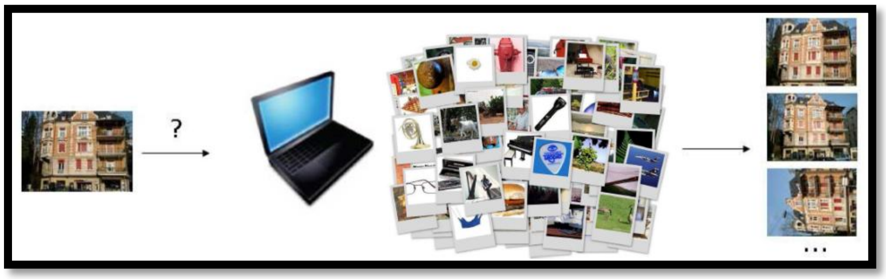


Figure (1.1): General View for Image Retrieval Problem.

1.3 Text-Based Image Retrieval

The earlier approach for image retrieval is *text-based*, in which images are indexed using keywords, subject headings, or classification codes which in turn are used as retrieval keys during search and retrieval [4]. Unfortunately, for the large database the difficulties faced by text-based retrieval became more and more severe and the process becomes very laborious and time consuming task. Another problem is that keyword is subjective and not unique and different people have different perception about an image, that is, text-based retrieval is non-standardized.

To overcome these problems and others, the image contents, features of the image, like color, texture and shape that are automatically extracted from the images themselves have been used for image retrieval. This method is called *content-based image retrieval* (CBIR) [5]. CBIR enables the elimination of the difficulties that exist in traditional text-based query for large image database and then the system will provide better indexing and return more accurate results [6].

1.4 Content-Based Image Retrieval

Content-based image retrieval (CBIR), also known as query by image content (QBIC) is the application of computer vision techniques to image retrieval problem, that is, problem of searching for digital images in large databases [7]. It aims to finding images of interest from a large image database using the visual content of the images. "Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself [8].

The main unit of CBIR is an image retrieval technique that used to retrieve from the database the most similar images to the query image [9]. A typical content-based retrieval system is divided into *off-line feature extraction* and *online image retrieval*. In off-line stage, the system automatically extracts visual attributes at either a low-level (such as color, texture, and shape) or at a high-level (such as a color histogram), or both for each image in the database based on its pixel values and stores them in a different database within the system called a feature database [4]. The feature data (also known as image signature) for each of the visual attributes of each image is very much smaller in size compared to the image data, thus the feature database contains an abstraction (compact form) of the images in the image database. One advantage of a signature over the original pixel values is the significant compression of image representation, so CBIR is cheap, fast and efficient over image search methods.

In on-line image retrieval, the user can submit a query example to the retrieval system to search for desired images. The system represents this example with a feature vector and the distances (i.e., similarities) between the feature vectors of the query example and those of the image in the feature database are then computed and ranked. Retrieval is conducted by applying an indexing scheme to provide an efficient way of searching the image database. Finally, the system ranks the search results and then returns the results that are most similar to the query examples [5]. If the user is not satisfied with the search results, he can provide relevance feedback to the retrieval system, which contains a mechanism to learn the user's information needs. A typical Architecture for CBIR System is illustrated in Figure 1.2.

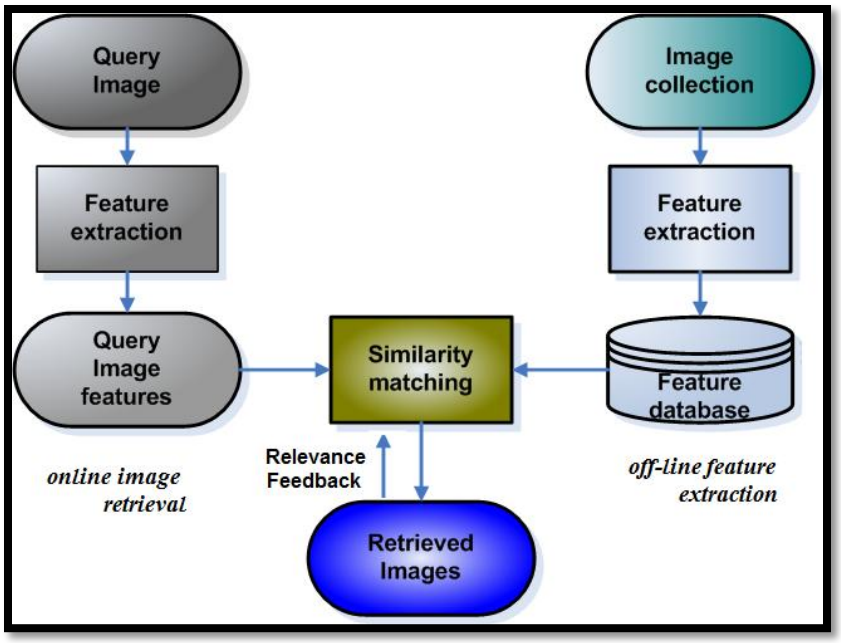


Figure (1.2): Typical Architecture of CBIR System.

The corner stone of the any CBIR system is a methodology known as relevance feedback (RF), in which the search/retrieval session is divided into a number of consecutive loops. At every loop, the user provides feedback regarding the results by characterizing the retrieved images as either relevant or irrelevant [10]. RF is typically based on some simple distance measures for image similarity, usually deal with small training samples (typically less than 20 per round of interaction), asymmetry in training sample (a few negative examples are usually fed back to the system), and real time requirement (RF algorithms should be fast enough to support real-time user interaction). Since the main goal of CBIR system is the efficiency during image indexing and retrieval, thus human intervention in the these processes must be reduced as much as possible. That is, the computer must be able to retrieve images from a database without any human assumption on specific domain (such as texture vs. non-texture). Thus, Instead of RF we can use any clustering algorithm (like K-means) that based on the features extracted from the images themselves, and allocates those images into the nearest cluster. The algorithm calculates and allocates until there is little variation in the movement of feature points in each cluster.

Clustering is the unsupervised classification of patterns (observations, data items, or feature vectors) into groups (clusters) [11]. Its main task is to assigning a set of objects into groups (called clusters) so that the objects in the same cluster are more similar (according to some defined similarity measure) to each other than to those in other clusters [12]. In testing phase of CBIR system, systems attempt to compare the query image with every target image in the database to find the top matching images, resulting in an essentially linear search, which is prohibitive when the database is large. We believe that it is not necessary to conduct a whole database comparison. Since 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 groups (using any clustering algorithm) where images with similar features are clustered to one group. This method saves significant query processing time and computation load without compromising the retrieval accuracy.

One of the main tasks for CBIR systems is similarity comparison; extracting feature signatures of every image based on its pixel values and defining rules for comparing images. These features become the image representation for measuring similarity with other images in the database. An image is compared to other images by calculating the similarities (or differences) between their corresponding features [2].

Implementation of a CBIR system using one content feature doesn’t give sufficient retrieval accuracy [13]. To overcome this problem, any novel model for the content based image retrieval system must combine multiple features for the image like color, texture, and shape. Unfortunately, assigning equal weights for each feature can’t achieve good result [14]. Moreover, these weights must be optimized using any search optimization procedure (like genetic algorithm) to increase the average accuracy of the image retrieval.

1.5 Practical Applications of CBIR Systems

CBIR systems have become a reliable tool for many image database applications and they were used in various fields and spheres of human activity. There is a growing interest in CBIR systems because of the limitations inherent in metadata based systems, as well as the large range of possible uses for efficient image retrieval systems [15]. The CBIR technology has been used in a plethora of applications such as fingerprint identification, digital libraries, crime prevention, medical diagnosis, historical research, architectural and engineering design, publishing and advertising, art, education, fashion and graphic design, geographical information and remote sensing systems, etc [3]. Some of these applications are presented below:

1.5.1 Medical Applications

The use of CBIR can result in powerful services that can benefit biomedical information systems. Three large domains can instantly take advantage of CBIR techniques: teaching, research, and diagnostics [16]. Clinicians usually use similar cases for case-based reasoning in their clinical decision-making process. In the medical field, some ailments require the medical practitioner to search and review similar X-rays or scanned images of a patient before proffering a solution.

1.5.2 Digital Libraries

There are several digital libraries that support services based on image content. One example is the digital museum of butterflies [17], aimed at building a digital collection of Taiwanese butterflies. This digital library includes a module responsible for content-based image retrieval based on color, texture, and patterns.

1.5.3 Crime Prevention

One of the main jobs of police is to identify and arrest criminals in the country. However, to achieve that, the department of security investigation must identify the identity of criminals as fast as possible and with a high accuracy rate. Day after day, the crime rate is increasing so that the police must deal with a large number of criminals images that stored in a database. Once a new image is arrived, it must be compared with all of these images to classify it correctly. It is clear that, doing this job manually takes a long time so, the need for criminal recognition system is strongly highlighted here.

1.5.4 Web Searching

The most important application, however, is the Web, as a big fraction of it is devoted to images, and searching for a specific image is indeed a daunting task. 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. Today it is estimated that there are 30 billion images in Imageshack, Facebook holds 35 billion photos and Corp's PhotoBucket has 10 billion photos [18].

1.5.5 Other Applications

In the commerce department, before trademark is finally approved for use, there is a need to find out if such or similar ones ever existed. In architectural and engineering design, image database exists for design projects, finished projects, and machine parts. In publishing and advertising, journalists create image databases for various events and activities such as sports, buildings, personalities, national and international events, and product advertisements. In historical research, image databases are created for archives in areas that include arts, sociology, and medicine [18].

1.6 Thesis Significance and Contribution

With the rapid increase of the volume of digital image collections, CBIR is becoming an active research area [19]. The design and development of effective and efficient CBIR systems are still a research problem with many important issues like:

1. Make semantic gap between image representation and image semantics narrow as much as possible.
2. Select suitable image features that will represent the image.
3. Extracting such features from raw images.
4. Providing compact storage for large image databases.
5. Efficiently accessing stored images by content.
6. Matching query and stored images in a way that reflects human similarity judgments.
7. Providing usable human interfaces to CBIR systems.
8. Get sufficient generalization performance and high accuracy.
9. Get Adequate system speed and low computational load.

When we want to develop an efficient algorithm for CBIR, some problems have to be solved. The first problem is to select the features that will represent the images. Naturally, the images are rich with information and features that can be used for image retrieval. But we must choose and extract the most important features that lead to a good retrieval result. The second problem is the computational load 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 features extracting and images retrieving, so we need a system with high speed and low computational load.

Since most of previously designed CBIR system may suffer from insufficient generalization performance and unsatisfactory accuracy, the goal of our research is to propose a new CBIR system that has a good generalization performance, high accuracy and adequate speed.

The major contributions of this thesis can be summarized as follows:

1. Our thesis proposes novel system architecture for CBIR system which combines techniques includes content-based image retrieval, multi-features analysis, artificial intelligence procedure, as well as data mining techniques. To our best knowledge in this field, this is the first model or one of the first models that combine content-based, multi-features extraction, k-means clustering and GA to build a CBIR system.

2. As we said before, implementation of a CBIR system with one images' feature descriptor doesn’t give sufficient retrieval accuracy. In our thesis, to increase the performance of the system, a fusion of multiple features (color, texture and shape) as a descriptor for the image is used to compute the distance between two images.

3. 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 our research, 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.

4. Low-level texture features are extracted from arbitrary-shaped regions using Gabor filter, which has been a widely acclaimed natural and excellent tool in texture feature classification, segmentation, and extraction [58]. In many systems, texture features are obtained during segmentation from pixels or small blocks [62]. Such features may not well represent the property of an entire region. In some other systems, segmentation does not produce texture features. Hence, it is necessary to study texture feature extraction from the whole region after segmentation.

5. Shape is known to play an important role in human recognition and perception and object shape features provide a powerful clue to object identity. Histogram is the most commonly used characteristic to represent the global feature composition of an image. It is considered to be very useful for indexing and retrieving images [20]. Edge is a local shape feature and it captures the general shape information in the image [36]. Since edges play an important role for image perception, it is frequently used as a feature descriptor in image retrieval. The *Edge Histogram Descriptor* is such an example; which represents the spatial distribution of five types of edges, namely four directional edges and one non-directional edge. To increase efficiency of the proposed system, edge features that include these five categories are used as shape features.

6. Assigning equal weights for each feature can't achieve good results in terms of average precision, and recall [14]. This problem can be solved by assigning different weights to each feature and optimize these weights using GA with a suitable fitness function to select optimum weights of features. This exactly what we did in the proposed system.

7. Data clustering is used in many fields, including machine learning, data mining, pattern recognition, image analysis and bioinformatics [11]. 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 clustering process is performed offline and each class will be indexing along with its associated class ID in the index files. 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 significant query processing time and computation load without compromising the retrieval precision.

1.7 Outline of Rest of Thesis

The rest of the thesis is organized as follows. Chapter 2 summarizes some of the related works in the topic of CBIR and the primary research issues. In Chapter 3, we introduce an overview of the CBIR system, its principle, and the techniques used for feature extraction, similarity measure, and indexing structures. Genetic Algorithm, the essential technique used for feature weights optimization in our proposed systems, is also discussed in this chapter. In Chapter 4, we introduce our proposed system for CBIR and talk about some methods for image indexing and clustering. Simulation results and evaluation of our system are detailed in Chapter 5. Finally, Chapter 6 concludes our work and suggests future work.

Chapter 2
Related Work

2.1 Introduction

Nowadays, CBIR is a hotspot of digital image processing techniques. CBIR research started in the early 1990's and it is likely to continue during the first two decades of the 21st century [20]. It is a problem of searching for digital images in large databases and it aims to finding images of interest from a large image database using the visual content of the images. Before CBIR, the traditional image retrieval is usually based on text [19]. Text-based image retrieval has been discussed over those years and it is easy to find out some disadvantages such as:

- ❖ Manually annotation is always involved by human's feeling, situation, etc. which directly results in what it is in the images and what is it about.
- ❖ Annotation is never complete.
- ❖ Language and culture difference always cause problems, the same image is usually text out by many different ways.
- ❖ Mistakes such as spelling error or spell difference leads to totally different results.

There is a growing interest in CBIR because of the limitations inherent in metadata-based systems, as well as the large range of possible uses for efficient image retrieval. In order to overcome these limitations, CBIR was first introduced by Kato in 1992 [7]. The term, CBIR, is widely used for retrieving desired images from a large collection, which is based on extracting the features from images themselves. In general, the purpose of CBIR is to present an image conceptually, with a set of low-level visual features such as color, texture, and shape [21].

The common ground for CBIR systems is to extract a signature for every image based on its pixel values and to define a rule for comparing images. The signature serves as an image representation in the "view" of a CBIR system. The components of the signature are called *features*. One advantage of a signature over the original pixel values is the significant compression of image representation. However, a more important reason for using the signature is to gain an improved correlation between image representation and semantics. Actually, the main task of designing a signature is to bridge the gap between image semantics and the pixel representation, that is, to create a better correlation with image semantics [22]. After extracting signatures, the next step is to determine a comparison rule, including a querying scheme and the definition of a similarity measure between images.

One highly problem when designing CBIR system is to make a system general-purpose. CBIR for general-purpose image databases is a highly challenging problem because of the large size of the databases, the difficulty of understanding images both by people and computers, the diversity of real world images, and the issue of evaluating results properly.

However, all current CBIR systems suffer from insufficient generalization performance and accuracy as they are not able to establish a robust link/map between image features and high-level concepts. As a result, we can say that "there is no complete and perfect solution for this issue from user and system points of view".

A number of general-purpose image search engines have been developed. In the commercial domain, QBIC [23] is one of the earliest systems. Recently, additional systems have been developed such as VIR [24], AMORE [25], and Bell Laboratory WALRUS [26]. In the academic domain, MIT Photobook [27] is one of the earliest systems. Berkeley Blobworld [28], Columbia Visualseek and Webseek [29], Natra [30], and Stanford WBIIS [31] are some of the recent well known systems.

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 that 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

Query by Image Content (QBIC) [23] 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, 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 [30] 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 [32], Key-point Indexing Web Interface, 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 [33] has been developed by Technology-Zentrum Informatics at University 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 [27] 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.

However, although these systems formulate the special semantic features for image retrieval, there still have not been perfect descriptions for semantic features. This is due to the diversity of visual features, which widely exists in real applications of image retrieval. For example, all of these systems can't be useful for some special images (like medical images for example) because these systems uses some simple feature extraction methods which may provide unwanted results and they are not that much precise.

2.3 Global Feature Based CBIR Systems (GFBIR)

For most image retrieval systems, a query is specified by an image to be matched. We refer to this idea as "*global search*" since similarity is based on the overall properties of images. By contrast, there are also "*partial search*" querying systems called *Region-based Image retrieval* (RBIR) that retrieve results based on a particular region in an image. Even though RBIR systems increased the retrieval accuracy, they require high complex computations to calculate similarity; since these systems need to consider each region in the database images resulting in high retrieval response time [22]. Basically, one of the key points of realizing CBIR is to extract appropriate feature vectors to represent image content correctly. Color, texture and shape features have been used for describing image content.

Color is one of the most widely used low-level visual features and it is invariant to image size and orientation [21]. Color histogram is invariant to orientation and scale which makes it powerful in image classification. Hence, color histogram-based descriptor has been extensively studied and widely used in CBIR systems. This is due to its simplicity and effectiveness. Before a color descriptor is selected, the underlying color space has to be specified. For CBIR, the RGB space was used by many researchers to extract the color features in it. Unfortunately, the RGB is not well suited for describing colors in terms that are practical for human interpretation [5]. While the color histogram is robust to translation of object and rotation about the viewing axis, it does not include any spatial information. Different images can have same color distribution; however, large appearance changes in an image can easily change the histogram. Unfortunately, Image retrieval using color features only often gives disappointing results, because in many cases, images with similar colors do not have similar content. This is due to the fact that information about object location, shape and texture is discarded.

Texture is another important visual feature to characterize the content of one image and it has been widely used in applications such as remote sensing image classification, face recognition, image retrieval et al. Based on personal perceptions or driven by special applications, vision researches had presented a number of different definitions of ‘‘Texture’’. It is an innate property of virtually all surfaces, including clouds, trees, bricks, hair, fabric, etc. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment [13].

Object shape features can also provide powerful information for image retrieval, because humans can recognize objects solely from their shapes. Usually, the shape carries semantic information, and shape features are different from other elementary visual features such as color or texture features [15]. Basically, shape features can be categorized as *boundary-based* and *region-based*. The former extracts features based on the outer boundary of the region while the latter extracts features based on the entire region [41]. Retrieving images based on their shape feature have also been considered in many researches works. Edge is local shape feature and it captures the general shape information in the image. Since edges play an important role for image perception, it is frequently used as a feature descriptor in image retrieval. The edge histogram descriptor is such an example; which represents the spatial distribution of five types of edges, namely four directional edges and one non-directional edge [36]. These five types of edges evolve from the color distribution within the edges; more precisely it can be said that these edges immerse from the color distribution of pixels and from an internal feature of edge shape descriptor.

Over the past decades, many researchers have focused on the studies of CBIR by using only a single feature. However, it is hard to gain satisfactory retrieval results using a single feature because an image generally contains various visual characteristics [37]. Therefore, it is necessary to extract and select efficient features that are complementary to each other so as to achieve a satisfactory retrieval performance. Peiqiang Zhang et al. [38] have proposed edge histogram for image retrieval. In [39], Salih, N.D. et al. have used shape features for image retrieval and classification.

D. Zhang [40] proposed a method combining both color and texture features to improve retrieval performance. By computing both the color and texture features from the images, the database images are indexed using both types of features. During the retrieval process, given a query image, images in the database are firstly ranked using color features. Then, in a second step, a number of top ranked images are selected and re-ranked according to their texture features. Two alternatives are provided to the user, one is the retrieval based on color features, and the other is retrieval based on combined features. When the retrieval based on color fails, the user will use the other alternative which is the combined retrieval. Since the texture features are extracted globally from the image; they are not an accurate description of the image in some cases, which degrades the system performance.

Saad, M.H. et al. [42] have used color histogram and shape features for image retrieval. In [43], Fakhri, M. et al. have utilized color and texture features for image retrieval. Rai, H.G.N. et al. have proposed shape and texture features for image retrieval in [44]. In [45], Chen et al. have proposed multi features for CBIR By assigning equal weights for each feature. In [15], EI-Kholy, Abdel-Haleim et al. have proposed a new CBIR search engine using combined of two features (color and shape) and weighted similarity.

In [46], a framework for image retrieval using combined features was presented: it utilizes color histograms to extract color features in HSI space, applying gray-level co-occurrence matrix to extract the texture features and it utilizes Zernike moments to extract the shape features.

In [13], Hiremath, et al. have proposed color, texture and shape features for CBIR. Color moments and moments on Gabor filter responses as local descriptors of color and texture respectively. While Shape information is captured in terms of edge images computed using Gradient Vector Flow field. Invariant moments are then used to record the shape features.

2.4 Cluster-Based Retrieval Systems

Clustering is the task of assigning a set of objects into groups (called clusters) so that the objects in the same cluster are more similar (according to some defined similarity measure) to each other than to those in other clusters [47]. Data clustering is a common technique for statistical data analysis, which is used in many fields, including machine learning, data mining, pattern recognition, image analysis and bioinformatics.

In [12], the authors developed a new approach named cluster-based retrieval of images by unsupervised learning (CLUE), in which the system aims to retrieve images by including the similarity knowledge between target images through user interaction. They claim that the degree of user involvement with CBIR system can assist to reduce the semantic gap. Although, results of this approach showed its efficiency but from our point of view, high computational cost is one of the main draw back in this sort of clustering methods.

Chang et al. [6] have proposed novel system architecture for CBIR which combines segmentation and grid module, feature extraction module, K-means clustering and neighborhood module to build the CBIR system. Actually, although the experimental results confirm that this proposed CBIR system architecture attains better solution for image retrieval and improves its precision but this system also suffers from insufficient generalization performance.

In [47], the authors proposed a new partitional clustering algorithm and apply this algorithm to content-based image retrieval. They claim that their algorithm optimizes on both intra-cluster and inter-cluster similarity measures and improves the recall. But unfortunately, this content-based image retrieval technique uses only the RGB color histogram as the visual content descriptor of an image and the improving of recall at the cost of precision.

2.5 Genetic Algorithm for CBIR Systems

Genetic algorithm (GA) is an artificial intelligence procedure based on the theory of natural selection and evolution [7]. It is an efficiently global searching algorithm based on the principle of 'survival of the fittest' and used for optimization and searching problems. As mentioned before, implementation of content-based image indexing and retrieval (CBIR) using one content feature doesn't give sufficient retrieval accuracy. To overcome this problem, any novel model for the content based image retrieval system must combine multiple features for the image like color, texture, and shape. Unfortunately, assigning equal weights for each feature can't achieve good result. These weights must be optimized using any search optimization procedure like genetic algorithm (GA) for increasing average precision and average recall of image retrieval.

In [14], Color, Texture and Shape features were extracted and combined to form feature vector of image and optimized using GA and adapted in similarity/distance measurement to perform retrieval image from database.

Shao et al. changed the problem of weight assignment into optimization problem and genetic algorithm was used for finding the optimization weight in order to obtain better image retrieval results [48]. In [49], an optimum weighted Manhattan distance function was designed using a genetic algorithm utilizing the Mantel test as a fitness function by Celebi et al. In [50], feature selection based on GA whose fitness function combined the number of features to be used and the error rate of the Bayesian classifier was presented.

2.6 Research Issues

Remarkable observations in the review of related works are as follows:

1. There still have not been perfect descriptions for semantic features. This is due to the diversity of visual features, which widely exists in real applications of image retrieval.

2. Implementation of content-based image indexing and retrieval (CBIR) using one content feature doesn’t give sufficient retrieval accuracy.

3. For combining of different types of features, there is a need to train these features with different weights to achieve good results. Assigning equal weights for each feature can’t achieve good result.

4. It is more suitable and it has a great benefit to classify the images into clusters so as to be able to reduce the search domain in such search engines. Data Clustering is often took as a step for speeding-up image retrieval and improving accuracy especially in large databases.

5. There are many of methods used to measure the similarity between different entities, such as information content [51], Dice coefficient, cosine coefficient and distance-based measurements. In our thesis, a new function is designed to combine features and calculate similarity between two images based on the Euclidean distance.

6. The existing CBIR systems use either global features, or region based features to represent the content of an image. Even though RBIR systems can increase the retrieval accuracy, they require high complex computations to calculate similarity; since these systems need to consider each region in the database images especially and color images have large dimensions and the computations are quite time consuming, RBIR systems need a high retrieval response time.

7. All current CBIR systems suffer from insufficient generalization performance and accuracy. One highly problem when designing CBIR system is to make a system general-purpose. When we combine some techniques like content-based, multi-features extraction, clustering and artificial intelligence to build the CBIR system, we can get closer to generalization more and more.

8. In some of previous works, a combination of GA and K-means was used especially to optimize the main input of k-means, k. In our thesis, we will use this combination but in different manner; hence we will use GA to optimize features' weights which contributes significantly in overall system performance.

Chapter 3

Background of Content-based Image Retrieval

3.1 Introduction

With the growth of technology and internet, images had become really famous nowadays and the search for similar images in large-scale image databases has been an active research area in the last couple of years. 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 very promising approach to do this task is content based image retrieval (CBIR). 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. In such systems, images are typically represented by approximations of their contents. Typical approximations consist of statistics, and Fourier or wavelet transformations of the raw image data. This so-called feature extraction which aims to extracting information that is semantically meaningful but needs a small amount of storage [52]. These features are used for computing the similarity between images. Then, some measurement methods are used to calculate the similarity between images. For fast retrieval, an indexing structure based on the query model is developed. These main steps to build a CBIR system are illustrated in Figure 3.1.

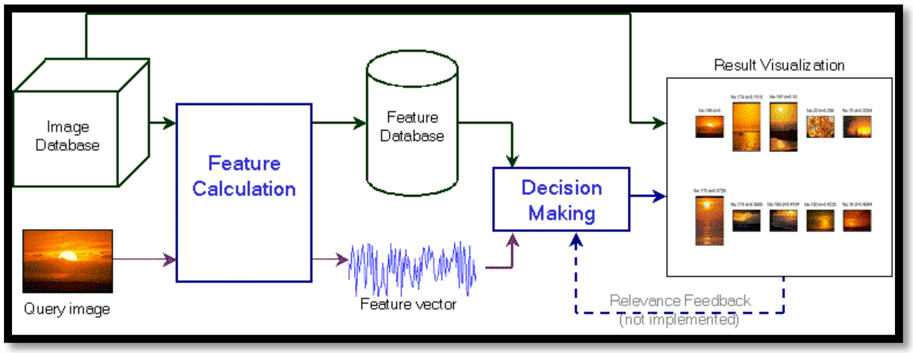


Figure (3.1): An Overview of A CBIR System.

In this chapter, we will define image features and explain their properties in section 3.2. An overview of some methods for similarity measures will be given in section 3.3. In section 3.4, we will present some of the indexing structures that are commonly used in CBIR systems. Finally, GA will be discussed in section 3.5.

3.2 Feature Extraction

Feature extraction is very crucial step in image retrieval system to describe the image with minimum number of descriptors. It is a means of extracting compact but semantically useful information from images which can describe the image with its content. 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. These Features are used as a signature for the image. Similar images should have similar signatures. We mean by image features the characteristic properties. For example if we look at the image shown in Figure 3.2, the white color and the texture of the building are characteristic properties. In a similar way, the sky can be described by its blue color. Furthermore, we can take the size of the objects in the image into account.

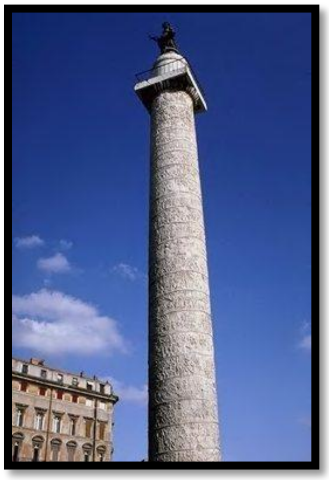


Figure (3.2): An Example of Color Image Properties.

A wide variety of features had been considered for image retrieval. To describe an image, we have to consider its main features. Selecting suitable image features is an important step so that it can represent the content of the image very well. Representation of images needs to consider which features are most useful for representing the contents of images and which approaches can effectively code the attributes of the images. Feature extraction of the image in the database is typically conducted off-line so computation complexity is not a significant issue. 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. This section introduces three features: color, texture, and shape, which are used most often to extract the features of an image.

3.2.1 Color Features

One of the most important features visually recognized by humans in images is color. Color is the sensation caused by the light as it interacts with our eyes and brain. Humans tend to distinguish images based mostly on color features. Because of this, color features are the most widely used in CBIR systems and it is the most studied in literature. Color is a powerful descriptor that simplifies object identification, and it is one of the most frequently used visual features for content-based image retrieval. To extract the color features from the content of an image, a proper color space (also called color models or color systems) and an effective color descriptor have to be determined.

- **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 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. 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 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 [53].

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. The purpose of a color space is to facilitate the specification of colors. Each color in the color space is a single point represented in a coordinate system. Several color spaces, such as RGB, HSV, CIE L*a*b, and CIE L*u*v, have been developed for different purposes [54]. Although there is no agreement on which color space is the best for CBIR, an appropriate color system is required to ensure perceptual uniformity. In most digital image processing, RGB 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 will use RGB as a color space.

- **RGB Color space**

RGB color model is the most common color model in use. The primary colors are red, green, and blue. We can imagine the RGB color space as a unit cube with red, green, and blue axes as shown in Figure 3.3. Any color in this space can be represented by a vector of three coordinates. 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 they 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 3.4 shows an RGB image and its three colors components.

After selecting a color space, an effective color descriptor should be developed in order to represent the color of the global area. Several color descriptors have been developed from various representation schemes, such as color histograms [55], color moments [56], color edge [57], color texture [58], and color correlograms [29]. The most important of them are the color histogram and the color moments which will be explained briefly in the next subsections.

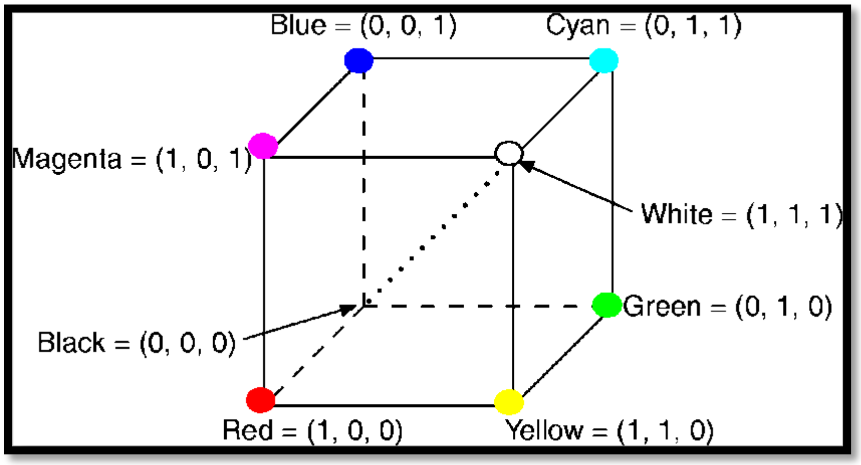


Figure (3.3): RGB Color Space.

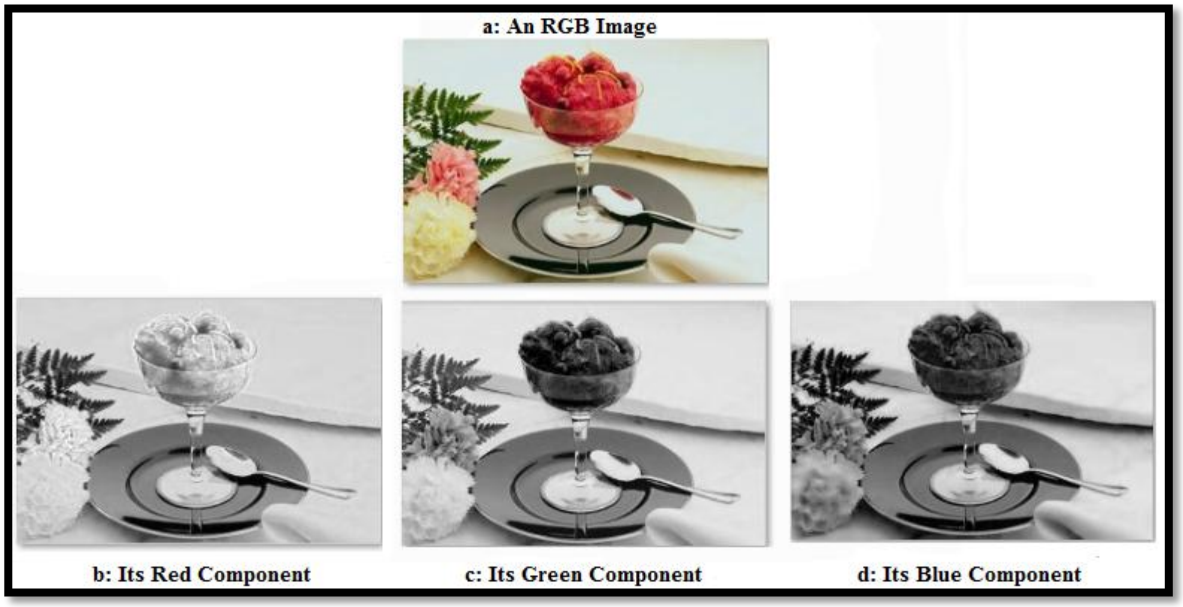


Figure (3.4): An RGB Image and Its Three colors Components.

- **Color Histograms**

As mentioned before, the most commonly used method to represent color feature of an image is the color histogram. Many CBIR systems use color histograms as a color feature to represent the image. A color histogram is a type of bar graph, where the height of each bar represents an amount of particular color of the color space being used in the image [54]. The bars in a color histogram are named as bins and they represent the x-axis where the number of bins depends on the number of colors in the image. The number of pixels in each bin denotes y-axis, which shows how many pixels in an image are of a particular color. The color histogram can not only easily characterize the global and regional distribution of colors in an image, but also be invariant to rotation about the view axis.

In color histograms, quantization is a process where number of bins is reduced by taking colors that are similar to each other and placing 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. Quantizing reduces the space required to store the histogram information and time to compare the histograms. Obviously, quantization reduces the information regarding the content of images; this is the tradeoff between space, processing time, and accuracy in results [60].

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, the most popular method, 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). In the contrary, an LCH divides an image into fixed blocks or regions, and takes the color histogram of each of those blocks 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. Although LCH contains more information about an image, but when comparing images, it is computationally expensive and it does not work well when images are translated or rotated. Figure 3.5 shows an example of color histogram for an image in RGB color space.

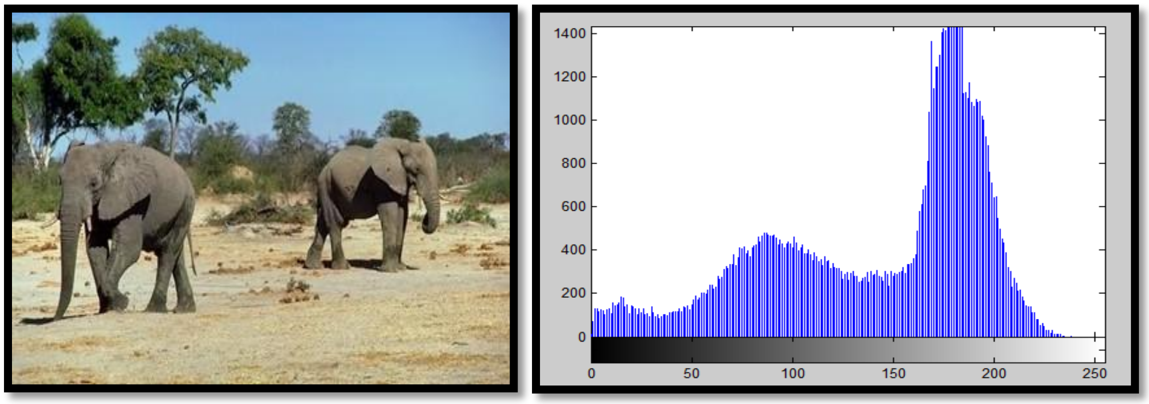


Figure (3.5): An RGB Image and Its Histogram.

- **Color Moments**

Color moments are measures that can be used differentiate images based on their features of color. Once calculated, these moments provide a measurement for color similarity between images. These values of similarity can then be compared to the values of images indexed in a database for tasks like image retrieval. The basis of color moments lays in the assumption that the distribution of color in an image can be interpreted as a probability distribution. Probability distributions are characterized by a number of unique moments. It therefore follows that if the color in an image follows a certain probability distribution, the moments of that distribution can then be used as features to identify that image based on color.

There are many central moments of an image's color distribution. The most important of them are *Mean*, *Standard deviation* and *Skewness*. Mean can be understood as the average color value in the image. The standard deviation is the square root of the variance of the distribution. Skewness can be understood as a measure of the degree of asymmetry in the distribution.

Therefore, **in our thesis**, the moments of the color distribution are the features extracted from the images, and we will use them as a color descriptor for the image in our proposed global features based retrieval system, as will be detailed in Chapter 4.

3.2.2 Texture Features

In the field of computer vision and image processing, there is no clear-cut definition of texture. This is because available texture definitions are based on texture analysis methods and the features extracted from the image. However, texture can be thought of as repeated patterns of pixels over a spatial domain, of which the addition of noise to the patterns and their repetition frequencies results in textures that can appear to be random and unstructured. Texture properties are the visual patterns in an image that have properties of homogeneity that do not result from the presence of only a single color or intensity. The different texture properties as perceived by the human eye are, for example, regularity, directionality, smoothness, and coarseness, see Figure 3.6(a). In real world scenes, texture perception can be far more complicated. The various brightness intensities give rise to a blend of the different human perception of texture as shown in Figure 3.6(b).

Image textures have useful applications in image processing and computer vision. They include: recognition of image regions using texture properties, known as texture classification, recognition of texture boundaries using texture properties, known as texture segmentation, texture synthesis, and generation of texture images from known texture models. Since there is no accepted mathematical definition for texture, many different methods for computing texture features have been proposed over the years. Unfortunately, there is still no single method that works best with all types of textures. According to

Manjunath and Ma [61], the commonly used methods for texture feature description are statistical, model-based, and transform-based methods.

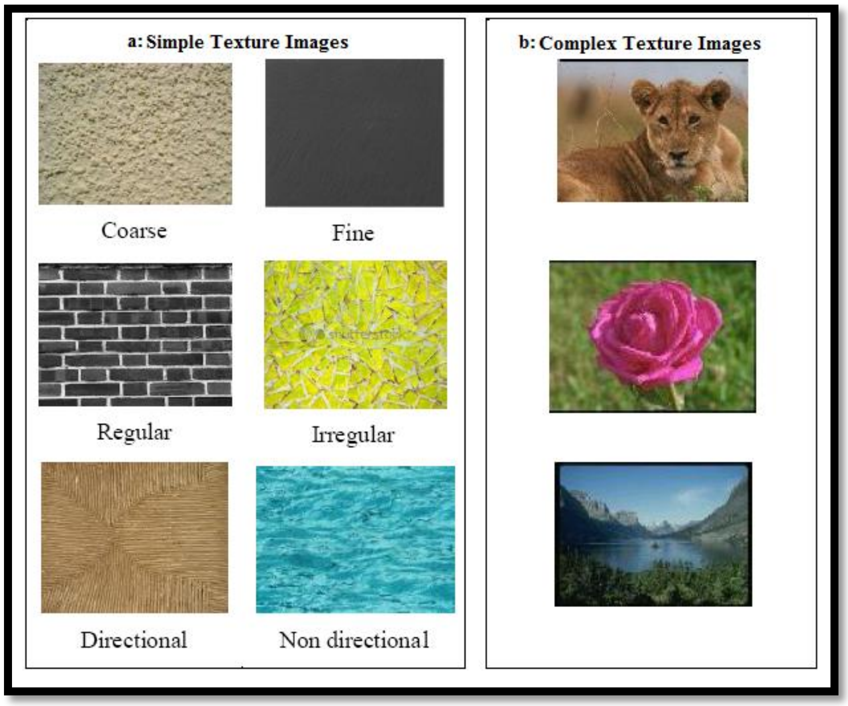


Figure (3.6): Examples of Texture Images.

❖ **Statistical Methods**

Statistical methods analyze the spatial distribution of grey values by computing local features at each point in the image, and deriving a set of statistics from the distribution of the local features. They include co-occurrence matrix representation; statistical moments, gray level differences, autocorrelation function, and grey level run lengths.

The most commonly used statistical method is the Gray-level Co-occurrence Matrix (GLCM). It is a two-dimensional matrix of joint probabilities $P_{d,r}(i,j)$ between pairs of pixels, separated by a distance, d, in a given direction, r. It is popular in texture description and it is based on the repeated occurrence of some gray level configuration in the texture; this configuration varies rapidly with distance in fine textures and slowly in coarse textures. Haralick [62] defined 14 statistical features from gray-level co-occurrence matrix for texture classification, such as energy, entropy, contrast, maximum probability, autocorrelation, and inverse difference moment. Gray-level co-occurrence matrix method of representing texture features has found useful applications in recognizing fabric defects, and in rock texture classification and retrieval [61].

❖ **Model Based Approaches**

Model-based texture methods try to capture the process that generated the texture. By using the model-based features, some part of the image model is assumed and an estimation algorithm is used to set the parameters of the model to yield the best fit [61]. To describe a random field, assume the image is modeled as a function $f\ (r, \omega)$, where r is the position vector representing the pixel location in the 2-D space and ω is a random parameter. For a given value of r, $f\ (r, \omega)$ is a random variable (because ω is a random variable). Once a specific texture ω is selected, $f\ (r, \omega)$ is an image, which is a function over the two-dimensional grid indexed by r. Function $f\ (r, \omega)$ is called as a random field. There are currently three major model based methods: Markov random fields, Fractals and The multi-resolution autoregressive features.

❖ **Transform Domain Features**

The word transform refers to a mathematical representation of an image. There are several texture classifications using transform domain features in the past, such as discrete Fourier transform, discrete wavelet transforms, and Gabor wavelets. Transform methods analyze the frequency content of the image to determine texture features. Fourier analysis consists of breaking up a signal into sine waves of various frequencies. On the other hand, wavelet analysis breaks up a signal into shifted and scaled versions of the original wavelet (mother wavelet), which refers to decomposition of a signal into a family of basis functions obtained through translation and dilation of a special function. Moments of wavelet coefficients in various frequency bands have been shown to be effective for representing texture [58]. Gabor filter (or Gabor wavelet) has been shown to be very efficient. Manjunath and Ma [61] have shown that image retrieval using Gabor features outperforms that using other transform features.

Therefore **in our thesis,** we will use Gabor wavelet transform as our technique to extract the texture features. Gabor wavelet and its implementation for texture feature extraction will be detailed briefly in chapter 4.

3.2.3 Shape Features

Shape is known to play an important role in human recognition and perception and object shape features provide a powerful clue to object identity. Humans can recognize objects solely from their shapes. The significance of shape as a feature for content-based image retrieval can be seen from the fact that every major content-based image retrieval system incorporates some shape features in one form or another [49]. Shape of an object is the characteristic surface configuration as represented by the outline or contour. Shape recognition is one of the modes through which human perception of the environment is executed. It is important in CBIR because it corresponds to region of interests in images. Shape feature representations are categorized according to the techniques used. They are boundary-based and region-based. In region-based techniques, all the pixels within a shape are taken into account to obtain the shape representation. Common region based methods use moment descriptors to describe shape [44]. Region moment representations interpret a normalized gray level image function as a probability density of a 2-D random variable.

Because moments combine information across an entire object rather than providing information just at a single boundary point, they capture some of the global properties missing from many pure contour-based representations. Comparing with region based shape representation; contour based shape representation is more popular. Contour based shape representation only exploits shape boundary information. Simple contour-based shape descriptors include area, perimeter, compactness, eccentricity, elongation, and orientation. Complex boundary-based descriptors include Fourier descriptors, grid descriptors, and chain codes.

Edge is local shape feature and it captures the general shape information in the image [38]. Since edges play an important role for image perception, it is frequently used as a feature descriptor in image retrieval. The edge histogram descriptor is such an example; which represents the spatial distribution of five types of edges, namely four directional edges and one non-directional edge [36]. These five types of edges evolve from the color distribution within the edges; more precisely it can be said that these edges immerse from the color distribution of pixels and from an internal feature of edge shape descriptor.

In our thesis, edge histogram features that include five categories will be used as shape descriptor. Our techniques to extract this shape features will be detailed in chapter 4.

3.3 Similarity Measure

The similarity between two images (represented by their features values) is defined by a *similarity measure*. Selection of similarity metrics has a direct impact on the performance of content-based image retrieval [26]. The kind of features vectors selected determines the kind of measurement that will be used to compare their similarity [8]. If the features extracted from the images are presented as multi-dimensional points, the distances between corresponding multi-dimensional points can be calculated. Euclidean distance is the most common metric used to measure the distance between two points in multi-dimensional space [8]. Many systems used the Euclidean Distance such as Netra, MARS, and Blobworld. The distance between two images X and Y with n-dimensional features vectors, is calculated by Equation 3.1:

$$D(X,Y) = \sqrt{\sum_{k=1}^{n}(x_k - y_k)^2} \tag{3.1}$$

A number of other metrics, such as Mahalanobis distance, Minkowski distance, Earth Mover’s distance, and Proportional Transportation distance, have been proposed for specific purposes. **In our thesis**, we will use Euclidean Distance as a basis to design our new similarity metric to compute similarities between images.

3.4 Indexing Structures

The large numbers of images has posed increasing challenges to computer systems to store and manage data effectively and efficiently. Our world contains many digital images of different categories. Images are stored in digital libraries or databases. When manipulating massive databases, a good indexing is a necessity. Processing every single item in a database, when performing queries, is extremely inefficient and slow, because the databases contain huge number of images. When working with text-based documents, creating good indexes is not very difficult. Simply maintaining a list of all words in the database, and information on which documents contain which words, is quite good. When searching for a phrase, the system first checks the index for which documents contain all the necessary search words. Next, in-depth processing only needs to be done with these documents.

When searching for images, however, this approach is much more difficult. Raw image data is non-indexable as such, so the feature vectors must be used as the basis of the index. 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. Popular multi-dimensional indexing methods include the R-tree and the R*-tree algorithms. The k-means is also one of the indexing structures [6].

In our thesis, we will use k-means algorithm as a clustering algorithm for indexing. K-means algorithm will be used to cluster the database into clusters. Within 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 which, in this case, depends only on the number of clusters and the number of images in the top ranked cluster. This cuts down processing time quite a lot. K-means, the indexing technique used in this thesis, will be discussed in Chapter 4.
In the end, our feature vector consists of three parts, types of features, namely color, texture and shape. By assigning equal weights for each feature type, we can't achieve good results in terms of average precision and recall (will be defined in chapter 5). This problem can be solved by assigning different weights to each feature and these weights must be optimized using genetic algorithm (GA) with a suitable fitness function to select optimum weights of features. This exactly, what we will do in our system design. GA will be discussed in the following section.

3.5 Genetic Algorithms

In 1975, Holland described a methodology for studying natural adaptive systems and designing artificial adaptive systems [14]. It is now frequently used as an optimization method, based on an analogy to the process of natural selection in biology. The biological basis for the adaptation process is evolution from one generation to the next, based on elimination of weak elements and retention of optimal and near-optimal elements ("survival of the fittest”). Searching this representation space is performed using so-called “Genetic Algorithms” (GA’s). The genetic algorithm is now widely recognized as an effective search paradigm in artificial intelligence, image processing, VLSI circuit layout, optimization of bridge structures, solving of non-linear equations, correction of test data with functional grouping, and many other areas.

In a genetic algorithm approach, a solution (i.e., a point in the search space) is called a “chromosome” or string [19]. A GA approach requires a population of chromosomes (strings) representing a combination of features from the solution set, and requires a cost function (called an evaluation or fitness function) F(.). This function calculates the fitness of each chromosome. The algorithm manipulates a finite set of chromosomes (the population), based loosely on the mechanism of evolution. In each generation, chromosomes are subjected to certain operators, such as selection, crossover, and mutation, which are analogous to processes which occur in natural reproduction. So GA can be divided to four sequential main operations namely as population, selection, recombination (or crossover) and mutation as shown in Figure 3.7 below. These operations will be illustrated in detail later.

The optimization process is performed in cycles called generations. During each generation, a set of new chromosomes is created using crossover, inversion, mutation and other operators. Since the population size is fixed, only the best chromosomes are allowed to survive to the next cycle of reproduction. (There is considerable variation among various implementation of the genetic algorithm approach in the strictness with which the principle of “survival of the fittest” is applied. In some system, the fitness affects only the probability of survival, whereas in others, only the N fittest individuals are allowed to survival at each generation).

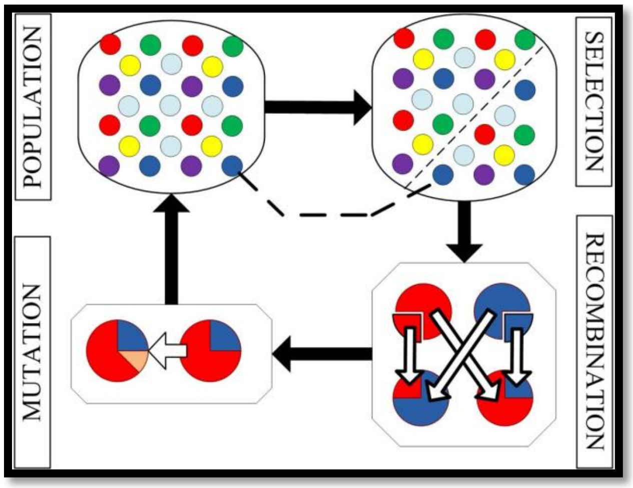


Figure (3.7): Main Operators of Genetic Algorithm.

The crossover rate usually assumes quite a high value (on the order of 80%), while the mutation rate is small (typically 1- 15%) for efficient search [16]. The cycle repeats until the population "converges", that is all the solutions are reasonably the same and further exploration seems fruitless, or until the answer is "good enough". Note that the number of generations required could be anywhere from hundreds to millions. A block diagram for GA is shown in Figure 3.8.

The popularity of GA is motivated by a number of factors including:

- ❖ Evolution is known to be a successful, robust method for adaptation within biological systems.
- ❖ GA can search spaces of hypotheses containing complex interacting parts, where the impact of each part on overall hypothesis fitness may be difficult to model.
- ❖ GA are easily parallelized and can take advantage of the decreasing costs of powerful computer hardware.

GA has been increasingly applied in conjunction with other AI techniques. However, few studies have dealt with the combining GA and K-means, though there is a great potential for useful applications in this area. The problem addressed by GA is to search a space of candidate hypotheses to identify the best hypothesis. In GA the "best hypothesis" is defined as the one that optimizes a predefined numerical measure for the problem at hand, called the *fitness*. For example, if the learning task is the problem of approximating an unknown function given training examples of its input and output, then fitness could be defined as the accuracy of the hypothesis over this training data. If the task is to learn a strategy for playing chess, fitness could be defined as the number of games won by the individual when playing against other individuals in the current population.

Although different implementations of genetic algorithms vary in their details, they typically share the following structure: The algorithm operates by iteratively updating a pool of hypotheses, called the population. On each iteration, all members of the population are evaluated according to the fitness function. A new population is then generated by probabilistically selecting the fittest individuals from the current population. Some of these selected individuals are carried forward into the next generation population intact. Others are used as the basis for creating new offspring individuals by applying genetic operations such as crossover and mutation.

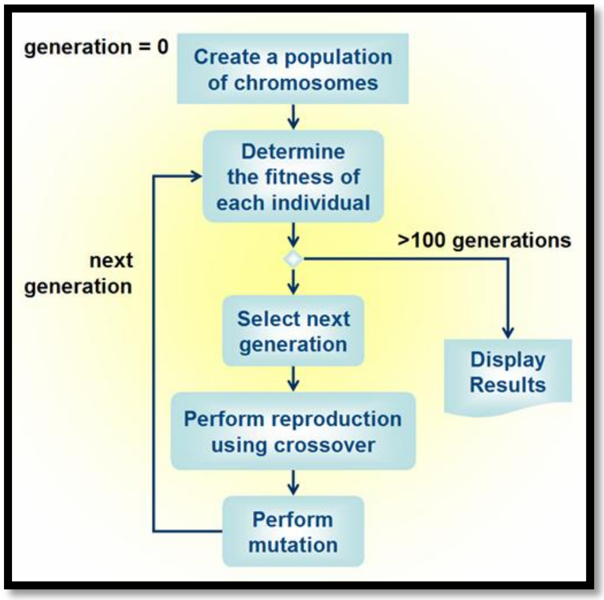

generation = 0
Create a population of chromosomes
Determine the fitness of each individual
>100 generations
next generation
Select next generation
Display Results
Perform reproduction using crossover
Perform mutation

Figure (3.8): Block Diagram of GA.

3.5.1 Genetic Operators

GA searches for better solutions by genetic operations, including *selection* operation, *crossover* operation and *mutation* operation.

1. Selection Operation

Selection operation is to select elitist individuals as parents in current population, which can generate offspring. Fitness values are used as criteria to judge whether individuals are elitist. There are many methods how to select the best chromosomes, for example *roulette wheel* selection, *Boltzman* selection, *tournament* selection, *rank* selection, *steady-state* selection, elitism selection and some others. Some of them will be described shortly.

- **Roulette Wheel Selection**

Parents are selected according to their fitness. The better the chromosomes are, the more chances to be selected they have. Imagine a roulette wheel where are placed all chromosomes in the population, every has its place big accordingly to its fitness function like on the Figure 3.9. Chromosome with bigger fitness will be selected more times.

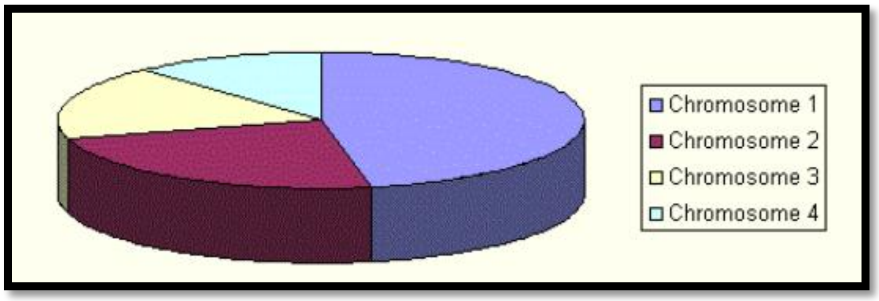


Figure (3.9): Roulette Wheel Selection.

- **Rank Selection**

The previous selection method will have problems when the fitness's differ very much. For example, if the best chromosome fitness is 90% of the entire roulette wheel, then the other chromosomes will have very few chances to be selected. Rank selection first sorts the population by fitness and then every chromosome receives fitness from this ranking. The worst will have fitness *1*, second worst *2* etc. and the best will have fitness *N* (number of chromosomes in population). After this, all the chromosomes have a chance to be selected. The probability that a chromosome will be selected is then proportional to its rank in this sorted list, rather than its fitness. But this method can lead to slower convergence, because the best chromosomes do not differ so much from other ones.

- **Elitism Selection**

When creating new population by crossover and mutation; we have a big chance, that we will lose the best chromosome. Elitism is name of method, which first copies the best chromosome (or a few best chromosomes) to new population. The rest is done in classical way. Elitism can very rapidly increase performance of GA, because it prevents losing the best found solution.

2. Crossover Operation

The generation of successors in a GA is determined by a set of operators that recombine and mutate selected members of the current population. The two most common operators are crossover and mutation. The crossover operator produces two new offspring from two parent strings, by copying selected bits from each parent. The bit at position i in each offspring is copied from the bit at position i in one of the two parents. The choice of which parent contributes the bit for position i is determined by an additional string called the *crossover mask*. Figure 3.10 below illustrates crossover operator briefly. There are three types of crossover operators, namely as *single-point*, *two-point* and *uniform* crossover.

- **Single-Point Crossover**

In the single-point crossover, the crossover mask is always constructed so that it begins with a string containing n contiguous 1s, followed by the necessary number of 0s to complete the string. This results in offspring in which the first n bits are contributed by one parent and the remaining bits by the second parent. Each time the single-point crossover operator is applied, the crossover point n is chosen at random, and the crossover mask is then created and applied. To illustrate, consider the single-point crossover operator at the top of the figure and consider the topmost of the two offspring in this case. This offspring takes its first five bits from the first parent and its remaining six bits from the second parent, because the crossover mask 11111000000 specifies these choices for each of the bit positions. The second offspring uses the same crossover mask, but switches the roles of the two parents. Therefore, it contains the bits that were not used by the first offspring.

- **Two-Point Crossover**

In two-point crossover, offspring are created by substituting intermediate segments of one parent into the middle of the second parent string. Put another way, the crossover mask is a string beginning with n_0 zeros, followed by a contiguous string of n_l ones, followed by the necessary number of zeros to complete the string. Each time the two-point crossover operator is applied, a mask is generated by randomly choosing the integers n_0 and n_l. For instance, in the example shown in Figure 3.10 the offspring are created using a mask for which n_0= 2 and n_l = 5. Again, the two offspring are created by switching the roles played by the two parents.

- **Uniform Crossover**

Uniform crossover combines bits sampled uniformly from the two parents, as illustrated in Figure 3.10. In this case the crossover mask is generated as a random bit string with each bit chosen at random and independent of the others.

3. Mutation Operation

In addition to recombination operators that produce offspring by combining parts of two parents, a second type of operator produces offspring from a single parent. In particular, the *mutation* operator produces small random changes to the bit string by choosing a single bit at random, then changing its value. Mutation is often performed after crossover as in Figure 3.10.

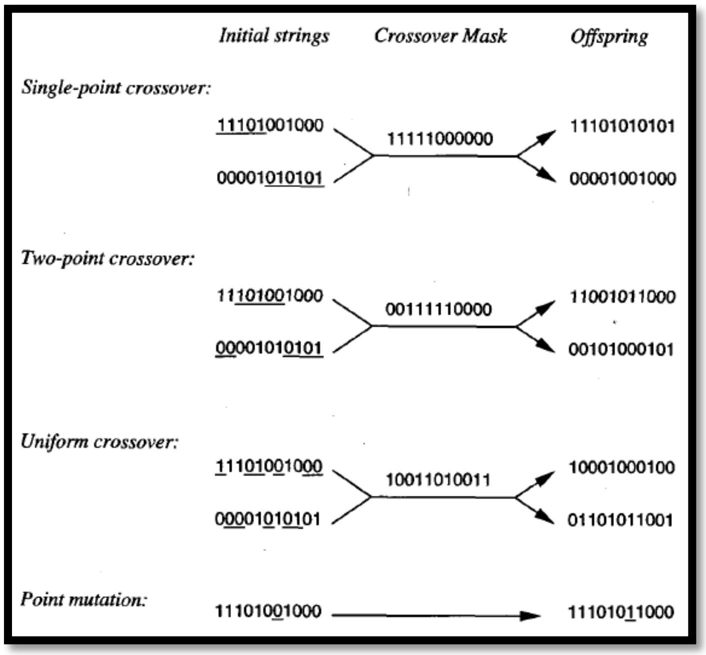


Figure (3.10): Crossover and Mutation Operators.

3.5.2 Fitness Function

The fitness function defines the criterion for ranking potential hypotheses and for probabilistically selecting them for inclusion in the next generation population. If the task is to learn classification rules, then the fitness function typically has a component that scores the classification accuracy of the rule over a set of provided training examples. Often other criteria may be included as well, such as the complexity or generality of the rule. More generally, when the bit-string hypothesis is interpreted as a complex procedure (e.g., when the bit string represents a collection of if-then rules that will be chained together to control a robotic device), the fitness function may measure the overall performance of the resulting procedure rather than performance of individual rules.

3.5.3 Outline of the Basic Algorithm

Genetic Algorithm is starts with a set of solutions represented by chromosomes, called population. Solutions from one population are taken and used to form a better new population. Solutions which are selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce [37]. This is repeated until some condition (for example number of populations or improvement in the best solution) is satisfied. Genetic Algorithm is given in table 3.1:

3.5.4 Weights Optimization Problem

The focus of our research is to build a universal CBIR system using low level features. These features are moments of the image color, the texture feature using Gabor transform and the edge histogram. We assign different weights to each feature type and these weights must be optimized using GA with a suitable fitness function to select optimum weights for the features. This problem can describe formally as follow:

If we define w, the weight vector, to be a vector generated by the GA, then we multiply w by each pattern vector x, yielding the new feature vector y. That is,

$$y = w\, x \qquad (3.2)$$

Where, $w = [w_1, w_2, \ldots, w_N]$, $x = [x_1, x_2, \cdots, x_N]$, $N = |x|$ and $w_k > 0$

Table (3.1): Genetic Algorithm

Purpose: Genetic algorithm to search a space of candidate solutions to identify the best one.

Input: Fitness function, crossover probability, mutation probability, population size, maximum iteration.

Output: The fittest solution.

Procedure:

{

1. [***Start***] Generate random population of n chromosomes (suitable solutions for the problem).
2. [***Fitness***] Evaluate the fitness f(x) of each chromosome x in the population.
3. [***New population***] Create a new population by repeating following steps until the new population is complete
    a. [***Selection***] Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected).
    b. [***Crossover***] With a crossover probability cross over the parents to form a new offspring (children). If no crossover was performed, offspring is an exact copy of parents.
    c. [***Mutation***] With a mutation probability mutate new offspring at each locus (position in chromosome).
    d. [***Accepting***] Place new offspring in a new population.
4. [***Replace***] Use new generated population for a further run of algorithm.
5. [***Test***] If the end condition is satisfied, stop, and return the best solution in current population.
6. [***Loop***] Go to step 2.

}

Chapter 4
The Proposed CBIR System

4.1 Introduction

In this chapter, we introduce our proposed CBIR system. In this system, we will extract some features to represent the image and use these features to compare between the images. This system defines the similarity between contents of two images based on global features (i.e., features extracted from the whole image).

Color is a powerful descriptor that simplifies object identification, and it is one of the most frequently used visual features for content-based image retrieval. To extract the color features from the content of an image, a proper color space and an effective color descriptor have to be determined. In addition, color histogram technique is applied for color feature representation combined with histogram intersection technique for color similarity measure.

Texture is one of the crucial primitives in human vision and texture features have been used to identify contents of images. Moreover, texture can be used to describe contents of images, such as clouds, bricks, hair, etc. Both identifying and describing contents of an image are strengthened when texture is integrated with color, hence the details of the important features of image objects for human vision can be provided. In the proposed system, Gabor filters, a tool for texture features extraction that has been proved to be very effective in describing visual contents of an image via multi-resolution analysis, is used.

Shape is known to play an important role in human recognition and perception. Object shape features can also provide powerful information for image retrieval, because humans can recognize objects solely from their shapes. Usually, the shape carries semantic information, and shape features are different from other elementary visual features, such as color or texture features [39]. Basically, shape features can be categorized as boundary-based and region-based. The former extracts features based on the outer boundary of the region while the latter extracts features based on the entire region [44]. The significance of shape as a feature for content-based image retrieval can be seen from the fact that every major CBIR system incorporates some shape features in one form or another. Our techniques to extract shape feature will be detailed later in this Chapter.

A similarity distance between two images is defined based on color, texture and shape features to decide which images in the image database are similar to the query and should be retrieved to the user. Figure 4.1 shows a block diagram for the proposed CBIR system The architecture details of this proposed system are described in the following sections.

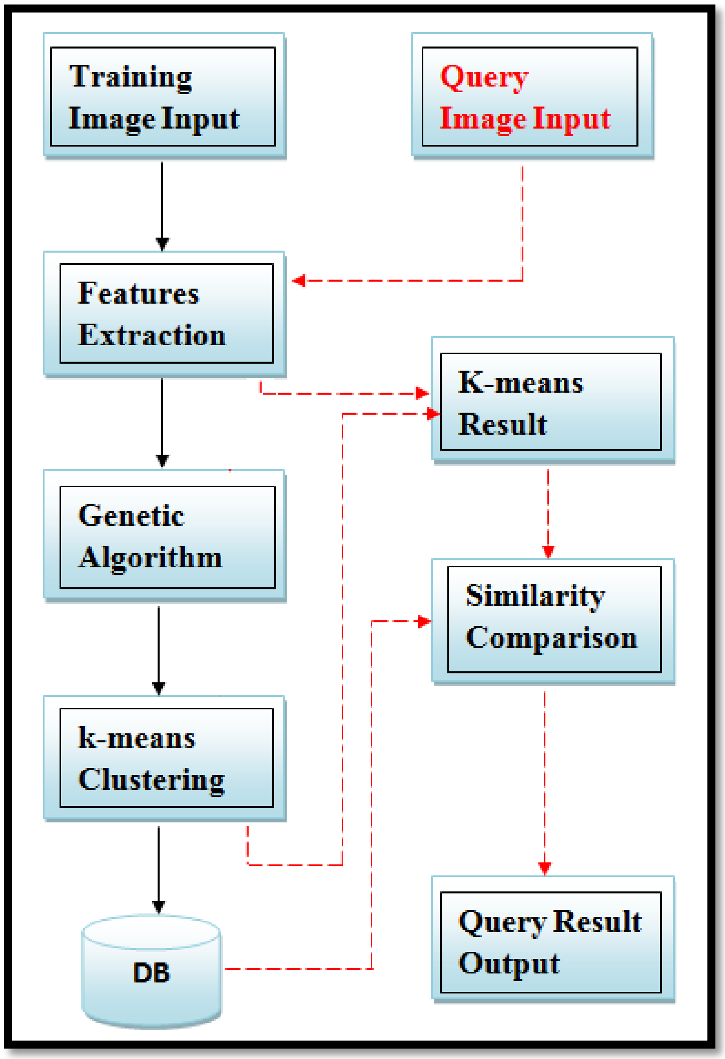


Figure (4.1): Block Diagram for the Proposed CBIR System.

4.2 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 thesis, the moments of the color distribution are the color features that used to describe the image.

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. Since we are working with RGB image (H x W x 3), we have to calculate mean, standard deviation and skewness separately for each channel. In this case, each of them will be 3-values vector. In total we have 3 x 3 = 9 values for each image.

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***

$$E_i = \frac{1}{N} \sum_{j=1}^{N} p_{ij} \tag{4.1}$$

❖ **Moment 2: *Standard Deviation***

$$\sigma_i = \sqrt{\left(\frac{1}{N} \sum_{j=1}^{N} \left(p_{ij} - E_i\right)^2\right)} \tag{4.2}$$

❖ **Moment 3: *Skewness***

$$s_i = \sqrt[3]{\left(\frac{1}{N} \sum_{j=1}^{N} \left(p_{ij} - E_i\right)^3\right)} \tag{4.3}$$

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

4.2.1 Color Similarity Measure

To test the similarity between a query image *q* and a database image *d* based on their color feature, A function of the similarity between two image distributions is defined as the sum of the weighted differences between the moments of the two distributions. Formally this is:

$$D_c(q,d) = \sum_{i=1}^{r} \left|\left(E_i^1 - E_i^2\right)\right| + \left|\left(\sigma_i^1 - \sigma_i^2\right)\right| + \left|\left(s_i^1 - s_i^2\right)\right| \tag{4.4}$$

Where:	q and d	: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.
	E_i^1, E_i^2	:are the means of the two images in the i^{th} component.
	σ_i^1, σ_i^2	:are the standard deviations of the two images in the i^{th} component.
	s_i^1, s_i^2	:are the skewness of the two images in the i^{th} component.

4.3 Texture Feature Extraction

Texture feature is computed using Gabor wavelets. Gabor function is chosen as a tool for texture feature extraction because of its widely acclaimed efficiency in texture feature extraction. Manjunath and Ma [61] recommended Gabor texture features for retrieval after showing that Gabor features performs better than that using pyramid-structured wavelet transform features, tree-structured wavelet transform features and multi-resolution simultaneous autoregressive model. The detailed descriptions for using Gabor filters in texture extraction are mentioned below.

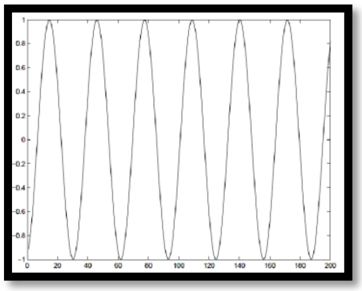
4.3.1 The Complex Gabor Function

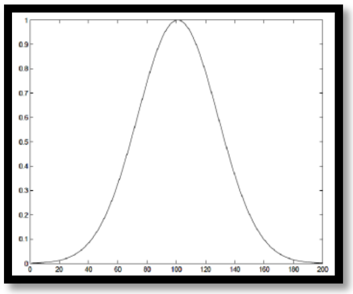
In 1946, Dennis Gabor proposed to represent signals in time and frequency domain by the use of elementary functions constructed from a single block, or "mother" signal, by translation and modulation [43]. By his proposal, any signal of finite duration T and bandwidth F can be divided into a finite number of elementary information cells, called *logons*. Each logon is of duration Δt and bandwidth Δf, and is localized at a different time and frequency in each of the domains. If we let $\Delta t = T/M$ and $\Delta f = F/N$, then there are MN elementary information cells, and any signal is considered to represent MN logons of information, namely, the MN coefficients associated with the cells. This is the most information that can be represented by the signal, and these MN complex coefficients are sufficient to regenerate the signal.

Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction. Expanding a signal using this basis provides a localized frequency description, therefore capturing local features/energy of the signal. Texture features can then be extracted from this group of energy distributions. The scale (frequency) and orientation tunable property of Gabor filter makes it especially useful for texture analysis. A Gabor function is obtained by modulating a complex sinusoid by a Gaussian envelope. For the case of one dimensional (1-D) signals, a 1-D sinusoid is modulated with a Gaussian. This filter will therefore respond to some frequency, but only in a localized part of the signal. This is illustrated in Figure 4.1 [43]. For two dimensional (2-D) signals such as images, consider the sinusoid shown in Figure 4.2(a). By combining this sinusoid with a Gaussian shown in Figure 4.2(b), we obtain a Gabor filter as in Figure 4.2(c).

The 2-D Gabor function can be specified by the frequency of the sinusoid W and the standard deviation σx and σy, of the Gaussian envelope as:

$$g(x, y) = \frac{1}{2\pi\sigma_x\,\sigma_y} \exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi jWx\right) \tag{4.5}$$


a) 1-D Sinusoid.


b) A Gaussian Kernel.

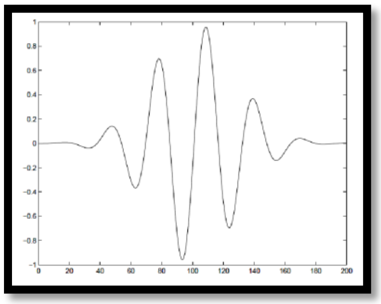
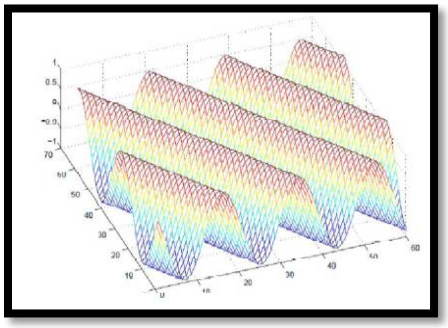
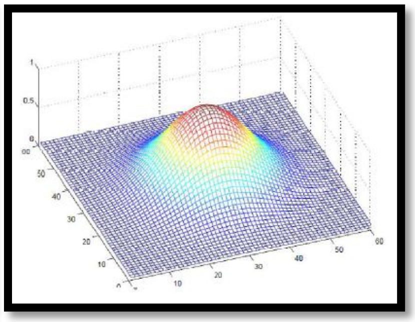

(c) The Corresponding Gabor Filter.

Figure (4.2): Gabor Filter Composition for 1-D Signals.


(a) 2-D sinusoid


(b) 2-D Gaussian kernel

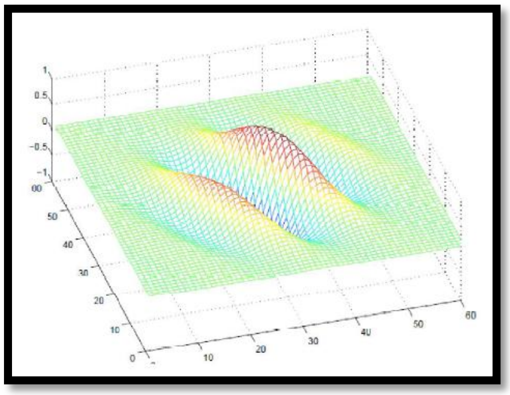

(c) The Corresponding Gabor Filter.

Figure (4.3): 2-D Gabor Filter Composition.

4.3.2 Texture Representation

The Gabor wavelet image representation is a convolution of that image within the same family of Gabor kernels given in Equation 4.5. Let $I(x, y)$ be the gray level distribution of an image, the convolution of the image I together with a Gabor kernel g_{mn} is defined as follows:

$$G_{mn}(x, y) = \sum_s \sum_t I(x - s, y - t)\, g^*_{mn}(s, t) \tag{4.6}$$

Where, s and t are the filter mask size variables, g^*_{mn} is the complex conjugate of the mother Gabor function g_{mn} , and G_{mn} is the convolution result corresponding to the Gabor kernel at orientation m and scale n.

After applying Gabor filters on the image with different orientation at different scale, we obtain an array of magnitudes:

$$E(m, n) = \sum_s \sum_t \ |G_{mn}(x, y)| \tag{4.7}$$

These magnitudes represent the energy content at different scale and orientation of the image. The main purpose of texture-based retrieval is to find images or regions with similar texture. It is assumed that we are interested in images or regions that have homogenous texture, therefore the following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used to represent the homogenous texture feature of the region:

$$\mu_{mn} = \frac{E(m,n)}{P \times Q} \tag{4.8}$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y \ (|\, G_{mn}(x,y)\,| - \mu_{mn})^2}}{P \times Q} \tag{4.9}$$

A feature vector F (texture representation) is created using μ_{mn} and σ_{mn} as the feature components. With M scales and N orientations used in common implementation; the feature vector is given by:

$$F_{\text{Texture}} = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots\ldots\ldots\ldots\ldots\ldots, \mu_{MN}, \sigma_{MN}) \tag{4.10}$$

4.3.3 Texture Extraction using Gabor wavelets

A total of twenty-four wavelets are generated from the "mother" Gabor function given in Equation 4.5 using four scales of frequency and six orientations. Redundancy, which is the consequence of the non-orthogonality of Gabor wavelets, is addressed by choosing the parameters of the filter bank to be set of frequencies and orientations that cover the entire spatial frequency space so as to capture texture information as much as possible in accordance with filter design [46]. The lower and upper frequencies of the filters are set to 0.04 octaves and 0.5 octaves, respectively, the orientations are at intervals of 30 degrees, and the half-peak magnitudes of the filter responses in the frequency spectrum are constrained to touch each other as shown in Figure 4.4. Note that because of the symmetric property of the Gabor function, wavelets with center frequencies and orientation covering only half of the frequency spectrum ($0, \frac{\pi}{6}, \frac{\pi}{3}, \frac{\pi}{2}, \frac{3\pi}{2}, \frac{5\pi}{6}$) are generated.

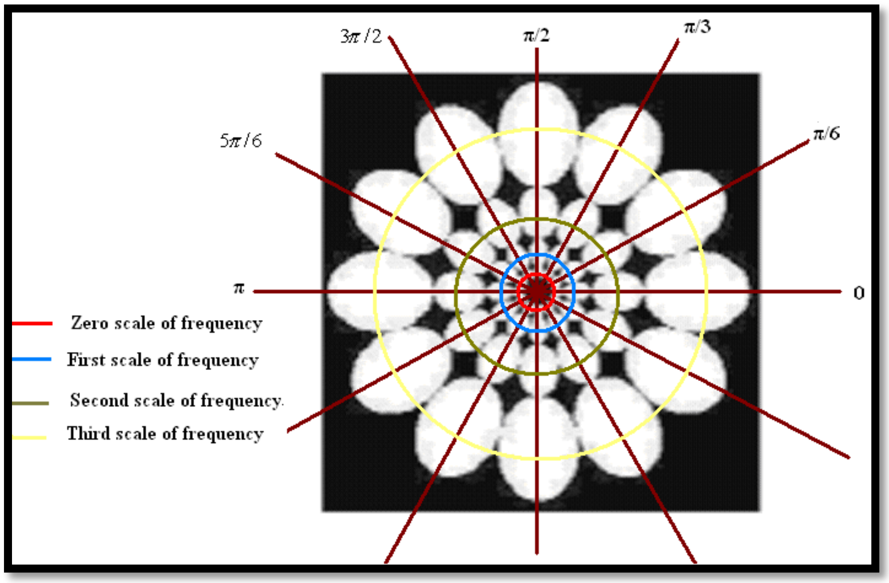


Figure (4.4): 2-D Frequency Spectrum View of Gabor Filter Bank.

To extract texture feature from an image, Algorithm in table 4.1 is applied. We first convert the image from the RGB color space into gray level and implement the group of designed Gabor filters. Twenty-four filtered images (by using 4 frequencies and 6 orientations), $G_{mn}(x,y)$, are produced by convolution of the gray level image and the Gabor filters as given in Equation 4.6. Using Equations 4.7, 4.8, and 4.9 given in the previous subsection, the mean μ_{mn} and variance σ_{mn} of the energy distribution $E(m,n)$ of the filters responses are computed to finally get the texture feature vector $F_{texture}$ with 48 attributes:

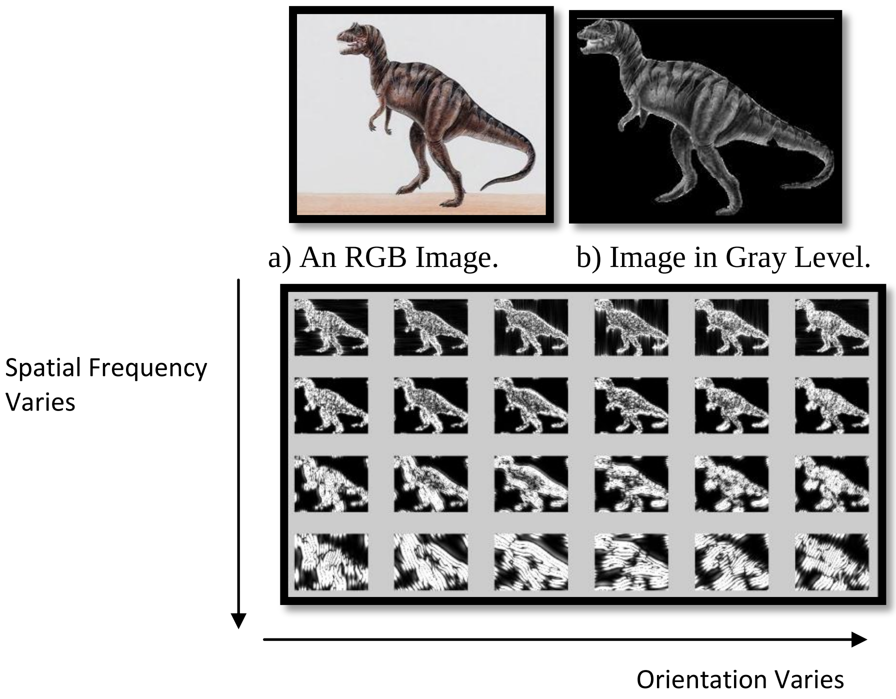
$$F_{texture} = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots, \mu_{35}, \sigma_{35}).$$

Our algorithm to extract texture features from an image is summarized in table 4.1 and an example of the an image and its filter responses is shown in Figure 4.5.

Table (4.1): Algorithm for Texture Feature Extraction

Purpose: To extract texture features from an image.
Input: RGB colored image.
Output: Multi-dimension texture feature vector.
Procedure:

```
{
  Step1: Convert the RGB image into gray level.
  Step2: Construct bank of 24 Gabor filters using the mother Gabor function with 4
         scales and 6 orientations.
  Step3: Apply Gabor filters on the gray level of the image by convolution.
  Step4: Get the energy distribution of each of the 24 filters responses.
  Step5: Compute the mean μ and the standard deviation σ of each energy distribution.
  Step6: Return the texture vector consisting of 48 attributes calculated from step 5.
}
```



a) An RGB Image. b) Image in Gray Level.

c) Filtered Image Responses.

Figure (4.5): An Example of Image Response to Bank of Gabor Filters.

4.3.4 Texture Similarity Measure

To test the similarity between a query image *q* and a database image d based on their texture feature we proposed to use the Euclidian distance for its simplicity. Let T_q and T_d denote the texture vector of a query image and an image in the database respectively, we define the distance between the two texture vectors denoted as $D_t(q, d)$ by the Euclidian distance as:

$$D_t(q,d) = \sqrt{\sum_{i=1}^{48}\left(T_{q_i} - T_{d_i}\right)^2} \tag{4.11}$$

4.4 Shape Feature Extraction

Shape is known to play an important role in human recognition and perception and object shape features provide a powerful clue to object identity. Histogram is the most commonly used characteristic to represent the global feature composition of an image. It is invariant to translation and rotation of the images and normalizing the histogram leads to scale invariance. Exploiting the above properties, the histogram is considered to be very useful for indexing and retrieving images [50]. Edge is a local shape feature and it captures the general shape information in the image [36]. Since edges play an important role for image perception, it is frequently used as a feature descriptor in image retrieval. The *Edge Histogram Descriptor*, EHD, is such an example; which represents the spatial distribution of five types of edges, namely four directional edges and one non-directional edge. To increase efficiency of the proposed system, edge features that include these five categories are used as shape features.

4.4.1 Edge Histogram Descriptor

The edge histogram descriptor (EHD) basically represents the distribution of 5 types of edges in each local area called a sub-image. As shown in figure 4.6, the sub-image is defined by dividing the image space into 4x4 non-overlapping blocks. Thus, the image partition always yields 16 equal-sized sub-images regardless of the size of the original image. To characterize the sub-image, we then generate a histogram of edge distribution for each sub-image. Edges in the sub-images are categorized into 5 types: vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non-directional edges, as shown in Figure 4.7 [36]. Thus, the histogram for each sub-image represents the relative frequency of occurrence of the 5 types of edges in the corresponding sub-image.

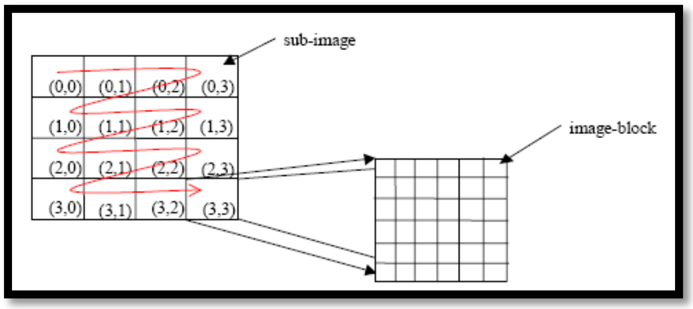


Figure (4.6): Definition of Sub-image and Image-block in the EHD.

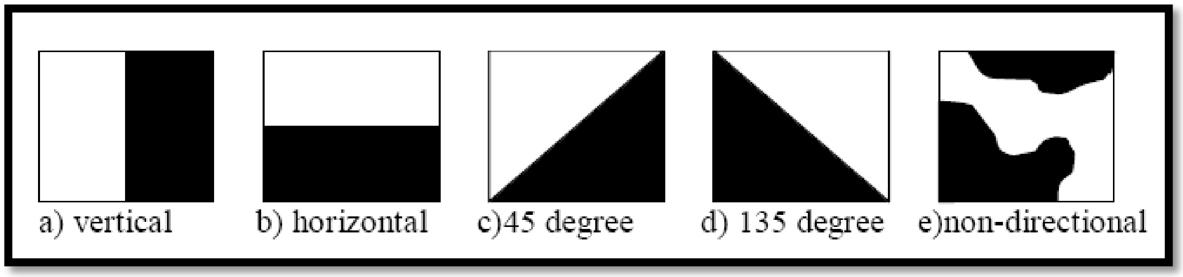
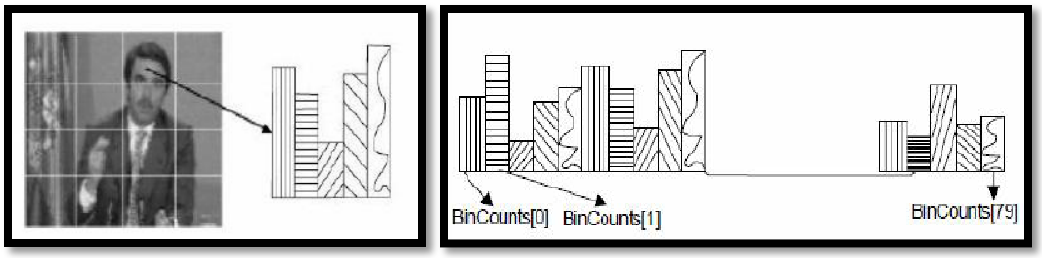


Figure (4.7): Five Types of Edges in the EHD.

As a result, as shown in Figure 4.8(a) below, each local histogram contains 5 bins where each bin corresponds to one of 5 edge types. Since there are 16 sub-images in the image, a total of 5x16=80 histogram bins is required (shown in Figure 4.8(b)).



a) Five Types of Edge bins. **b)** 1-D array of 80 bins of EHD.

Figure (4.8): A Sub-image and Its Corresponding EHD.

- **Semantics of Local Edge Histogram**

Note that each of the 80-histogram bins has its own semantics in terms of location and edge type. For example, the bin for the horizontal type edge in the sub-image located at (0, 0) in Figure 4.8(a) carries the information of the relative population of the horizontal edges in the top-left local region of the image. The semantics of the 1-D histogram bins starts from the sub-image at (0,0) and ending at (3,3), 16 sub-images are visited in the raster scan order and corresponding local histogram bins are arranged accordingly. Within each sub-image, the edge types are arranged in the following order: vertical, horizontal, 45-degree diagonal, 135-degree diagonal, and non-directional. Table 4.2 summarizes the complete semantics for the EHD with 80 histogram bins.

Table (4.2): Semantics of Local Edge Bins

Histogram bins	Semantics
Local_Edge [0]	Vertical edge of sub-image at (0,0)
Local_Edge [1]	Horizontal edge of sub-image at (0,0)
Local_Edge [2]	45degree edge of sub-image at (0,0)
Local_Edge [3]	135 degree edge of sub-image at (0,0)
Local_Edge [4]	Non-directional edge of sub-image at (0,0)
: :	: :
Local_Edge [75]	Vertical edge of sub-image at (3,3)
Local_Edge [76]	Horizontal edge of sub-image at (3,3)
Local_Edge [77]	45degree edge of sub-image at (3,3)
Local_Edge [78]	135 degree edge of sub-image at (3,3)
Local_Edge [79]	Non-directional edge of sub-image at (3,3)

- **Edge Extraction Method**

To extract both directional non-directional edge features, we need to define a small square image-block. That is, we divide an image space into non-overlapping square blocks and then we can extract edge information from each block. Note that, regardless of the image size, we divide the sub-image into a fixed number of image-blocks. That is, the size of the image-block is proportional to the size of original image to deal with the images with different resolutions. Equations (4.12) and (4.13) show how to decide the size of the image-block for a given image. The size of image-block, x, is assumed to be a multiple of 2. If it is not a multiple of 2, we can simply ignore some outmost pixels so that the image-block becomes a multiple of 2.

$$x = \sqrt{\frac{image\_width \times image\_hieght}{desired\_no\_block}} \tag{4.12}$$

$$block\_size = \left\lfloor \frac{x}{2} \right\rfloor \times 2 \tag{4.13}$$

Where, $image\_width$ and $image\_hieght$ represent the horizontal and vertical sizes of the image, respectively. The $desired\_no\_block$ is given and fixed to cope with the various image resolutions.

A simple method to extract an edge feature in the image-block is to apply digital filters in the spatial domain. To this end, we first divide the image-block into four sub-blocks as shown in Figure 4.9. Then, by assigning labels for the four sub-blocks from 0 to 3, we can represent the *average* gray levels for the four sub-blocks at $(i,j)^{th}$ image-block as $a_0(i,j)$, $a_1(i,j)$, $a_2(i,j)$, and $a_3(i,j)$ respectively. Also, we can represent the filter coefficients for vertical, horizontal, 45-degree diagonal, 135-degree diagonal, and non-directional edges as $f_v(k)$, $f_h(k)$, $f_{d45}(k)$, $f_{d135}(k)$, and $f_{nd}(k)$ respectively, where $k = 0, \dots, 3$ represents the location of the sub-blocks. We have the coefficients of the vertical edge filter in Figure 4.10 - a) as follows. Similarly, we can represent the filter coefficients for other edge filters as shown in Figure 4.10 – b), c), d) and e).

Now, the respective edge *magnitudes* $m_v(i,j)$, $m_h(i,j)$, $m_{d45}(i,j)$, $m_{d135}(i,j)$, and $m_{nd}(i,j)$ for the $(i,j)^{th}$ image-block can be obtained as follows:

$$m_v(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_v(k)\right| \quad (4.14)$$

$$m_h(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_h(k)\right| \quad (4.15)$$

$$m_{d45}(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_{d45}(k)\right| \quad (4.16)$$

$$m_{d135}(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_{d135}(k)\right| \quad (4.17)$$

$$m_{nd}(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_{nd}(k)\right| \quad (4.18)$$

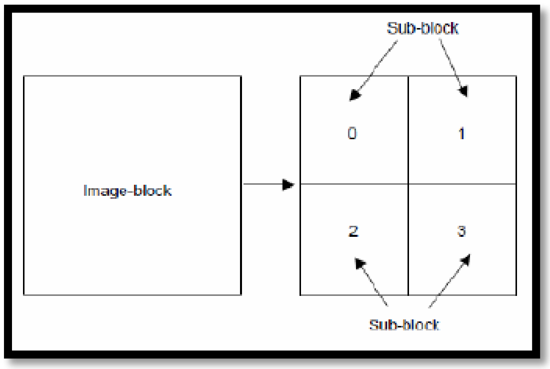


Figure (4.9): Sub-blocks and their Labeling.

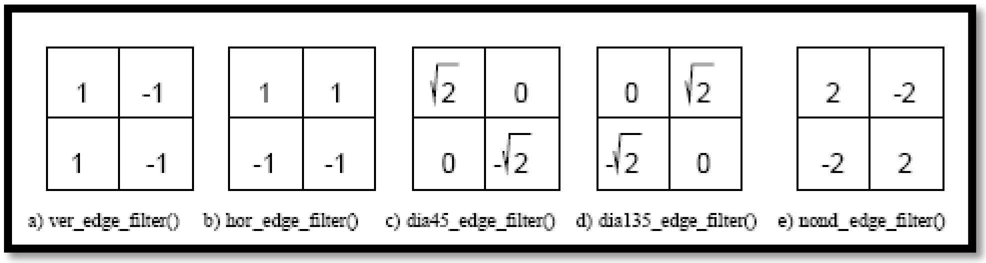


Figure (4.10): Filters for Edge Detection.

Among the calculated five directional edge strengths for five edge types, obtained from (4.14) to (4.18), if the maximum one of them is greater than a threshold value (T_{edge}), then we accept that the block has the corresponding edge type. Then the image-block is considered to have the corresponding edge in it. Otherwise, the image-block contains no edge. That is, the image block have an edge if the equation 4.19 below is achieved

$$\max \ \{m_v(i,j), m_h(i,j), m_{d45}(i,j), m_{d135}(i,j), m_{nd}(i,j)\} > T_{edge} \tag{4.19}$$

- **Non-Normative Global Edge Histogram**

To achieve a high retrieval performance, the local histogram alone may not be enough [52]. Rather, we may need edge distribution information for the whole image space as well. That is, beside the local histogram, we need the global histogram. The global edge histogram represents the edge distribution for the whole image space. Note that the bin values for all global histograms can be obtained directly from the local histogram. Since there are five edge types, the global edge histogram also has five bins. Consequently, we have total 80 bins (local) + 5 bins (global) = 85 bins as shown in Figure 4.11.

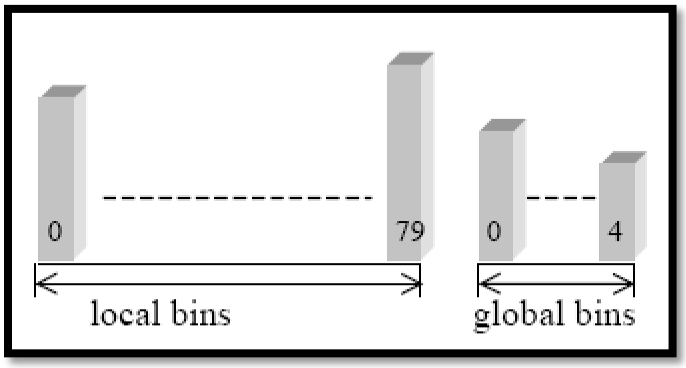


Figure (4.11): Total EHD Bins.

4.4.2 Shape Similarity Measure

In the retrieval process where EHD is used, we have used expression (4.20) as an appropriate similarity distance measure:

$$D_s(d,q) = \sum_{i=0}^{79} |h_d(i) - h_q(i)| + \sum_{i=0}^{4} |h_d^g(i) - h_q^g(i)| \tag{4.20}$$

Where $h_d(i)$ and $h_q(i)$ represent the normalized histogram bin values of image d and q, respectively, $h_d^g(i)$ and $h_q^g(i)$ represent the normalized bin values for the global edge histograms of these images respectively; which are obtained from the corresponding local histograms $h_d(i)$ and $h_q(i)$. Smaller values imply greater similarity.

4.5 Genetic Algorithm to Optimize Features Weights

As discussed previously, genetic algorithm searches for the “best” weight vector w for the extracted features. We use k-means classification accuracy, given by equation 3.4, as a fitness function. That is, we need to find the “best” transformation from pattern space to feature space for improving the performance of the K-means classifier [47]. This process is divided into several steps summarized as follows:

A. Similarity Measurement

In order to compute the similarity/distance between the query image and the images in the database, the feature vector of query image and feature vectors of database images have been compared. So, we get n similarities /distances for every comparison. We can't consider this summation of n similarities/distances one similarity/distance. Sometimes using a fewer types of features gives better results and sometimes combination of other features out of the n give improved result [8]. In order to overcome this problem, new similarity/distance metric has been formed from Equation 3.1 with different weight assigned to each feature. Considering different weights w_k may be assigned to different features, a weighted Euclidean distance is defined as:

$$D(X,Y) = \sqrt{\sum_{k=1}^{n} w_k (x_k - y_k)^2} \tag{4.21}$$

Where w_k is the weight to be assigned to individual content features. Hence, the task of the GA consists of finding the w_k that maximizes the retrieval accuracy to the context defined by the query image.

B. Chromosome Encoding and initial population

In order to apply GA to a given problem the first decision one has to make is to determine the kind of genotype the problem needs, i.e., the chromosome representation. That means, a decision must be taken on how the parameters of the problem will be mapped into a finite string of symbols (genes), encoding a possible solution in a given problem space. The chromosome should in some way contain information about solution which it represents. In this work a chromosome represents the weights assigned to the similarity/distance of the features. Each gene G_j of a chromosome corresponds to one feature weight, being mapped by any of feature weights assigned to similarity/distance associated with that comparison. This type of encoding is called *value encoding* where every chromosome is a string of real numbers.

Let *m* as the number of feature descriptors, N the size of population. Commonly, population size *N* is $20<N<100$. Chromosome *C* of *m* genes is used to represent the weights w_k of feature descriptors. That is, $C=w_1w_2....w_k$. In initial population $P=\{C_1,C_2,...,C_N\}$, all the genes of the first chromosome C_1 are '1.0', which means the weights of all the descriptors are equal. For the other individuals, we randomly generate a set of real numbers w_k, where $w_k > 0$ and $k=1,2,\dots,m$.

C. Fitness Function Design

The GA which has been previously optimized has been used. Classification accuracy of k-means classifier is used to evaluate the fitness of individuals. Fitness function *Fitness* is designed as the following:

$$Fitness = K - means_{accuracy} \tag{4.22}$$

Where *K-means$_{accuracy}$* in equation (4.22) is the k-means classification accuracy which can be calculated by Equation 4.23 below:

$$K - means_{accuracy} = {}^{t}/_{d} \qquad (4.23)$$

Where *t* is the number of correctly classified images and *d* is the number of images in the training set.

D. Genetic Operations

For *selection* operation, chromosomes are selected from the population to be parents to crossover. The problem is how to select these chromosomes. According to evolution theory the best ones should survive and create new offspring. In our system design, we preferred to use ***roulette wheel selection*** with ***elitist preserved model*** for selection operation to increase performance of GA. For *crossover* operation, we preferred to use ***single-point*** **crossover** with crossover rate 90%. *Mutation* operation will be done with mutation rate 0.5% by adding a small number to selected values like next example

C_1= (0.29 0.68 **0.86** 0.17 **0.25**) => C_1= (0.29 0.68 **0.96** 0.17 **0.35**).

E. Termination Criteria

We proceed with the next generation until the process reaches the maximum iteration Gen$_{max}$. When the process ends, the fittest individual is output as the optimum feature weights result. The whole structure of the GA/K-means hybrid approach is shown on Figure 4.12.

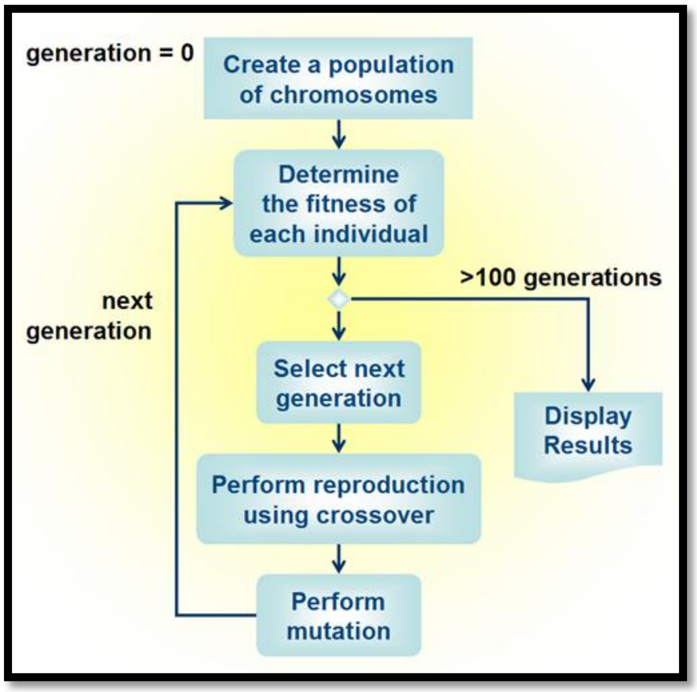

generation = 0
Create a population of chromosomes
Determine the fitness of each individual
>100 generations
next generation
Select next generation
Display Results
Perform reproduction using crossover
Perform mutation

Figure (4.12): GA/K-Means Hybrid Approach.

4.6 K-Means for Database Clustering

The time of image retrieval in almost all CBIR systems depends in a large degree on the number of images in the database. Many existing systems attempt to compare the query image with every target image in the database to find the top matching images, resulting in an essentially linear search, which is highly computationally inefficient when the database is large. 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 so that when a query is received, only a part of the database needs to be searched, while a large portion of the database may be eliminated in the search. This certainly saves significant query processing time without compromising the retrieval precision. Clustering algorithms are used as a preprocessing step, performed offline, to cluster the database into *N* different categories [12] and each feature vector, along with its associated class number, is recorded in the database files.

In the proposed system, we use 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.

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 intra-cluster similarity is high but the inter-cluster 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 [6].

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. The centroid for each cluster is a point to which the sum of distances from all objects in that cluster is minimized. 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, which defined by:

$$E = \sum_{i=1}^{k} \sum_{p \epsilon c_i} |p - m_i|^2 \qquad (4.24)$$

In equation 4.24, 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 4.3 [64].

Table (4.3): 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.
Procedure:
{
    Step1: Arbitrarily choose k objects as the initial cluster centers.
    Step2: (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.
    Step3: Update the cluster means, i.e., calculate the mean value of the objects for each
           cluster.
    Step4: Repeat steps 2 and 3 until no changes.
}
```

4.7 Image Matching

Once we have extracted color, texture and shape feature vectors from the query image, as well as the database images, we can use these feature vectors to measure the similarity between images in order to retrieve the most similar DB images to the query. The similarity between a query image q and a DB image d is defined by a distance between them, denoted as $D(q, d)$, which is assessed according to the extracted color, texture and shape features. Two images are equivalent when the distance value between them approaches zero and the similarity between them decreases as the distance value between them increases.

❖ **Normalization of Feature Vector**

As different feature components have different ranges, the original low-level feature vector of each descriptor is normalized so that each dimension contributes equally in the similarity measure. Though the attributes of one feature vector may have different ranges (one of very small value and one of very high value), therefore a normalization method should be applied to make all features have the same effect in measuring image similarity. The Min-Max algorithm [63] is employed as a normalization technique; it performs a linear transformation on the original data.

Suppose that min_A and max_A are the minimum and maximum values of the attribute A, the Min-Max normalization maps a value, v_k of attribute A to $\tilde{v}_k$ in the range [0,1] by computing:

$$\tilde{v}_k = \frac{v_k - min_A}{max_A - min_A} \qquad A = 3\,,\ k = 1, \ldots, N \tag{4.25}$$

Where, $\tilde{v}_k$ is the normalized feature vector of A^{th} attribute and N is the number of values in each feature vector. Then, normalized $\tilde{v}_k$ forms normalized image feature vector V, i.e. $V = \{\tilde{v}_1, \tilde{v}_2, \tilde{v}_3\}$.

❖ **Distance Measure**

Using the color distance $D_c(q,d)$, the texture distance $D_t(q,d)$ and the shape distance $D_s(q,d)$, given in equations (4.4), (4.11) and (4.20) respectively, we define the weighted distance between two images, $D(q,d)$, as following:

$$\boldsymbol{D(q,d) = w_c\, D_c + w_t\, D_t + w_s\, D_s} \tag{4.26}$$

In equation 4.26, $w_c, w_t\ and\ w_s$ are weights for the color, texture and shape features respectively. These weights are generated and optimized using genetic algorithm.

4.8 The Proposed CBIR System Architecture

In this section we are introducing our proposed method for CBIR. More specifically, the proposed method for image retrieval is composed of two phases. ***Learning*** and ***Querying***.

Phase 1: Offline Preparing the features database (learning)

The learning phase tells about the training process which a huge mount sample images are input in the first step, then the images' features will extract and go to the second step, in which we combine these different types of features using genetic algorithm (GA) to train these features with different weights to achieve good results. K-means classification accuracy is used as fitness function to optimize feature weights. In the third step, the resulted fusion feature vector from step two will classify using K-means algorithm. Finally, the training part outputs the classifying result and stores it in the feature database. All of these steps are performed offline and each class will be indexing along with its associated class ID in the index files. Figure 4.13 illustrates the process of preparation of the features database.

Phase 2: Online Image retrieval (querying)

The querying phase describes the images searching process. The image retrieval methodology proposed in our system goes throughout the steps shown in the block diagram Figure 4.1 which repeated in more details in Figure 4.13. The user enters a query image for which the system extracts color, texture and shape features as explained in the previous sections, the features vectors of database images are previously extracted and stored. Using the similarity metrics defined for color, texture and shape, the similarity distances between the query image and the centroid image of each class are calculated according to Equation 4.26. 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 using Equation 4.26 again. The most matching images will be retrieved and then they are sorted in ascending order. The first N similar target images (with smallest distance value to the query) are retrieved and shown to the user, where N is the number of the retrieved images required by the user. Figure 4.13 shows the architecture of the proposed CBIR System and the proposed algorithm is stated in Tables 4.4 and 4.5.

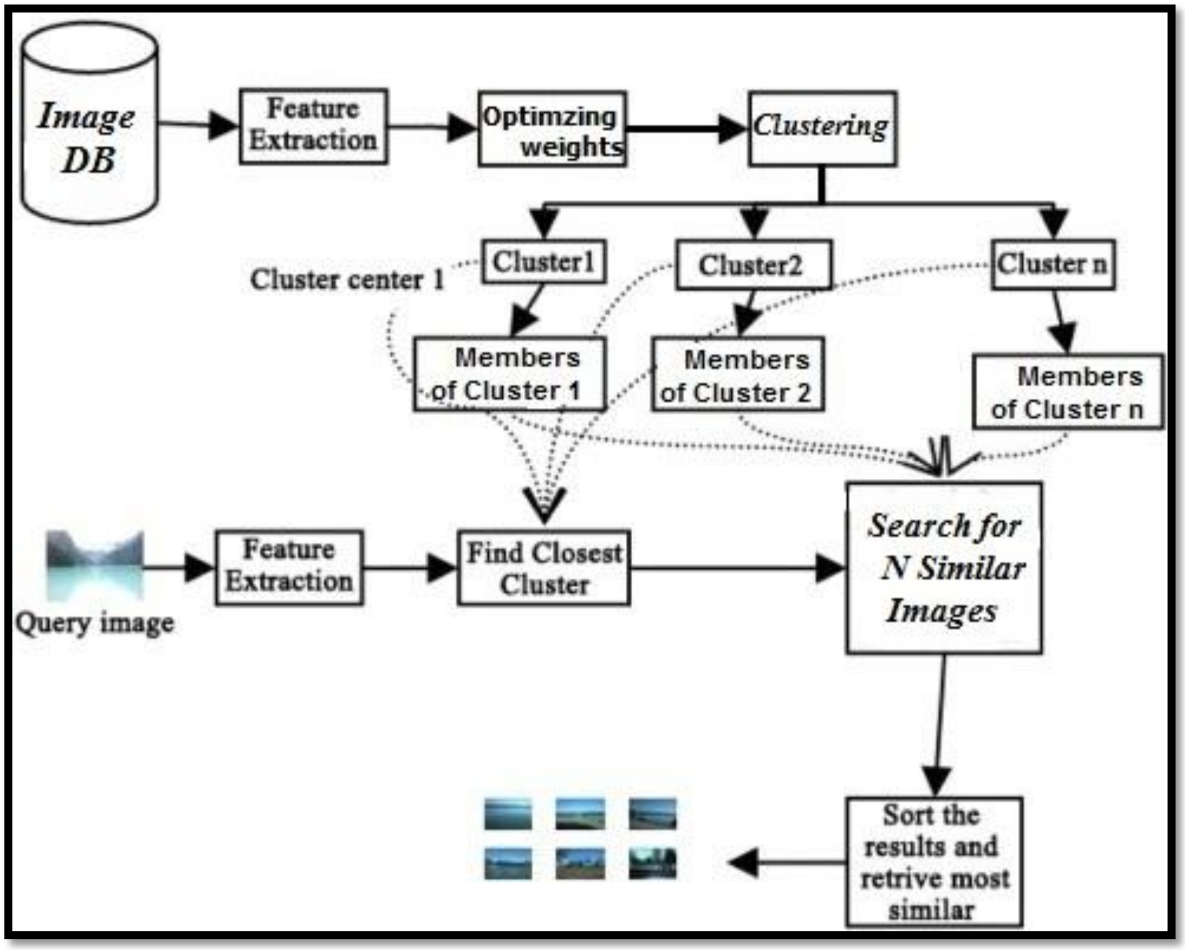


Figure (4.13): The Proposed System Architecture.

Table (4.4): The Proposed CBIR Algorithm (Phase 1: Learning)

Purpose: Construct the features database and the index files.
Input: RGB images.
Output: Image's features database and its index files.
Procedure:

```
{
  Step 1: The input images are color images in RGB color space.
  Step 2: Calculate the color features (moments) using equations 4.1, 4.2, and 4.3.
  Step 3: Calculate the texture features using equations 4.8 and 4.9.
  Step 4: Calculate the shape features (edge histogram) using equations 4.14 to 4.18.
  Step 5: Construct features vectors that will represent the images where each vector
          containing 142 numerical values .
  Step 6: Using genetic algorithm (Table 3.1) to optimize features weights.
  Step 7: Save weighted features vectors in the features database.
  Step 8: Cluster the images in the database using k-means algorithm (Table 4.4) into
          different categories.
  Step 9: Save index files which indexing each class along with its associated class ID.
}
```

Table (4.5): The Proposed CBIR Algorithm (Phase 2: Querying)

Purpose: Retrieving N images similar to the input image.
Input: RGB image, number of retrieved images *N*.
Output: N images similar to the input image.
Procedure:

```
{
  Step 1: The input image is a color image in RGB color space.
  Step 2: Extract the features vector for the input image by using the same
           techniques as given in phase 1.
  Step 3: Calculate  the weighted features vector for the input image by multiplying its
           features vector by the optimal weight vector that generated by GA.
  Step 4: Calculate the distance between the input image and the centroid of each cluster
          using equation 4.26, and find the smallest distance.
  Step 5: Calculate the distance between the input image and the images in the cluster
           that has the smallest distance with the input image using equation 4.26.
  Step 6: Retrieve the first N images that are more similar to the input image.
}
```

Chapter 5

System Results and Evaluation

5.1 Introduction

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

5.2 Image Database

The images database that we used in our evaluation is WANG database [65]. It is a subset of the Corel database of 1000 images in JPEG format. These images are grouped into 10 classes, each class contains 100 images. Within this database, it is known whether any two images are of the same class. Classification of the images in the database into 10 classes makes the evaluation of the system easy. Figure 5.1 shows 10 sample images in each image class. Where the images in the same row belong to the same class.

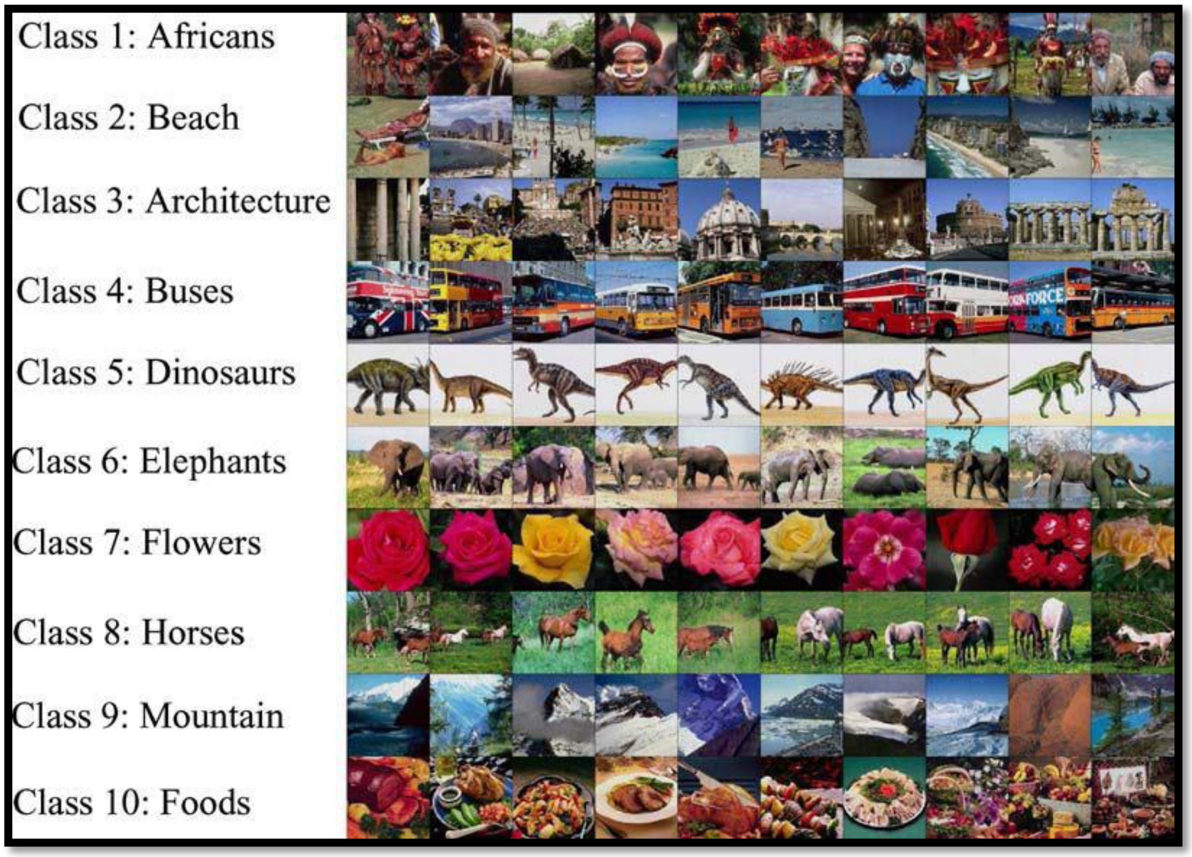


Figure (5.1): Example Images from Each of the 10 Classes of WANG Database.

Additional some information about WANG database are:

- ✓ It was created by the group of Professor James Wang from the Pennsylvania State University.
- ✓ It 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 $\times$ 256 or 256 $\times$ 384 pixels as well.

As we have said before, we chose this database for many reasons, including:

- ✓ 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) so, it is almost sure that a user wants to find the other images from a class if the query is from one of these 10 classes that is due to the given classification it is possible to evaluate retrieval results.
- ✓ The diversity in the images in this database helps us to get good results and enhance our system.
- ✓ Finally, the most interesting point is that the images are familiar to human, and they are very friendly to us.

5.3 Implementation Environment

The proposed CBIR system is implemented using MATLAB program of version 7.8.0.347 (R2011a) which imbedded with image processing tools and statistical tools. We use a platform of Intel Core 2 Due Processing power of 2 GHz CPU with 3 GB RAM during the implementation. 1000 image database went through our implemented system to extract the features and stored them. The extracted features are weighted by GA and they are used for classification using the k-means clustering algorithm. This step is made offline for all images in the database. The database now is ready for testing and evaluating our CBIR proposed system.

5.4 Performance Evaluation Metrics of CBIR Systems

The level of retrieval accuracy achieved by a system is important to establish its performance. If the outcome is satisfactory and promising, it can be used as a standard in future research works. Unfortunately, when we want to evaluate a CBIR system, we may face some problems. One of them 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**, P, is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images [66]. This means that precision measures the accuracy of the retrieval. Let the number of all retrieved images be n and let r be the number of relevant images according to the query then the Precision value is:

$$\boldsymbol{P} = \frac{\textbf{\textit{Number of Relevant Images Retreived}}}{\textbf{\textit{Total Number of Images Retreived}}} = \frac{\boldsymbol{r}}{\boldsymbol{n}} \qquad (6.1)$$

Recall, R, is defined as the ratio of the number of retrieved relevant images to the total number of relevant images in the database [66]. This means that recall measures the robustness of the retrieval. Let r be the number of relevant images among all retrieved images according to the query and let M be the number of all relevant images to the query in the whole database then the Recall value is:

$$\boldsymbol{R} = \frac{\textbf{\textit{Number of Relevant Images Retreived}}}{\textbf{\textit{Total Number of Relevant Images in the DB}}} = \frac{\boldsymbol{r}}{\boldsymbol{M}} \qquad (6.2)$$

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, but we do not know the numbers of irrelevant images were also retrieved. In classification task, a precision of score 1.0 for a class C means that every object labeled as belonging to class C does indeed belong to class C, but we do not know the number of objects from class C that were not labeled correctly. Also, a recall of score 1.0 for a class C means that every object from class C was labeled as belonging to C, but we do not know the number of objects were also labeled as belonging to class C 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. As a result, precision and recall scores are not discussed in isolation. Instead, either values for one measure are compared for a fixed level at the other measure (e.g. precision at a recall level of 0.75) or both are combined into a single measure, such as **Precision/Recall graph**.

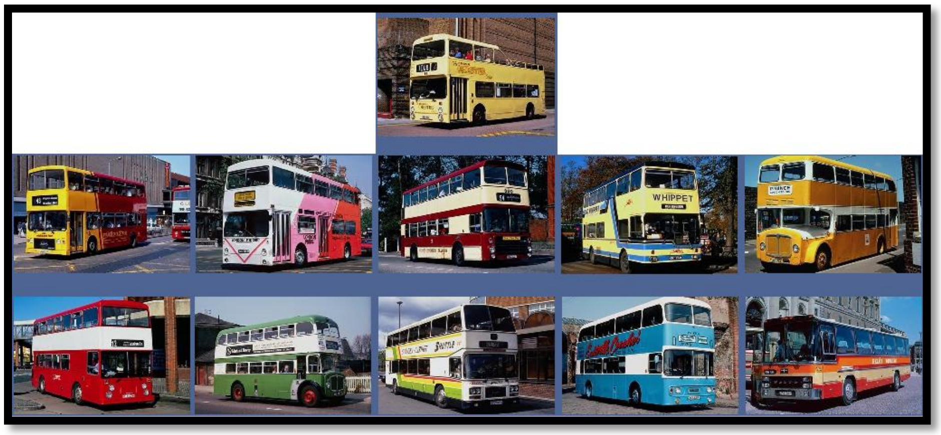
In general, when we want to evaluate the performance of a CBIR system, we use both the two metrics. The Precision/Recall graph is widely used. It provides meaningful results when the database is known and has been used in some earlier systems. Because we know every image in the database and also know the relevant images for each image, we can use any image from the database to be the query. For other data sets, especially those that have been created by collecting user generated images, the result may vary due to different human concepts of image classification.

5.5 The proposed System Evaluation

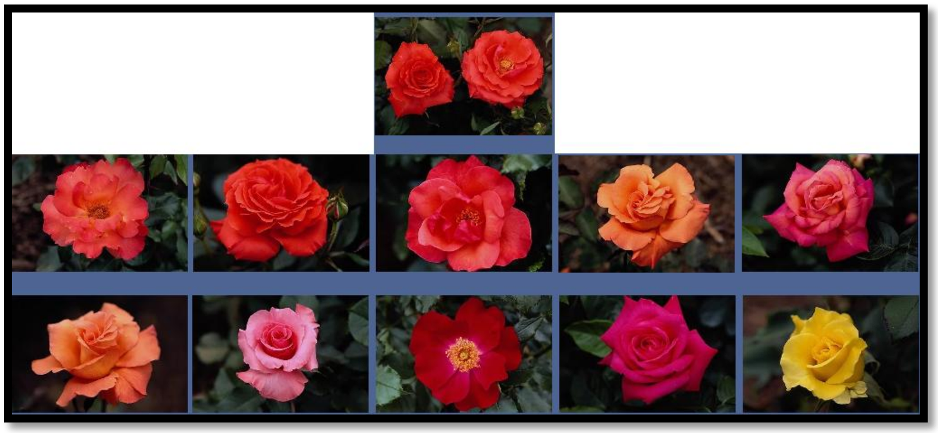
Here, we come to the most important section in the thesis. In this section, we test our proposed system and show the results. We explain the results, comment on them, and compare our system with other existing systems. We evaluate the system regarding two metrics: the ***Retrieval Effectiveness*** in terms of precision and recall, and the ***Retrieval Efficiency*** in term of the time the system takes to answer a query.

5.5.1 Retrieval Effectiveness

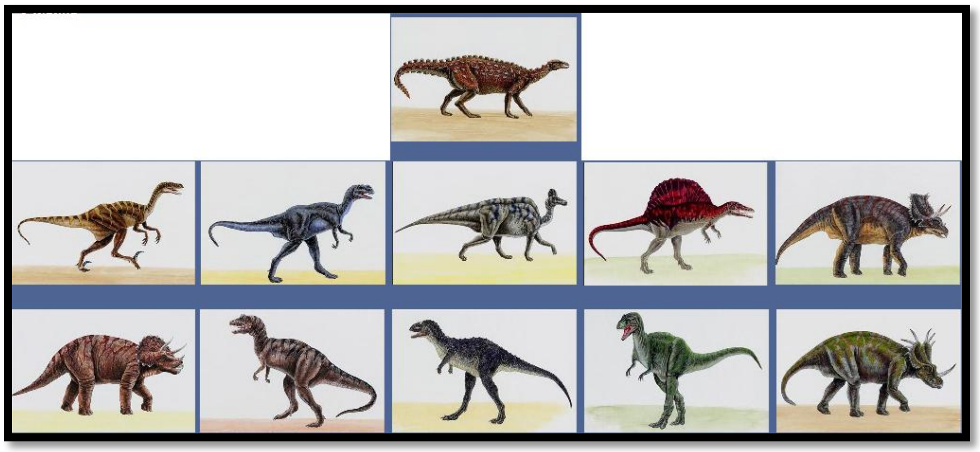
In order to check retrieval effectiveness of our proposed system, we have to test it by selecting some images randomly from different classes. Each query returns the top 10 images from the database. In particular, a retrieved image is considered a match if and only if it is in the same class as the query image. Figure 5.2 from (a) through (e) illustrates five query results from our proposed system.



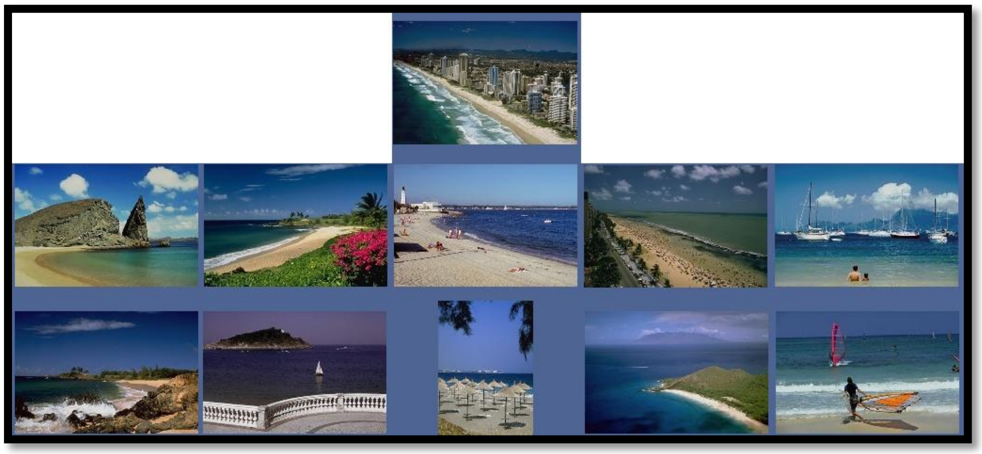
a) Buses Query, 10 Matches from Top 10 Retrieved Images.



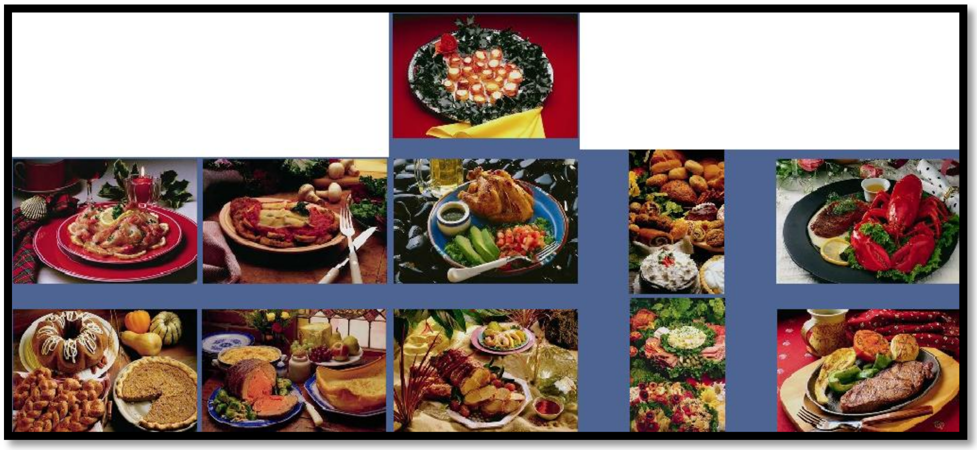
b) Flowers Query, 10 Matches from Top 10 Retrieved Images.



c) Dinosaurs Query, 10 Matches from Top 10 Retrieved Images.



d) Beaches Query, 10 Matches from Top 10 Retrieved Images.



e) Foods Query, 10 Matches from Top 10 Retrieved Images.

Figure (5.2): Five Query Response Examples of Our Proposed System.

The first test is selecting a random image from the Buses 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 5.2(a), all images retrieved by the system are relevant to the query image. Figure 5.2(b) shows another query image and its result. This is the second test for our proposed system. We select an image randomly from the Flowers 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. The third, the fourth and the fifth tests and their results for our proposed system are shown in Figure 5.2(c) for Dinosaurs class, Figure 5.2(d) for Beaches class and Figure 5.2(e) for Foods class respectively. As we can see from these Figures, all the images are similar to the query image and belong to the same class.

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 with different classes in the database if we use them as queries images. These good results were achieved as a regular result for using many different features as descriptors for the images. Not only this , but also by weighting these features optimally using GA and then classify the images perfectly using K-means Algorithm.

The precision values of the retrieval results for top 5, 10, 20, and 30 retrieved images in response to each of the five queries are given in Table 5.1. As can be noted from this table, the precision values are high for small number of retrieved images, and these values decrease as the number of retrieved image increases. This is a regular case since the increasing in the number of retrieved results will increase the number of relevant images, increase recall, but in the other hand the results will have quite large number of irrelevant documents retrieved. This decreases the precision. By the way, the results indicating that the system gives a good ranking of the retrieved images. For example in Buses query, the first top 5 and top 10 of the retrieved images are relevant, whereas in the top 20 and top 30 retrieved images only 1 of them is found to be irrelevant.

Table (5.1): Precision of the Proposed System for top 5, 10, 20, and 30 Retrieved Images for Some Different Queries.

Query Class	Top 5	Top 10	Top 20	Top 30
Buses	1.00	1.00	0.95	0.95
Flowers	1.00	1.00	0.75	0.70
Dinosaurs	1.00	1.00	1.00	1.00
Beaches	1.00	1.00	0.70	0.65
Foods	1.00	1.00	0.80	0.75

- **Average Precision/Recall**

To further evaluate the proposed system, 10 images are randomly selected as queries from each of the 10 semantic classes in the database, for each query the precision of the retrieval at each level of the recall is obtained by gradually increasing the number of retrieved images. The 100 retrieval results are averaged to give the final Precision/Recall chart of Figure 5.3.

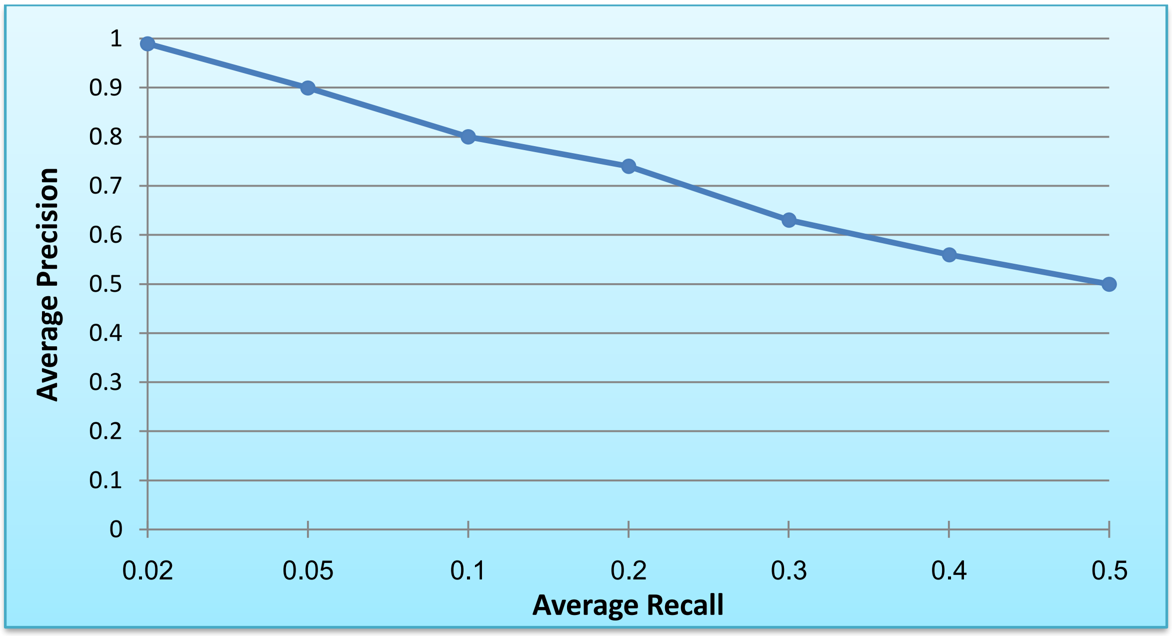


Figure (5.3): The Average Precision/Recall Chart of the proposed System Over 100 Queries.

From Figure 5.3, it can be noted that the system has good average precision values over different recall levels. It has a maximum average precision of 0.92 at recall level of 0.05, this value decreases to 0.51 precision value at 0.5 of recall level. For example, for an average recall value of 10%, we have an average precision value of 80% (i.e., if the user intends to get 10% of the relevant images in the database, he can get them with 80% of the retrieved images are relevant and 20% of them are irrelevant). As expected from a good retrieval system, the precision values are shown to decrease little as the recall levels increase. This clarifies that our system works well.

5.5.2 Retrieval Efficiency

We have improved the efficiency of the proposed system by assigning different weights to each feature and these weights optimized using genetic algorithm (GA) with a k-means accuracy as a fitness function to select optimum weights of features (Table 3.1). We perform GA on the database as an offline step, and then we use the weighted feature vectors to retrieve images relevant to the query image. To apply this, we chose some images randomly from each class as queries and applied them twice. In the first time, we use GA to weighting image's feature vectors in the database before image retrieval. In the second time, we retrieve images without weighting image's feature vectors in the database as a preprocessing step (i.e., concerning feature vectors with equal weight for image matching step). Table 5.1 shows the quantitative results obtained by the optimal weighted features (GA) to the database. The results of optimal weighted features show better performance in terms of average precision, and recall. This indicates that GA did its job perfectly and the weights of the features are optimal so the weighted feature vectors can distinguish between images in a high degree of accuracy. N in table 5.2 refers to the number of images ranked top of the retrieval result.

Table (5.2): Comparing the Implementation Results of Optimal Weighted Features (GA) for CBIR with Equally Weighted Features Results in Terms of Precision and Recall.

Class	Equally Weighted Features		Optimal Weighted Features (GA)	
	$\bar{P}$ (%) N = 20	$\bar{R}$ (%) N = 20	$\bar{P}$ (%) N = 20	$\bar{R}$ (%) N = 20
Africans	0.70	0.63	1.00	0.81
Beaches	0.65	0.42	0.93	0.66
Buildings	0.90	0.31	0.61	0.44
Buses	0.80	0.82	1.00	0.97
Dinosaurs	1.00	1.00	1.00	1.00
Elephants	0.45	0.34	0.63	0.40
Flowers	1.00	0.57	1.00	0.74
Horses	0.70	0.58	1.00	0.72
Mountains	0.45	0.34	0.65	0.45
Food	0.85	0.73	1.00	0.80
Total	**0.750**	**0.574**	**0.882**	**0.699**

From Table 5.2, A total average of 88.2% matched/retrieved images (precision) is achieved using the optimal weighted features and a total average of 69.9% of recall is achieved. The same experiment performed using equally weighted features demonstrated lower performance on average precision (about 75%), and recall (about 57.4%).

Furthermore, to speed up retrieval and similarity computation of our proposed system, the database images are clustered using k-means clustering algorithm (Table 4.4) according to their weighted feature vectors. 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 (i.e., concerning all images in the database for image matching step).

The average precisions for each group based on the returned top 20 images in case of using K-means clustering algorithm, without using clustering algorithm and using GA with K-means are shown in charts of Figure 5.4.

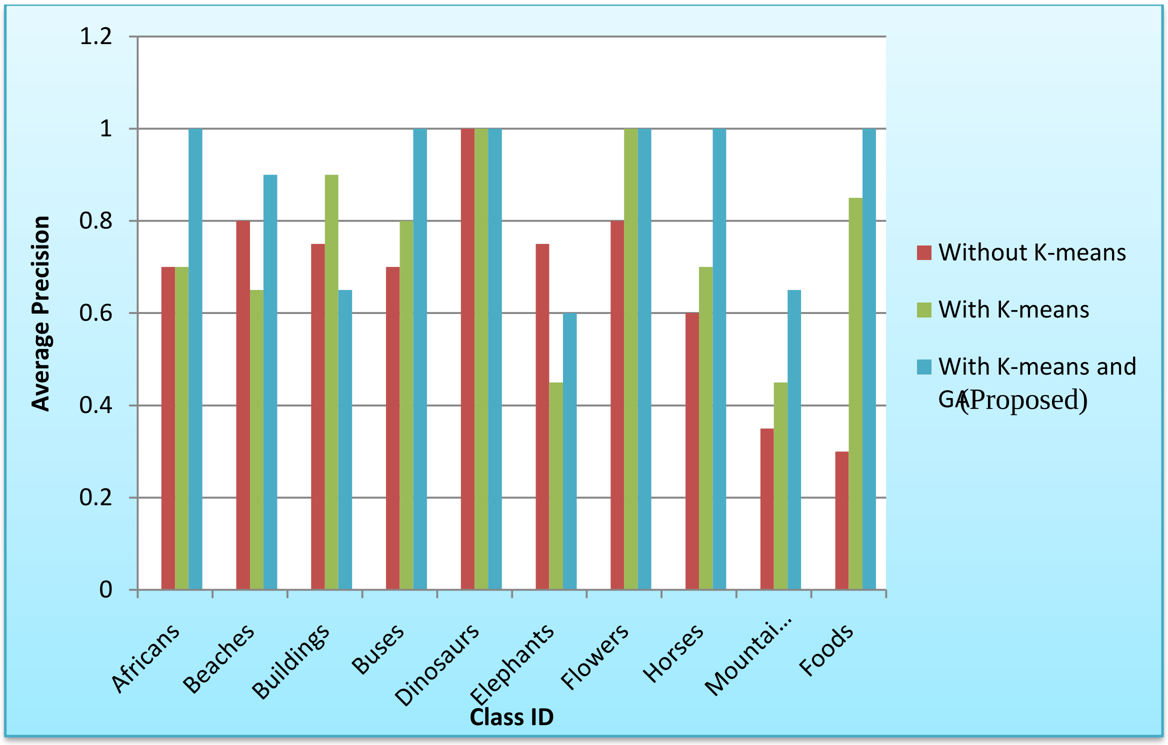


Figure (5.4): Comparison of Precision of the Proposed System Applied With K-means, Without k-means and With K-means and GA.

If we look carefully on the Figure 5.4, we can note that the precision of classes Buildings and Elephants without using k-means is better than the precision when using the k-means and GA. This is because some images from each class are incorrectly clustered as a result of weighting the features. However, the difference between the two precisions is small and negligible. In the other hand for all other classes, we note that the precision reached using k-means and GA are the better. This is because only a number of candidate images, image that lies in the same cluster with the query image, were considered in similarity comparison. Which in their turn, best classified according to optimally weighted features.

The average retrieval time that the proposed system takes for feature extraction is about 2 seconds per image. A comparison of the average retrieval time required for returning top 20 images, per query in seconds, recorded for each semantic group in the database over 20 randomly selected queries by the system applied with clustering and without using clustering is shown in Figure 5.5.

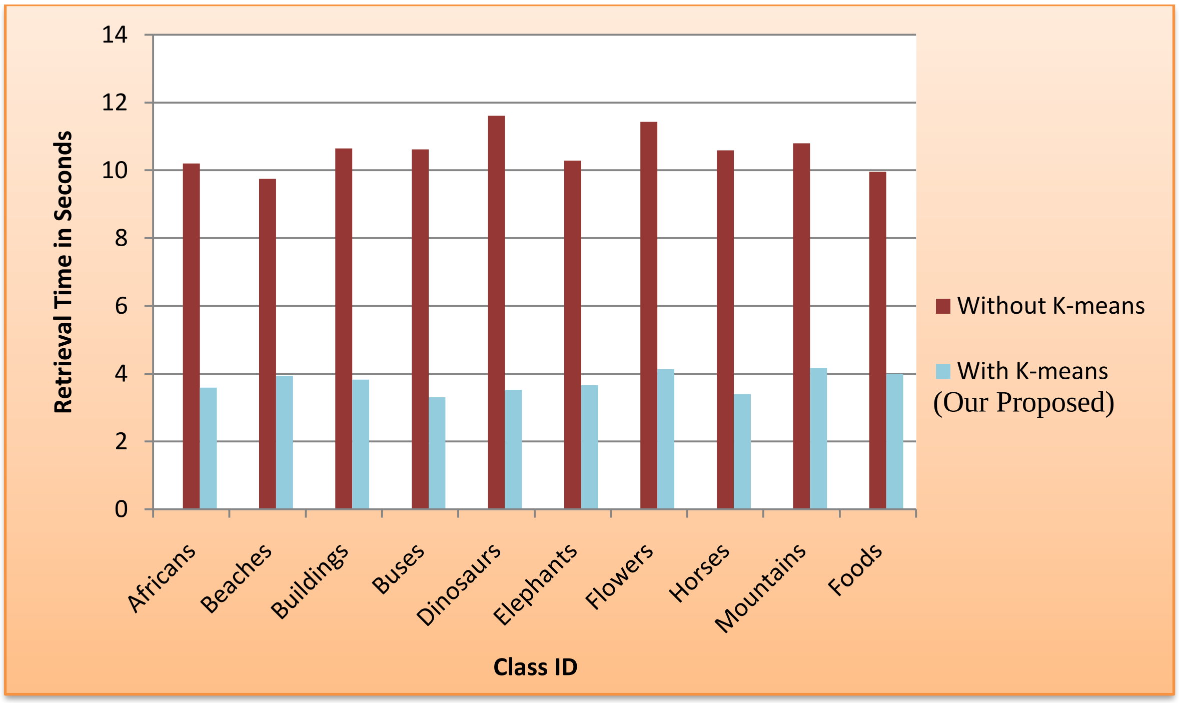


Figure (5.5): Comparison of Average Retrieval Time Required by the Proposed system Applied with Clustering and without Clustering.

We notice that using clustering pre-process of the database image via K-means algorithm decreases the average query response time, as well as it increases the efficiency of the system, as can be shown in Figure 5.4. Note that the system has the same feature extraction time, but using the clustering pre-process decreases the similarity search time for image matching, since it avoids searching all the database images, but some candidate images only. The query response time is reduced significantly using the clustering process, as noticed in Figure 5.5, hence we obtained an average reduction in time equals, 6.21 seconds.

5.6 Comparison of Our Proposed System with Other Systems

In this section, we evaluate the retrieval accuracy of our proposed system and compare it with some of the existing CBIR system's results. Here, we have two kinds of comparisons.

- ***The first one*** is a comparison of the proposed system with some other existing systems that use only color feature to represent images, Then, a comparison with the systems that use color and texture features to represent images. In both cases these systems are use the WANG database to evaluate their proposed systems.

Our proposed system precision result is compared against the precision of Afifi's method [55] that use only color as feature descriptor, Chaudhari's method [49] that use color and shape as a features descriptors and Salama's method [2] that use color and texture as a features descriptors. The comparison is shown in Figure 5.6.

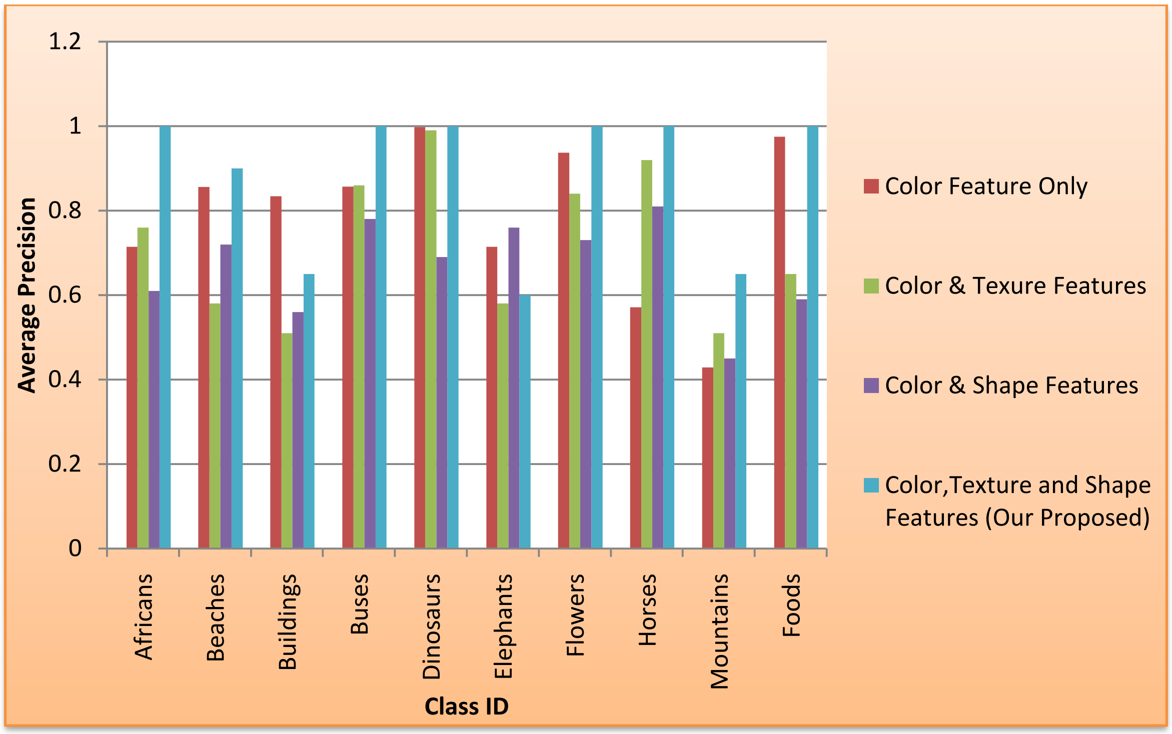


Figure (5.6): Comparison of Precision of the Proposed System with Previously Existed Systems with Different Kinds Of Features.

Figure 5.6 shows that the proposed system performs significantly better, over most classes, than other systems, those that use only color and those that use color and texture features to represent the images. This results confirm our assumption that a good fusion of multiple features (color, texture and shape) as a descriptor for the image can increase the performance of the system.

- ***The second one*** is a comparison of the proposed system with some other existing systems that use color, texture and shape features to represent images. Again, these systems are use the WANG database to evaluate their proposed systems.

In order to calculate the performance of our proposed system, we implement the proposed method on the WANG image database described in Section 5.1. For each class in the database, we randomly selected 20 images as queries. Since we have 10 classes in the database, we have 200 query images. For each query, we calculate the precision and recall of the retrieval. The average precisions and the average recall for each class based on the returned top 20 images were recorded. Moreover, our proposed system result is compared against the performance of Kang and Zhang's method [46], Gali and Dewal's method [14], and Hiremath and Pujari's method [13]. The comparison is recorded in Table 5.3 and Table 5.4.

Table (5.3): Comparison of Precision of the Proposed System with Previously Existed Systems with All kinds of Features.

No.	Class	Kang and Zhang	Gali and Dewal	Hiremath and Pujari	Proposed System
1	Africans	0.69	0.76	0.48	1.00
2	Beaches	0.55	0.58	0.34	0.93
3	Buildings	0.56	0.71	0.36	0.61
4	Buses	0.89	0.96	0.61	1.00
5	Dinosaurs	0.93	1.00	0.95	1.00
6	Elephants	0.70	0.74	0.48	0.63
7	Flowers	0.88	0.94	0.61	1.00
8	Horses	0.81	0.94	0.74	1.00
9	Mountains	0.64	0.45	0.42	0.65
10	Foods	0.69	0.73	0.50	1.00
	Total	**0.734**	**0.781**	**0.549**	**0.882**

Table 5.3 shows that the proposed system performs significantly better than other systems, in term of precision, for all classes except for classes 3 and 6 which are Buildings and Elephants respectively. This is a good indicator for the effectiveness of our system. The reason behind the limitation in two classes is that those classes' images are very similar in term of the dominant color, texture and shape so, our system may confused between them.
Figure 5.7 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 5.3 by a vertical bar. We can see that our proposed system performs significantly better, over most classes, than other systems, that use the color, texture and shape features to represent the images and also they use the same database for evaluation.

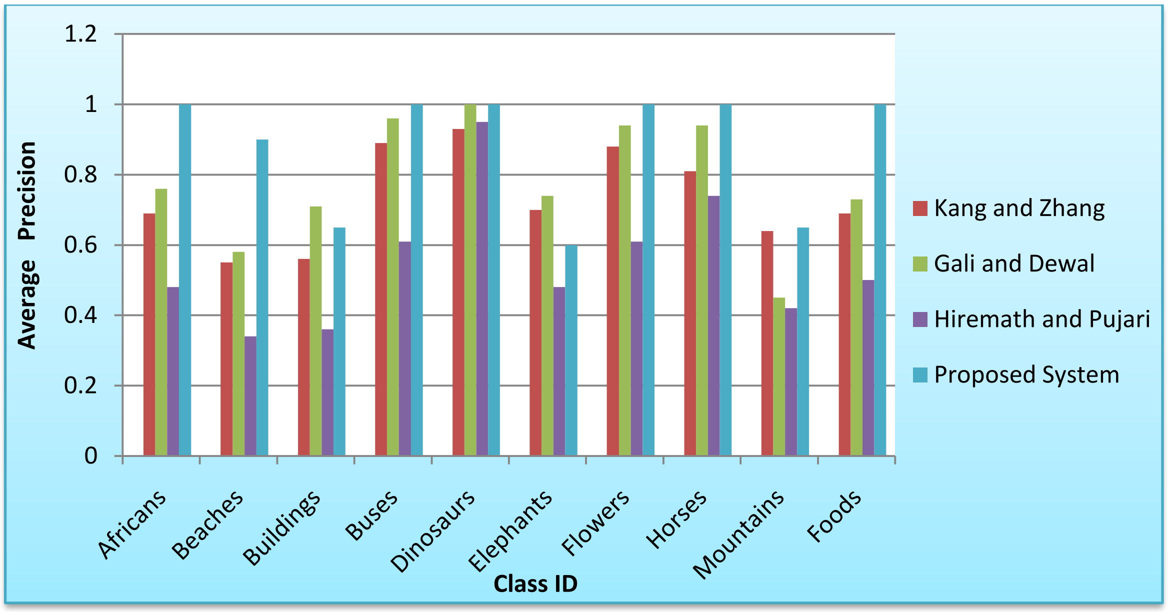


Figure (5.7): Comparison of Precision of the Proposed System with Previously Existed Systems with All kinds of Features.

Table (5.4): Comparison of Recall of the Proposed System with Previously Existed Systems with All kinds of Features.

No.	**Class**	**Kang and Zhang**	**Gali and Dewal**	**Hiremath and Pujari**	**Proposed System**
1	Africans	0.14	0.43	0.21	0.81
2	Beaches	0.18	0.32	0.25	0.66
3	Buildings	0.18	0.35	0.22	0.44
4	Buses	0.13	0.69	0.31	0.97
5	Dinosaurs	0.11	0.99	0.75	1.00
6	Elephants	0.16	0.35	0.25	0.40
7	Flowers	0.12	0.69	0.19	0.74
8	Horses	0.12	0.62	0.44	0.72
9	Mountains	0.19	0.24	0.14	0.45
10	Foods	0.15	0.36	0.19	0.80
	Total	**0.148**	**0.504**	**0.295**	**0.699**

Table 5.4 shows that the proposed system performs significantly better than other systems, in term of recall, for all classes. This means that the proposed system can retrieve most of database images that match query image. These images must be at the same class which in turn implies that our proposed system works well especially in the classification part as a result of using GA with K-means. Figure 5.8 shows the comparison of our proposed system with other systems. We represent the recall value of each system for each class using the value from Table 5.4 by a vertical bar. We can see that our proposed system outperforms

other existing systems, over most classes, that use the color, texture and shape features to represent the images and also they use the same database for evaluation.

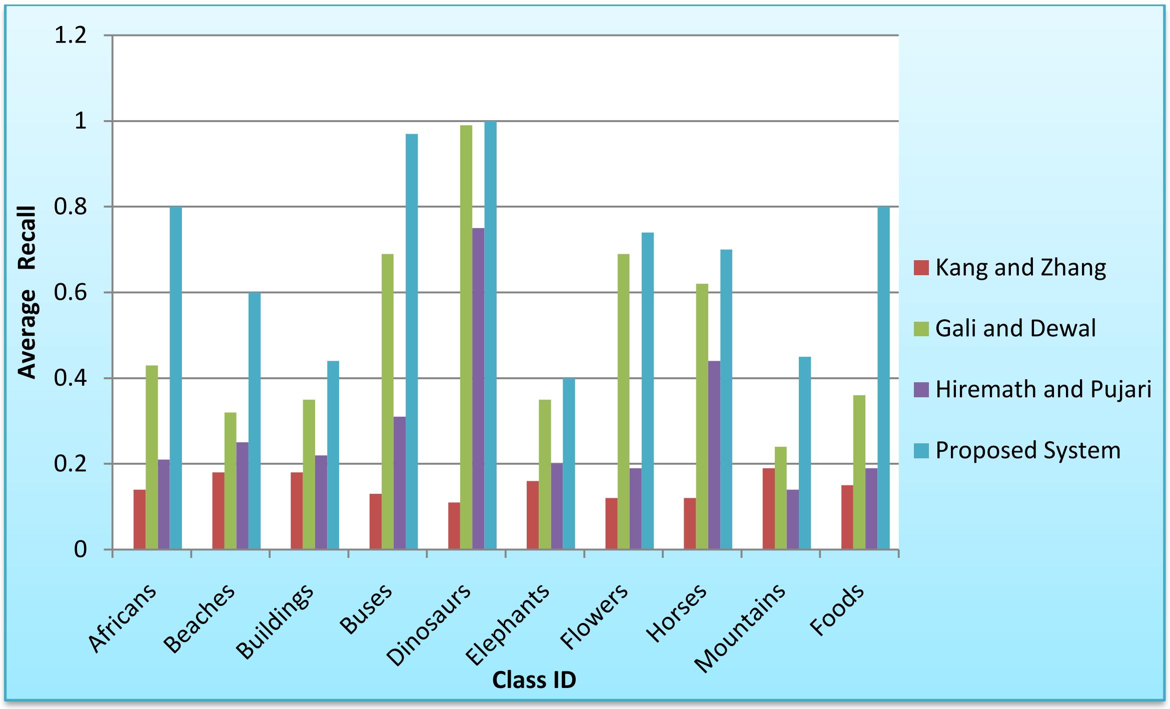


Figure (5.8): Comparison of Recall of the Proposed System with Previously Existed Systems with All kinds of Features.

Chapter 6

Conclusion and Future Work

In this Chapter, we present the conclusions from this thesis and some recommendation and future works. In section 6.1, we talk about the contributions we have achieved and a conclusion for the work. Some of the Future works are proposed in section 6.2.

6.1 Conclusion

Content based image retrieval is an active research issue that had been famous from 1990s till present. CBIR as a set of challenging techniques aims to retrieve semantically requested relevant image concepts from large-scale image databases. The main target of CBIR is to get accurate results with lower computational time. Although this area has been explored for decades and many researches have been done to develop some algorithms that solve some of its problems, no technique has achieved the accuracy of human visual perception in distinguishing images. Whatever the size and content of the image database is, a human being can easily recognize images of same category.

Many proposed algorithms use images to extract features and use their features for similarity matching. In this research, Color, Texture and Shape features were extracted and combined to form feature vector of image. For color features, the moments of the color distribution were calculated from the images and used as color descriptor. For texture features, We used Gabor filter, which is a powerful texture extraction technique in describing the content of image. For shape features, edge histogram features that include five categories were used as shape descriptor. These three descriptors were combined and optimized using GA with a k-means accuracy as a fitness function to select optimum weights of features. We performed GA with K-means on the database as an offline step, and adapted in similarity/distance measurement to perform retrieval image from database.

Furthermore, we have improved the efficiency of our system by not considering the whole database images for similarity computation but a number of candidate images were only considered. A candidate image is any database image that lies in the same cluster with the query image. The clustering process of the database images is performed offline using K-means algorithm. The simulation results have proved the benefit of this clustering process in decreasing the retrieval time without sacrificing the retrieval accuracy.

In our work, we used WANG database, which is widely used for CBIR, to evaluate the performance of our system by calculating the precision and recall metrics. We also compared our proposed system with other existing CBIR systems that use the same database for system evaluation. The performance of our algorithm in terms of average precision, recall and retrieval time has been shown to perform good. From the experimental results, it is evident that our proposed system surpassed its counterpart, other existing systems, in terms of precision, recall and retrieval time. The average precision increased from 78.1% to 88.2%, the average recall increased from 50.4% to 69.9% and we obtained an average reduction in time equals, 6.21 seconds.

The experimental results confirm that the proposed CBIR system architecture attains better solution for image retrieval. Furthermore, in our knowledge, our model represents one of the first times in which combine concepts and techniques to build CBIR system.

6.2 Future Work

The future works appear from the limitations and the difficulties when we develop our system. The following developments can be made in the future:

1. We hope to build more generalized CBIR system which increase the system searching ability and provide more accurate results.

2. To improve the retrieval 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.

3. To further improve the performance of the retrieval system, we hope to optimize some settings of the system architecture and techniques that used in this research. There exist some details setting that can be discussed and optimized with the images retrieval issues. This is like, the number of clusters k as an inputs for the K-means algorithm and input parameters of the genetic algorithm etc.

4. The results demonstrate that each type of feature is effective for a particular type of images according to its semantic contents, and using a combination of them gives better retrieval results for almost all semantic classes. In future, we hope to try different types of features.

5. Region-based retrieval attempt to overcome the deficiencies of global feature based search by representing images at the object-level. It applies image segmentation to decompose an image into regions, which correspond to objects if the decomposition is ideal [28]. We hope to try applying this technique in our proposed system to increase its efficiency especially when we can solve the main problem of this technique, long computational time, by any way. Parallel computing is one of the main ways to this purpose.

6. Using different benchmark image datasets with different semantics and categories to further evaluate our system and found its limitations and weaknesses and work to fix them.

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