SUDAN UNIVERSITY OF SCIENCE AND TECHNOLOGY

COLLEGE OF GRADUATE STUDIES

COLOR AND TEXTURE FUSION BASED METHOD FOR CONTENT BASED IMAGE RETRIEVAL

طريقة دمج خواص اللون والبنية لإسترجاع الصور بناءً على المحتوى

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طريقة دمج خواص اللون والبنية لإسترجاع الصور بناءً على المحتوى

A Thesis Submitted in Partial Fulfillment of the Requirements of Master Degree in Computer Science (Software Engineering track).

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September 2014

الايـة

قال تعالى :

(لَيْسَ عَلَيْكَ هُدَاهُمْ وَلَكِنَّ اللَّهَ يَهْدِي مَنْ يَشَاءُ وَمَا تُنْفِقُوا مِنْ خَيْرٍ فَلِأَنْفُسِكُمْ وَمَا تُنْفِقُونَ إِلَّا ابْتِغَاءَ وَجْهِ اللَّهِ وَمَا تُنْفِقُوا مِنْ خَيْرٍ يُوَفَّ إِلَيْكُمْ وَأَنْتُمْ لَا تُظْلَمُونَ).

صدق الله العظيم...

سورة البقرة – الآية(272).

DEDICATION

TO:

My lovely parents, wife (Nadia), brothers and sisters, I am very grateful for their faith, daily moral and financial support in my education. I appreciate their fantastic encouragement which helped me triumph over all difficulties uncounted during my research.

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First and foremost, I have to thank my parents for their love and support throughout my life. Thank you both for giving me strength to reach for stars and chase my dreams. My profound thanks go to my wife who supported me during this hard time.

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To all my friends, thank you for your understanding and encouragement in my many, many moment of crisis. Your friendship makes my life a wonderful experience. I cannot list all the names here, but you are always on my mind.

Thank you, Allah, for always being there for me.

ABSTRACT

Since the last decade, Content-based Image retrieval was a hot topic research. The computational complexity and the retrieval accuracy are the main problems that CBIR system have to avoid. In this study the method was proposed to overcome these problems by using the combine of color moment and texture features. The color feature was extracted by color moment where the images will be in the HSV color space. The textures features extracted by applying Gabor function where the images will be in grayscale. The similarity measure in this study was calculated by used Euclidian distance.

The experiments results show that using both color and texture features to describe the image and use them for image retrieval is more accurate than using one of them only.

المستخلص

ظهرت فى العقود الاخيره تقنية استرجاع الصور بناءاً على محتواها او خصائصها مثل اللون و الشكل ....الخ والتى تعرف بـ (CBIR). أصبحت هذه التقنية من المواضيع البحثية النشطة جداً . المشاكل الاساسية فى مثل هذه الأنظمة تتمثل فى دقة الاسترجاع و التعقيد المصاحب لاستخلاص هذه الخصائص (اللون او الشكل ....الخ).

لحل المشاكل المذكوره اعلاه اُقترح استخدام خصائص اللون وبنية (تركيب) الصور معاً. خاصية اللون تم استخلاصها بإستخدام طريقة تعرف بـ (Color moment) للصورة الممثله بنظام الالوان (HSV). خاصية بنية (او تركيب الصور) تم استخلاصها بإستخدام داله تعرف بـ (Gabor function) عندما تكون الصور ممثله بنظام الـ (Grayscale). اخيراً تم حساب التشابه باستخدام معامل التشابه المعروف بـ (Euclidian distance). النتائج التجريبية المتحصل عليها برهنت ان استخدام خصائص اللون والبنية (او التركيب) لوصف الصور واستخدامها فى استرجاع الصور لها دقة أفضل من استخدام خاصية واحده فقط.

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LIST OF ABBREVIATIONS

CBIR	-	Content Based Image Retrieval
2D	-	Two Dimension
3D	-	Three Dimension
RGB	-	Red, Green and Blue
HSV	-	Hue, Saturation and Value
CMY	-	Cyan, Magenta and yellow
CCH	-	Conventional Color Histogram
ICH	-	Invariant Color Histogram
FCH	-	Fuzzy Color Histogram
P	-	Precision
CM	-	Color Moment
IPT	-	Image Processing Toolbox

Chapter 1

INTRODUCTION

Introduction

1.1 Background of the Study

Content-based image retrieval is a technique uses visual contents to search images from large scale image databases according to users' interests[1].

Today technological advances in digital imaging, broadband networking, and data storage have motivated people to communicate and express by sharing images, video, graphics and other forms of media which has resulted into an explosion in the amount and complexity of digital data being generated, stored, transmitted, analyzed, and accessed. Much of this information is multimedia in nature, generated from diversity of sources like digital camera, scanner, the internet etc., which has caused technical challenges for computer systems to acquire, store or transmit and manage image data effectively to make such large collections easily accessible [2].

Although the problems of acquiring, storing and transmitting the images are well addressed [3, 4] capabilities to manipulate, index, sort, filter, summarize, or search through image database lack maturity; however there is a great the need for faster and better image retrieval techniques [5].

The old technique used for retrieve image is 'Text Based Image Retrieval', where images in the database are represented by adding text strings describing the content of an image [6, 7]. Based on the similarity of these text annotations given to the images, the relevance of images from the database to that of the query image is decided [8]. However, this method or technique has many major drawbacks. Such as, it is very time consuming and the major drawback is that the user of a Text Based Image retrieval must describe an image using nearly the same keywords that were used by the annotator in order to retrieve that image. Due to all these drawbacks, Content Based Image Retrieval is introduced [9].

A Content Based Image Retrieval (CBIR) is an interface between a high level system (the human brain) and a low level system (a computer). The human brain is capable of performing complex visual perception, but is limited in speed while a computer is capable of restricted visual capabilities at much higher speeds.

In a CBIR, visual image content is represented in form of image features, which are extracted automatically and there is no manual intervention, thus eliminating the dependency on humans in the feature extraction stage. These automated feature extraction approaches are computationally expensive, difficult and tend to be domain specific. So lot of scope for minimizing computational complexity, simplification and generic attempts do exist for research in CBIR [10].

A wide range of possible applications for CBIR technology has been identified. Some of these are listed below:

- Art galleries, museums, archaeology.
- Geographic information systems, weather forecast, aerial/astronomical images.
- Medical imaging (2D/3D data).
- Trademark databases (icons, binary images, or images containing only few homogeneous colors).
- Criminal investigations (e.g. Fingerprint matching, copyright violation on the Internet, face recognition).

1.2 Problem Statement

Early studies on CBIR used a single visual content such as color, texture, or shape to describe the image. The drawback of this method is that, using one feature is not enough to describe the image since the image contains various visual characteristics[11]. This study proposes a fusion based CBIR method that uses the combination of (hue, saturation, and value (HSV)) color moment feature and image texture feature. Here, the retrieval method based on combination of result from both color and texture features of the image. Color and texture feature extract are simpler compared to other features.

1.3 Research Question

The main research question of this study is: is the combination of both color and texture features improve and enhance the precision and recall of the CBIR method.

1.4 Objectives of the Research

This study focuses on efficient feature vector extraction to represent the visual image content for achieving better performance with high precision of image retrieval system. The specific objectives are:

- To extract and examine the use of (hue, saturation, and value (HSV)) color moment features for image retrieval.
- To extract and examine the use of image texture feature.

- To propose the use of combination or fusion of both color and texture features to improve and enhance the precision and recall of the CBIR method.

1.5 Scope of the Study

In CBIR, the most commonly used performance measures are precision and recall. Precision is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images, while the Recall is defined as the ratio of the number of retrieved relevant images to the total number of relevant images in the database [12].

Equations of recall (R) and precision (P) are shown as follow:

$$R = \frac{Number\_of\_revelent\_images\_retrieved}{Total\_number\_of\_revelent\_images\_in\_database}$$

$$P = \frac{Number\_of\_revelent\_images\_retrieved}{Total\_number\_of\_images\_retrieved}$$

We choose the database provided by James S. Wang for testing our proposed method. Wang et al., [13] database is an image database where the images are manually selected from the Corel database. In WANG database, the images are divided into 10 classes. Each class contains 100 images. It is widely used for testing CBIR systems. Classification of the images in the database into 10 classes makes the evaluation of the system easy. Our proposed system is implemented using Matlab image processing toolbox.

1.6 Summary

Content-based image retrieval is a technique uses to retrieve image by it is texture or color features. We will use Matlab image processing toolbox to extract the color and texture features, and Wang database for test our proposed method.

We will organize our research in five chapters, Chapter one is introduction which highlight a brief concepts of content-based image retrieval. Chapter two is the literature review and related work, chapter three is about description of the proposed method, chapter four shows the result and discussion, finally Conclusion and recommendation are reported in chapter five.

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Chapter 2

Literature review

Literature review

2.1 Introductions

Content based image retrieval system is the system to retrieve and search for images in images database by its visual content (also named features) such as color, texture, shape and any spatial relationship etc[14-16].

This visual content divide into local and global features, the local visual content descriptor uses the features in region or object from image to describe its visual content where as the global uses the features of the whole image[1].

Due to advanced in web and network that uses a lot of images the CBIR become the hot research area in last decade. There are many application uses CBIR such as economy, crime prevention , medical, academic, government and journalism because its deal with a large scale of image called image database[1].

CBIR is cheap, fast, and efficient over image search methods because it uses image features instead of using image itself[17].

CBIR system have two main steps :

- Preprocessing for image database called image features extraction: The challenge in this step is how extract features which describe the content of image accurately. There are many approaches or technologies proposed for this purpose, dependence on the type of features (color , texture and shape etc.) and on the type of image. More details in section 2.2, 2.3 and 2.4[18-21].

- Measurement of similarity : after extract images features and store it in any store media, the other important step is retrieval image. In this step the interesting query is selected and calculate the similarity between it and the image database. The images have enough similarity comparing with query will be retrieve. Also there are many ways for calculate the similarity, more details in section 2.5[22, 23].

2.2 Content based image retrieval using colors:

Color is the sensation caused by the light as interacts with our eyes and brain , color features are the fundamental characteristics of the content of images. Human eyes are sensitive to colors , and color features enable human to distinguish between objects in the image , colors are used in image processing because they provide powerful descriptors that can be used to identify and extract objects from a scene [24] .

Color feature provide sometimes powerful information about image and they are very useful for image retrieval.[24]

There are many approaches can be used to describe color feature for example colors histogram [25] , color moment [15] and color correlation [15] etc.

Before choosing the appropriate method for extract color features the color space must be determine first.

2.2.1 Color space

Color space or color model is mathematical way to describe color. The color can be presented in three value . as we know the image is group of pixels , each pixel present its color by three values. There are many color models such as

RGB, HSV and CMY etc. in the following some details for above color space examples[1]:

RGB color space : abbreviation for Red, Green and Blue. As we know each color is a mix of the three primary colors(Red, Green and Blue), in this color space each color pixels represented by three value ranging from (0,0,0) to (255,255,255). If the values of all primary colors equal 255 the color is white, and the color is black if the values of all primary colors equal zero. This color model is widely use in image display and as well as television and video etc[1, 26].

HSV color space : the three color components of this color model are Hue, Saturation and Value. The Hue is described with the words we normally thinks of as describing color red ,yellow, white etc. whereas the Saturation refer to prevalence of hue in color. The Value describe the intensity or strength of the light[1, 26, 27], as its shown in the following figure:

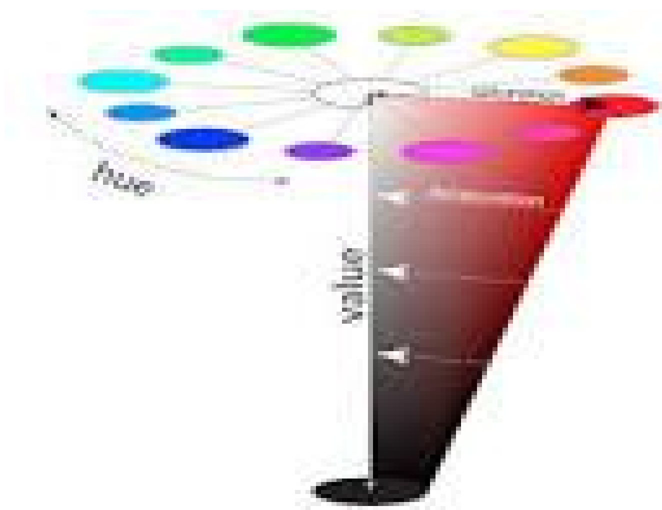


Fig1: saturation/value slices of a specific hue in the HSV model.

This model is widely use in computer graphics and is a more intuitive way of describing color. To convert RGB model to HSV model the following equations will be used[26, 27] :

In first find the maximum and minimum values from RGB. Then

Saturation: S

S= (max-min)/max

And Value: V

V= max

The hue is then calculated as follows. First calculate R' G' B':

$$R' = (max - R)/(max - min)$$

$$G' = (\max - G)/(\max - \min)$$

$$B' = (max - B)/(max - \min)$$

If R= max and G=min

$H = 5 + B'$

Else if R=G and $G \neq$ min

$H = 1 - G'$

Else if G= max and B= min

$H = R' + 1$

Else if G=max and $B \neq$ min

$H = 3 - B'$

Else if R =max

$H = 3 + G'$

Otherwise

$H = 5 - R'$

CMY color space: the three components of this color space are (C= cyan, M=magenta and Y= yellow), this color model widely use in printing . it is very device dependent (such as printer or type of paper)[1, 27].

The converting from RGB to CMY by following equations[27]:

Cyan =1- Red

Magenta=1- Green

Yellow=1- Blue

As we mentioned early there are many color spaces (models) that will be find in references [26, 27].

After we discuss the color spaces (or color models) the controversial question that appears here, what the best color spaces?. There's no color space appropriate for all application. In CBIR the HSV is more appropriate because the Hue is invariant to the change in illumination and camera direction and perceptually uniform and device independent and simple(easy for manipulation). Uniformity means that tow color pairs that are equal in similarity distance in color space are perceived as equal by viewers[1, 17, 27].

There are some other color spaces such as RGB and CMY are perceptually non-uniform and device dependent systems. Also RGB is complex computational because it is need analyzed pixel by pixel and their real combination[17, 19].

After we select the color space (or color model) the approach for extract color features must be determine, as we mentioned at the beginning of this section there are many approaches used by researchers for this purpose, the following are some of them with details.

2.2.2 Color histogram

color histogram is the distribution of color s on an image and the level of their appearance on an image[14, 26]. As we know each pixel in image represented by three components of color in certain color space for example (hue, saturation and value in HSV color space). The color histogram for image is constructed by quantizing the colors which are appear on image and counting the pixels of each color[14, 28]. The quantizing process is reduce the number of colors by putting the very similar colors in the same bins. There are many researcher used this method to extract color features and used it in CBIR.

In paper represented by P.S.SUHSINI and et al[29] , they used three color histograms . Conventional color histogram, invariant color histogram and fuzzy color histogram. Conventional color histogram(CCH) of an image is the distribution of appearance of every color in an image[1]. The simplicity and ease of computation characterized this method. But it's did not take the spatial relationship between bins under account, and did not handle the rotation and translation. To overcome the rotation widely use in object recognition. To extract color features by this method used certain equations will find in this paper[29]. To solve the relationship between bins problem that appear in CCH the Fuzzy color histogram also was used , this method used small number of bins producing by L*a*b* color space [27] into a single histogram by means of Fuzzy expert system , also more details can be find in this paper[29].

By their experimental work they proved the Conventional color histogram with (FG) similarity measure and Fuzzy color histogram with Euclidean distance are similar in their performance, but they did not work well to translated image. The Invariant color histogram given good result in solving the translation problem[29].

This method have some drawbacks, to increase discernment power we need more bins of colors, but the increase color bins that lead to increase the computational cost and represented drawback for building efficient index for image database. And high quality of bins not mean the high quality of retrieval performance in many applications[1, 28].

2.2.3 Color Correlogram

The color Correlogram is not only to describe the distribution color of pixel, but it consider the spatial correlation of colors. As we know, each pixel represented by three dimensional histogram. In this method the first and second are the colors of any pixel pair and the third dimension distance between this pairs colors. Informal definition of color Correlogram is the table indexed by the color pairs. Where the k-th entry for (i ,j) specified the probability of finding a pixel of color j at a distance k from another pixel of color i [1] . color Correlogram is define in[30] as the following :

$$r^{k}i, j = Pr\ (i, j|k)$$

Where the probability of color I occurring in the neighborhood of color j at distance k i.e.

This method known as standard color Correlogram because its assumed the neighboring pixel would be appear either to the lift or the right of reference pixel.

There if the all possible combination of reference pixel pairs are considered the number of color Correlogram well be very large.

This method was used by DEBASHIS and et al[30]. In first they reduced the number of color Correlogram by quantization process, they quantized the colors to six values the modified color Correlogram reduced to size of $O(6^2k)$ [30]. Due to the standard color Correlogram consider the horizontal neighborhood only, in their study they used the directional color Correlogram is used to get complete representation of the spatial distribution of colors in an image. In this case all neighborhoods pixels are considered (8 pixels ≡ two along the horizontal, tow along the vertical, two along the right diagonal and tow along the left diagonal), which was calculated by the following equation:

$$r^{k,}i, j = Pr\ (i, j|k,)$$

Where is the direction, it is have 8 possible values 0° , 45° , 90° , 135° , 180° , 225° , 270° , 315°[30]. In this study the authors applied the method for database contained 90 images and it is divided into three categories H, T, and Z. after the test phase they obtained the result as shown in following table :

Table 1:accuracy of experimental results [30].

Feature used	**H**	**T**	**Z**	**Percentage Accuracy**
Color histogram	2/10	6/10	8/10	53.33%
Standard Correlogram	7/10	10/10	7/10	80.00%
Directional Correlogram	8/10	10/10	7/10	83.33%

From this results the color Correlogram provide best retrieval result , but also need high computational cost due to high dimensionality.

2.2.4 Color moment

color moment is method that characterize the color distribution, color moments can be calculated for any color model. In this method three color moment are computed for each channel[31], this moments are define as the following [1, 31]:

1. The first order (mean) :

   moment (1) : mean

$$E_i = {}^{1}\!/_{N} \sum_{j=1}^{N} P_{ij}$$

2. Moment (2) : standard deviation

$$\sigma_i = \sqrt{\left(\frac{1}{N} \sum_{j=1}^{N} \left((P_{ij} - E_i) * (P_{ij} - E_i)\right)\right)}$$

3. Moment (3) : skewness

$$S_i = \sqrt[3]{\left(\frac{1}{N}\sum_{j=1}^{N}\left((Pij - Ei) * (Pij - Ei) * (Pij - Ei)\right)\right)}$$

This color moment calculated if the value of the i^{th} color channel at the j^{th} image pixel is P_{ij} [32].

Computing color moments for HSV color model give only 9 feature (three for Hue ‘mean, standard deviation, and skewness ‘ ,also three for Saturation and three for values). If the color models contain 4 channels color moments will be 12 features and so on[17, 31].

This method was used previously by Ahmed j.Afifi and et al [17], they used this method in their research, by computed color moments for HSV color model (HSV color model was selected because it is an intuitive system , which describe a specific color by it is hue , saturation , and brightness “value”[24]). In their research they used the Wang database to test their proposed method, this database containing 1000 images and classified into 10 categories (100 images for each).

The color moments method is overcome the quantization effecting in color histogram , and also is very compact (only three moment per color channel) comparing with color histogram and color Correlogram . due to this compactness, it may also lower computational cost needed[1, 17, 31].

In this study we apply color moment based on HSV color space because it is more suitable for CBIR (content-based image retrieval) and it has little vectors dimension and lower computational complexity.

2.3 Content based image retrieval using texture:

Texture is another important property of images can be uses in CBIR or any application deal with image database. It is contain important information about structural arrangement of surfaces and their relationship to the surrounding environment. There is no mathematical definition for texture, it can provides measures of properties such as smoothness, regularity, and coarseness etc. texture can be define semi- periodic patterns with spatial frequency representation. To extract texture features there are several methods was proposed for this purpose. This methods can be classified into two categories : structural and statistical method[17, 33, 34].

Structural method including morphological operator, adjacency graph, and so on. This is method is describe texture by identified structural primitives and their placement. This method more effective when it is use with very regular texture[1, 34].

Statistical method describe texture by statistical distribution of the image intensity. Statistical method including co-occurrence, Fourier power spectra, tamura features, and multi- resolution filtering techniques such as Gabor and wavelet transform[1, 34].

The structural methods are seldom use in CBIR because we cannot guarantee all images or (texture) are regular , but the statistical methods is frequently use and proven more effective in content based image retrieval[1].

In the following we have some representation for some methods which are frequently used in CBIR and proven more effective in this field.

2.3.1 Co-occurrence Matrices features

This method proposed by haralick and et al[36]. this approach explored the gray level spatial dependence of texture. It is first constructed a co-occurrence matrix based on the orientation and distance between image pixels and then extracted meaningful statistics from the matrix as the texture representation[35]. The G×G gray level co-occurrence matrix P_d for a displacement vector $d = (dx, dy)$ is defined as follows. The entry (i, j) of P_d is the number of occurrence of the pair of gray level i and j which are a distance d apart. Formally it is given as [36]:

$$P_d(i, j) = \{((r, s), (t, v)) : I(r, s) = i, I(t, v) = j\}$$

Where (r, s) , (t, v) $N \times N$, $(t, v) = (r + dx, s + dy)$, and □.□ is the cardinality a set.

There are many features proposed by haralick and et al [36]. Can be calculate from co- occurrence. There are some of these features are mentioned in the following table:

Table 2: some texture features extracted from gray level co-occurrence matrix[36]

Texture Feature	**Formula**
Energy	$\sum_i \sum_j Pd^2(i,j)$
Entropy	$-\sum_i \sum_j Pd(i,j) log Pd(i,j)$
Contrast	$\sum_i \sum_j (i-j)^2 Pd(i,j)$
Homogeneity	$\sum_i \sum_j \frac{Pd(i,j)}{1++i-j}$
Correlation	$\sum_i \sum_j (i-\mu)(j-\mu) Pd(i,j)/\sigma\sigma$

Where μ□ and μ□ are the means and σ□ and σ□ are the standard deviations of $P_d(x)$ and $P_d(y)$, respectively. Where $P_d(x) = \sum_j Pd(x,j)$ and $P_d(y) = \sum_i Pd(i,y)$.

There are many researchers used this approach in CBIR field. For example in paper was presented by Mrs. Smita jawale[37], she was used this method and Gabor wavelet transform to extract texture features from image. She used co-occurrence by find the co-occurrence matrix from given image in first then the Energy, Entropy, contrast and homogeneity were calculated. She obtained good result by using co-occurrence but not enough so she was improved her project by combined it with Gabor wavelet transform.

The co occurrence matrix features have some difficulties such as it need high computational cost and due to it have a large number of features can be calculated from the co- occurrence matrix we need to sort the relevant features[36, 37].

2.3.2 Gabor filter features

The Gabor filter has been widely use in to extract image texture features[1]. Basically Gabor filters are group of wavelets with each wavelet capturing energy at specific scale (frequency) and specific orientation (direction). From a localized frequency description obtained from expanding a signal the local features (energy) of the signal can be capturing. Then the texture features can be extracted from this energy distributions. The scale and orientation tunable property of Gabor filter makes it especially useful for textural analysis[37-39]. A two dimensional Gabor function g(x,y) is defined as[1, 39]:

$$g(x, y) = \frac{1}{2\pi\sigma\sigma} \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma^2} + \frac{y^2}{\sigma^2}\right) + 2\pi jWx\right]$$

Where σ□ and σ□ are the standard deviation of the Gaussian envelopes along the x and y direction. After applying Gabor transformation on the image with different orientations at different scales the following array of magnitudes can be obtained [38, 39]:

$$E(m, n) = \sum_{x}\sum_{y} |Gmn(x, y)|$$

Where m= 0,1,……,M-1 and n=0,1,…...N-1

These magnitudes represent the energy content at different scale and orientation of the image.

The mean and standard deviation of the magnitudes can be calculated in order to identify the homogenous texture features of the image. The feature vector constructed from these mean and standard deviation which calculating from magnitudes (the features number dependent on number of scaling and number of orientation) . mean μ_{mn} and standard deviation σ_{mn} are calculated by following equations[38]:

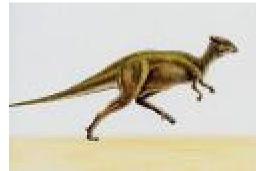
$$\mu_{mn} = \frac{E(m,n)}{P \times Q}$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (|Gmn(x,y)| - \mu mn)^2}}{P \times Q}$$

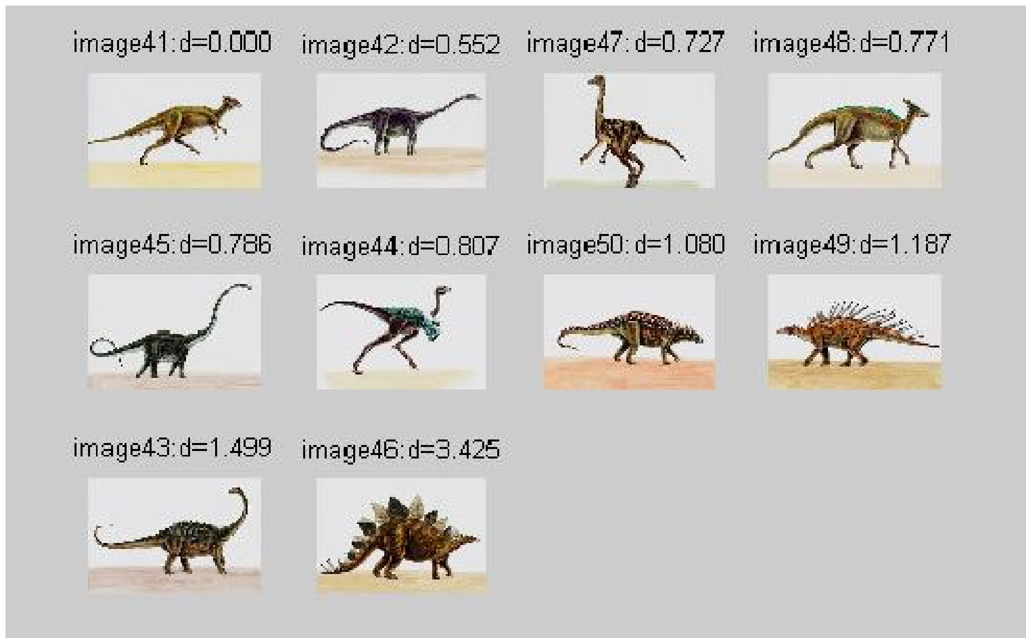
Where P and Q are the image size.

As we early mentioned this approach is widely uses to extract image features, specially the texture features which consider the important features can be uses in the CBIR field[37-39]. For example S.Mangijao Singh and et al[40] , was used this method in their CBIR system. In first they applied Gabor filter on the image with 4 scales and 6 orientation then they obtained an array of magnitudes, then calculated the mean μ_{mn} and standard deviation σ_{mn} of the magnitudes to create a texture features vector f_g of length 48. The similarity between query and other Gabor features in the dataset was measured by Canberra distance. The performance of the retrieval system was measured by precision and recall.

In their experimental result the obtained 43.6% as average precision. The following figure shown the query and the result based on Gabor texture features[40]:



(a)



(b)

Fig 2: (a) query image. (b) Result based on Gabor texture feature.

This approach has a spatial property that is similar to mammalian perceptual vision, thereby providing researchers a good opportunity to use it in image processing[41].

Gabor filters are found to perform better than wavelet transform and other multi-resolution approaches in representing textures and retrieving images due to its multiple orientation approach.

2.3.3 Tamura features

This is also is statistical method. Tamura et al[1]. proposed a texture representation on six statistical features based on human visualization and explored the feature representation from a different angle. Including coarseness, contrast, directionality, line-likeness, regularity, and roughness. These features considered to be most visually meaningful[42, 43]. The first three features has been widely used and realize good result. There we have some review for these features:

Coarseness has direct relationship with to scale and repetition rate . it is use to measure differences between coarse and fine textures. To measures coarseness we can follow this steps[44, 45] :

I. At each pixel (x,y), of input image compute the averages over the neighborhood, which size are $2^k \times 2^k$ (k=0,1,…,5)

$$Ak\,(x\,,\,y) = \frac{\sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} g(i,j)}{2^{2k}}$$

Where g (i,j) is the pixel intensity at (i,j).

II. At each pixel compute differences between pairs of averages of non-overlapping neighborhoods on opposite side of the pixel in horizontal and vertical direction.
horizontal case:

$$E_{k,h}(x,y)=|A_k(x+2^{k-1},y)-A_k(x-2^{k-1},y)|$$

Vertical case:

$$E_{k,v}(x\,,\,y) = |A_k(x\,,\,y+2^{k-1})-A_k(x\,,\,y-2^{k-1})|$$

III. At each pixel compute the size, that gives highest output value when considering all direction together . average of these values over the whole image will be the coarseness measure Fcrs for input image.

Contrast is measures how grey levels vary in the image and to what extent their distribution is biased to black or white. Contrast F_{con} can calculating by the following equation[1] :

$$F_{con} = \sigma / \alpha_4^{1/4}$$

Where the kurtosis $\alpha_4 = \mu_4/\sigma^4$ is fourth moment about the mean, and σ^2 is the variance.

Directionality: Degree of directionality is using the frequency distribution of oriented local edges against their directional angles. First for each pixel the local edge direction □ is calculating by following formula[1, 45]:

$$\square = \tan^{-1} \Delta_V / \Delta_H + \frac{\pi}{2}$$

where Δ_H and Δ_V are horizontal and vertical derivatives respectively. They can be calculated as the convolution of input image with the following 3×3 operators:

-1	0	1
-1	0	1
-1	0	1

1	1	1
0	0	0
-1	-1	-1

□ values are then used to form 16 bin histogram. Then use the sum of the second moment around each peak from valley to valley, to get F_{dir} [45].

In this method the most of researcher used the first three features (coarseness, contrast, and directionality). this method have high error rate in CBIR for features extraction, and give low precision as well as its high computational cost[46].

2.4 Content based image retrieval using shape:

Shape is one of the most important visual attributes in an image. Shape of features play important role in CBIR. the methods can be used to describe the shape are dividing into two main categories : Boundary-based methods (rectilinear shapes, finite element models and Fourier –based shape descriptor etc,) and Region-based methods (statistical moment). the shape features to provide good description of an object shape should be invariant to translation, scaling and rotation. Due to the shape usually described after image have been segmentation into regions or objects, the shape features is more suitable to application which the regions or objects can be easily available. Accordingly accurate segmentation form another challenge[47-50].

In this section have briefly description for some techniques that can be used to extract shape features.

2.4.1 Turning angles

The contour of 2D region can be represented as a sequence of coordinates (x_s , y_s) , where s=0, 1,…., N-1 and N is total number of pixels on the boundary. The turning angle function of a contour s is defined as the angle, which measured in counterclockwise targets as a function of the arc-length S according to a reference point on the object contour , can be defined as:

$$\square(s) = \tan^{-1}(y'_s/x'_s)$$

$$y'_s = dy_s/ds$$

$$x'_s = dx_s/ds$$

The main drawback of this method is variant to the rotation of object and the choice of the reference point. When the reference point is shifting by an amount l and some the rotation happen by angle r the amount of shift and angle of rotation must consider then new function become $\square(s+l)$ and $\square(s)+r$[1, 51].

2.4.2 Circularity, Eccentricity, and Major Axis Orientation

Circularity is computed by as:

$$\boldsymbol{\alpha = \frac{4\pi S}{P^2}}$$

Where S is the size and p is the perimeter of an object. The major axis orientation can define as the direction of largest eigenvector of the second order covariance matrix of a region or an object. The α value ranges between 0 and 1.

2.5 Similarity and Dissimilarity measures:

Similarity measurement (or dissimilaty) plays very important role in content-based image retrieval (CBIR). In CBIR system each image is represented as a vector of features derived from color, shape, and texture information. When the query is selected to retrieve it from dataset, the similarity (or dissimilarity) between a user provided image (query) and those pre-stored in the database is computed and compared to report a few of most similar images[22, 52].

If we have two sequences of measurement $X= \{X_i : i =1...N\}$ and $Y= \{Y_i : i = 1...n\}$, the similarity (dissimilarity) between them is a measure that quantifies the dependency (independency) between the sequences.

A similarity measure S is considered a metric if it produced a higher value as the dependency between corresponding values in the sequences increases. A metric similarity S satisfied the following[53] :

- limited range : $S(x,y) <= S_0$, for some arbitrarily large number S_0.
- Reflexivity: $S(x,y) = S_0$ if and only if x=y.
- Symmetry: $S(x,y) = S(x,y)$.
- Triangle inequality: $S(x,y) S(y,z) <= [z(x,y) + S(y,z))] S(x,z)$.

A dissimilarity measure D is considered a metric if it produces a higher value as corresponding values in X and Y become less dependent. A metric dissimilarity D satisfies the following for all sequences X and Y[53]:

- Non-negativity: $D(x,y) >= 0$.
- Reflexivity: $D(x,y) =0$ if and only if X=Y.
- Symmetry: $D(x,y) = D(y,x)$.
- Triangle inequality: $D(x,y) + D(y,z) >= D(x,z)$.

These measures are insensitive to radiometric changes in the scene or invarint to sensor parameters are often not metrices. There are many measures that are used to measure the similarity and dissimilarity, in the following the brief review for some of it.

2.5.1 Euclidean distance

The Euclidean distance between x,y $\in R^d$ is computed by[54]:

$$S_1\,(x, y) = \; x - y_2 = \sqrt{\sum_{j=1}^{d}(x-y)\text{^}2}$$

A similar measurement called the cityblock distance, which takes fewer operations, is computed by :

$$T^1(x, y) = x - y_1 = \sum_{j=1}^{d} x - y$$

A nother distance measurement called the supreme norm, is computed by:

$$T_2(x, y) = max1 \leq j \leq d|x - y|$$

2.5.2 Mahalanobis Distance

The Mahalanobis distance between two vectors x and y with respect to the training patterns x_i is computed by[11]:

$$S^2(x, y) = \sqrt{(x-y)^{t}\, S^{-1}\,(x-y)}$$

Where the mean vector **u** and the sample covariance matrix S from sample $\{x_i \mid 1 \leq i \leq n\}$ of size n are computed by: $S = \frac{1}{n}\sum_{i=1}^{n}(x-u)(x-u)$ with $u = \frac{1}{n}\sum_{i=1}^{n} x$.

This measures approprate when each dimenthion of image features vector is dependent of each other and is of different importance.

Chapter 3

Methodology and Tools

Methodology and Tools

3.1 Introduction

As we mentioned earlier the content based image retrieval system is technology for search in the image database by it is visual content such as color, texture and shape features.

This study use the color features and texture features to retrieve image from data base. Shape features was disregarding because extraction of this features is high computational complexity .

The color is powerful descriptor of image and easy to extract it is proprieties from image, texture features is another important features describe the image content and also easy to extract.

Due to the use of one attribute not accurate for retrieval we combine the color and texture features to improve the retrieval accuracy.

3.2 Research Framework

In this work the attributes (color and texture) are extracted directly from the image using color moment and Gabor filter transform, as will explain in Section 3.3 and 3.4 respectively. Then the retrieval process is based on similarity between visual content of selected query and image database. The main idea of CBIR represented in following figure:

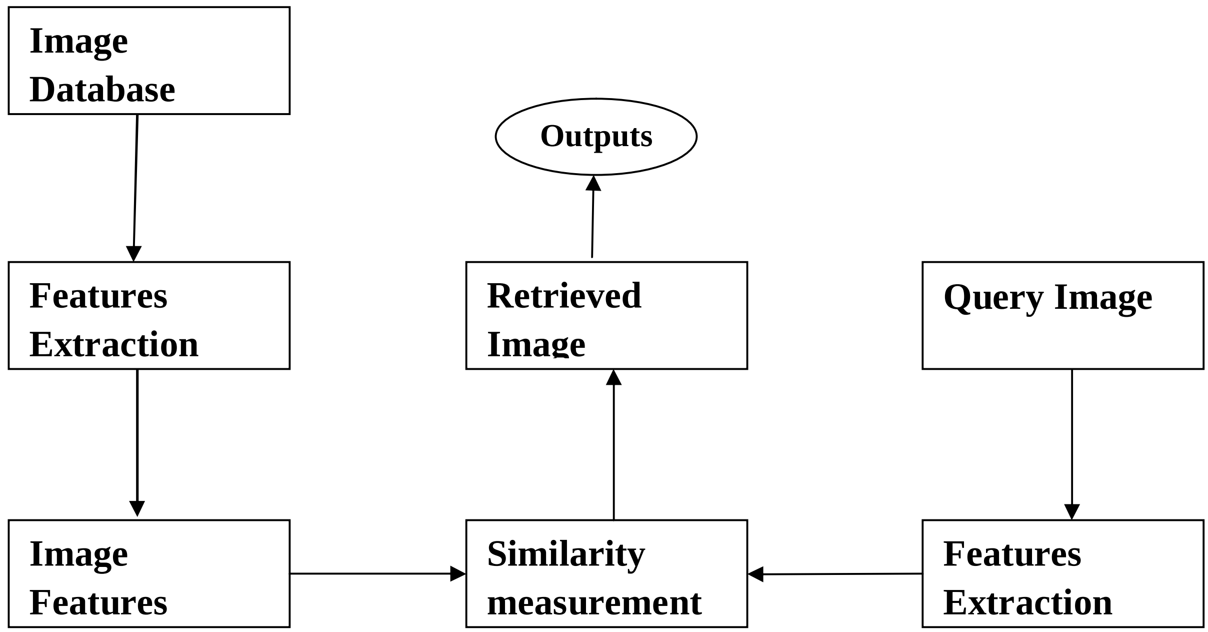


Fig 3. Framework of a CBIR system based on features extraction.

3.3 Features Extraction

Features extraction can be considered the main and important stage in CBIR system . The extract ideal content that describe veritable content of an images is still a challenging problem in the content based image retrieval system.

In our proposed algorithm we need to extract the feature for both color and texture.

3.3.1 Color features extraction

The color is most important features describe the content of the images. Due to it have less computational complexity the color features is widely used in the CBIR system. As we mentioned in literature the color is represented in form of tuples (generally of three) this represent known as color model. There are many color models used in computer vision , such as RGB (red , green , blue) model and HSV (hue , saturation , value) model etc. In this work we extract the color features automatically by using color moment function. This approach it is simple to use and given the more effective features.

In this method (color moment), first we select color space (color model) and use their properties in features extraction. Due to RGB color model is perceptually non-uniform and it is have complex computational because it need analyze the image pixel by pixel the HSV model is more suitable for calculating the color moment. For this purpose we used RGB to HSV conversion function, this function convert the RGB image to HSV image by the following syntax:

A= rgb2hsv(S).

A≡ RGB image.   S≡ HSV image.

After we convert the image to HSV color space we obtain matrices represented the image in HSV color space. From this matrices we calculate the color moment for the HSV (hue , saturation , value) by the following equations :

1. The first order (mean) :

   moment (1) : mean

$$Ei = {}^{1}/_{N} \sum_{j=1}^{N} P_{ij}$$

2. Moment (2) : standard deviation

$$\sigma i = \sqrt{\left(\frac{1}{N} \sum_{j=1}^{N} \left((Pij - Ei) * (Pij - Ei)\right)\right)}$$

3. Moment (3) : skewness

$$S_i = \sqrt[3]{\left(\frac{1}{N} \sum_{j=1}^{N} \left((Pij - Ei) * (Pij - Ei) * (Pij - Ei)\right)\right)}$$

Where P_{ij} is the color value of the i-th color component of the j-th image pixel and N is the total number of pixel in the image .

After the implementation of these equations we obtained the vector constructed from nine values for each image.

The main advantages for color moment are compact and robust but it has some disadvantage such as not enough to describe all colors and no spatial information. The process of color features extraction is shown in figure 4:

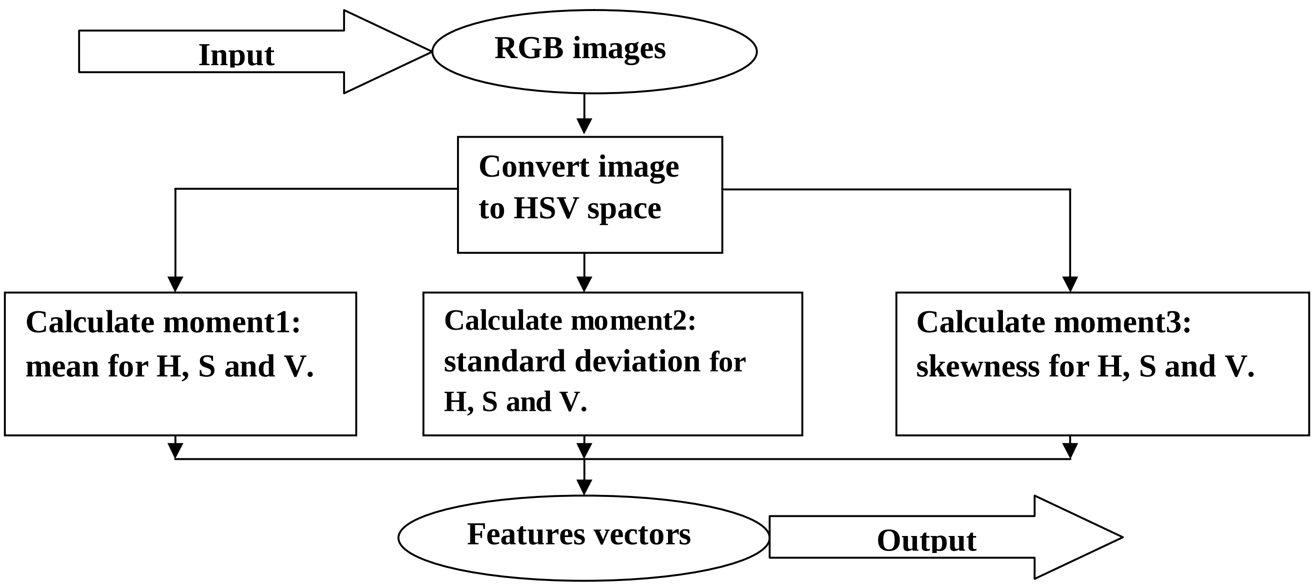


Fig 4. Color features extraction from image.

3.3.2 Texture features extraction

Texture feature is another important feature describe content of an image. In this study the texture feature is homogenous of texture which is extracted by 2D Gabor filter. Gabor filter is function to extract texture features from image in grayscale at different scaling and different rotation. for a given image g(x,y) with size M×N, its discrete Gabor wavelet transform is define as following equation:

$$g(x,y) = \frac{1}{2\pi\sigma\sigma}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma^2}+\frac{y^2}{\sigma^2}\right)+2\pi jWx\right]$$

Where σ□ and σ□ are the standard deviation of the Gaussian envelopes along the . x and y direction.

In this study Gabor filter is applying with 4 scaling and 4 rotation, after convert image to grayscale (because the Wang database is used in this study and its images is RGB images) after applying this function with these scaling and rotation the magnitudes array can be obtained which is define as follow:

$$E(m,n) = \sum_{x}\sum_{y}|Gmn(x,y)|$$

Where m= 0,1,……,M-1 and n=0,1,…...N-1

These magnitudes describe the energy content at 4 scales and 4 rotation of the image.

The number of magnitudes dependent on the number of scales and number of rotations (equal number of scaling multiplying by the number of rotation), so there are 16 magnitudes arrays can be obtained. To describe the homogenous texture, the mean μ_{mn} and standard deviation σ_{mn} of the magnitudes of the transformed coefficients are calculating by the following equations:

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

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (|Gmn(x,y)| - \mu mn)^2}}{P \times Q}$$

Where P and Q are the image size.

A feature vector **F** (texture representation) is constructed by using mean and standard deviation. The mean and standard deviation are the component of feature vector in this study with four scales and four rotations the feature vector **F** is has 32 components define as following :

$$\mathbf{F} = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots\ldots., \mu_{47}, \sigma_{47})$$

The process of texture feature extraction is shown in figure 5.

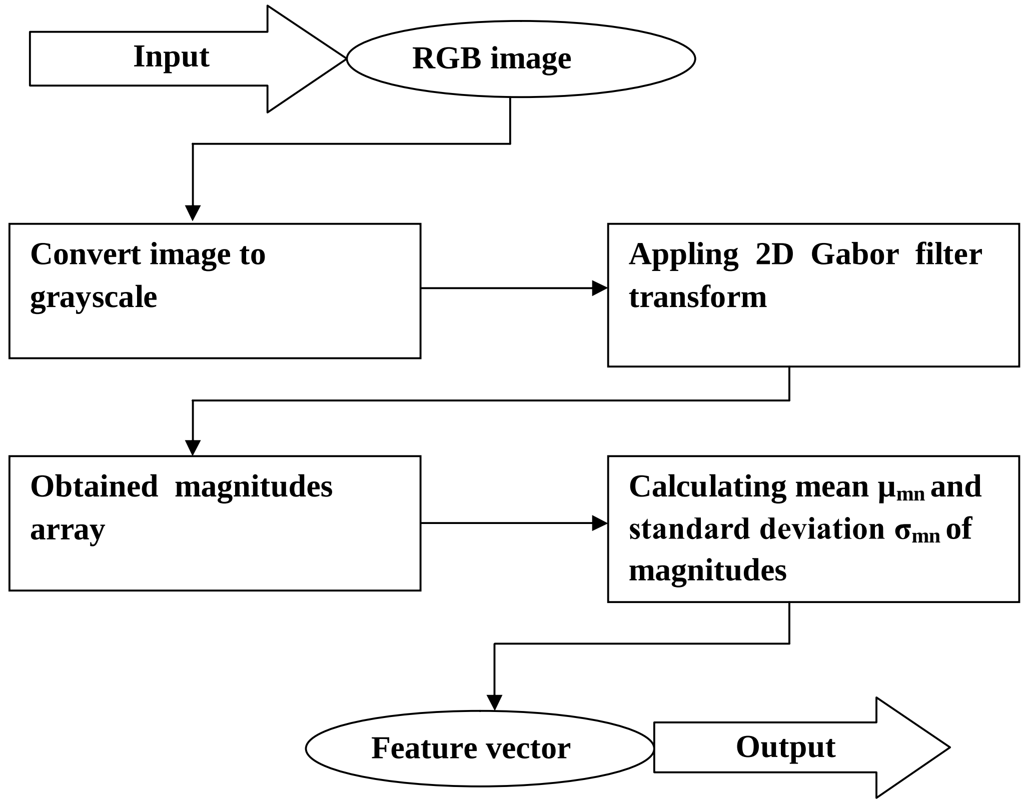


Fig 5. Texture features extraction from an image.

3.4 Similarity Calculation and performance evaluation:

in this study after the features (color and texture) are extracted, the similarity is appear as important step at this stage. A query from determined class of database is selected and deleted from the database, the similarity between this query and the remaining of database is calculated based on Euclidean distance as the following:

$$S_1(x, y) = \|x - y\|_2 = \sqrt{\sum_{j=1}^{d}(x_j - y_j)^2}$$

When the similarity is calculated many image will retrieve. then the performance must be evaluate. In this research the evaluation of performance by calculated the precision and recall.

Precision is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images, precision (P) is calculated by the following :

$$P = \frac{Number\_of\_revelent\_images\_retrieved}{Total\_number\_of\_images\_retrieved}$$

while the Recall is defined as the ratio of the number of retrieved relevant images to the total number of relevant images in the database, recall (R) is calculated by the following:

$$R = \frac{Number\_of\_revelent\_images\_retrieved}{Total\_number\_of\_revelent\_images\_in\_database}$$

In this study the evaluation of performance is testing by the following methods:

- Color features based retrieval method: retrieve images based on color features and calculate the precision for top 10, 20, and 50, then calculate the mean similarity for each class.

- Textual features based retrieval method : retrieve images based on texture features and calculate the precision for top 10, 20, and 50, then calculate the mean similarity for each class.

- Fusion based retrieval method: data fusion is merging the retrieval results of multiple systems, a data fusion algorithm accepts two or more ranked lists and merges these lists into a single ranked list with the aim of providing better effectiveness than all systems used for data fusion. The method used here is CombMEAN fusion approach, Finally Calculate the precision for the fusion of color and textures features, also we calculate the average of top 10, 20 and 50. In this method the mean of the scores from the previous two retrieval methods is calculated, then the precision for the top 10, 20, and 50 is considered and the average similarity is calculated for each class. The process of similarity calculate is shown in figure 6.

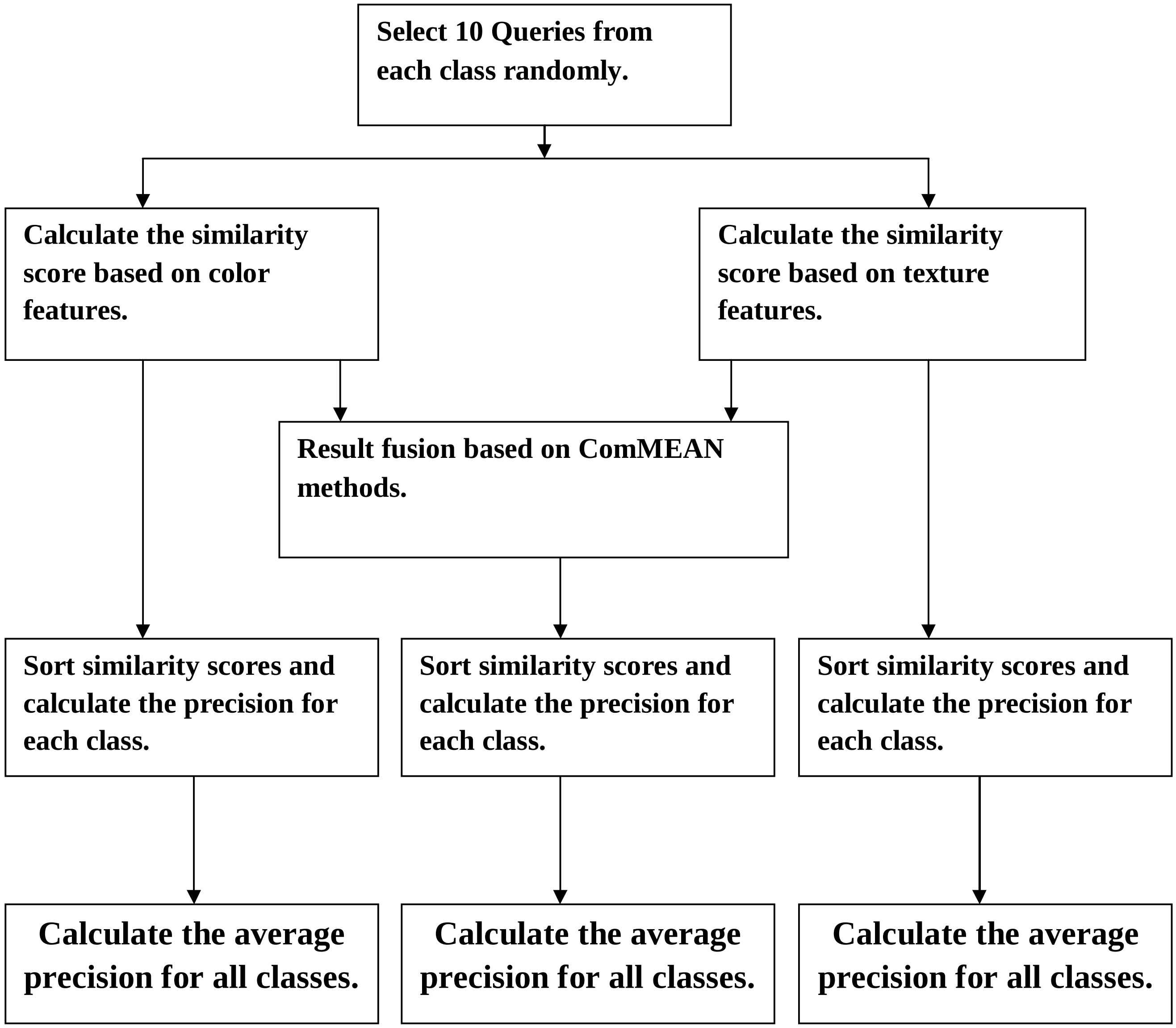


Fig 6. Similarity Calculation based on color, texture and fusion methods.

3.5 Dataset

3.5.1 Wang data base

The image database used in this study presented by James S. Wang[13]. It is subset of 1,000 images of the Corel stock database which have been manually selected and numbered from 0 to 999, and which divided into 10 classes of 100 images each. This classes are constructed as follows:

Table 3. The classes of WANG database.

class No	Class name	Class range
1	Africans	From 0 to 99 images
2	Beaches	From 100 to 199 images
3	Buildings	From 200 to 299 images
4	Buses	From 300 to 399 images
5	Dinosaurs	From 400 to 499 images
6	Elephants	From 500 to 599 images
7	Flowers	From 600 to 699 images
8	Horses	From 700 to 799 images
9	Mountains	From 800 to 899 images
10	Foods	From 900 to 999 images

This classes are used to evaluate our proposed method by select the query from any class and assumed the 99 residual images of the same class are relevance to the query and the all images in the other classes are irrelevance of the query.

Fig 7. Examples images from the Wang database (one image from each class).

This database can be considered similar to common stock photo retrieval tasks with several images from each category and a potential user having an image from a particular category and looking for similar images which have e.g. cheaper royalties or which have not been used by other media.

The dimension of all images in this database is 384 x 256 , and it is JPG types which considered one of the best format in term of modern lightness and small size of the file

2.5.2 Matlab Image Processing Toolbox

The Image Processing Toolbox (IPT) is a collection of functions that extend the capability of the MATLAB ® numeric computing environment. The toolbox supports a wide range of image processing operations, including:

- Geometric operations
- Neighborhood and block operations
- Linear filtering and filter design

- Transforms
- Image analysis and enhancement
- Binary image operations
- Region of interest operations

All experiments in this study were implemented using IPT of Matlab.

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Chapter 4

Results and discussion

Result and discussion

4.1 Introductions:

In this chapter three retrieval methods or approaches are examined. The first approach is image retrieval method based on color features, the second approach is textual features based image retrieval and the last approach is an enhancement method based on CombMEAN fusion method. The following section describes the results obtained of these approaches. Furthermore, our proposed method results was compared with similar previous study proposed by Ahmed j.Afifi et al (2012)[11].

4.2 Result of proposed method:

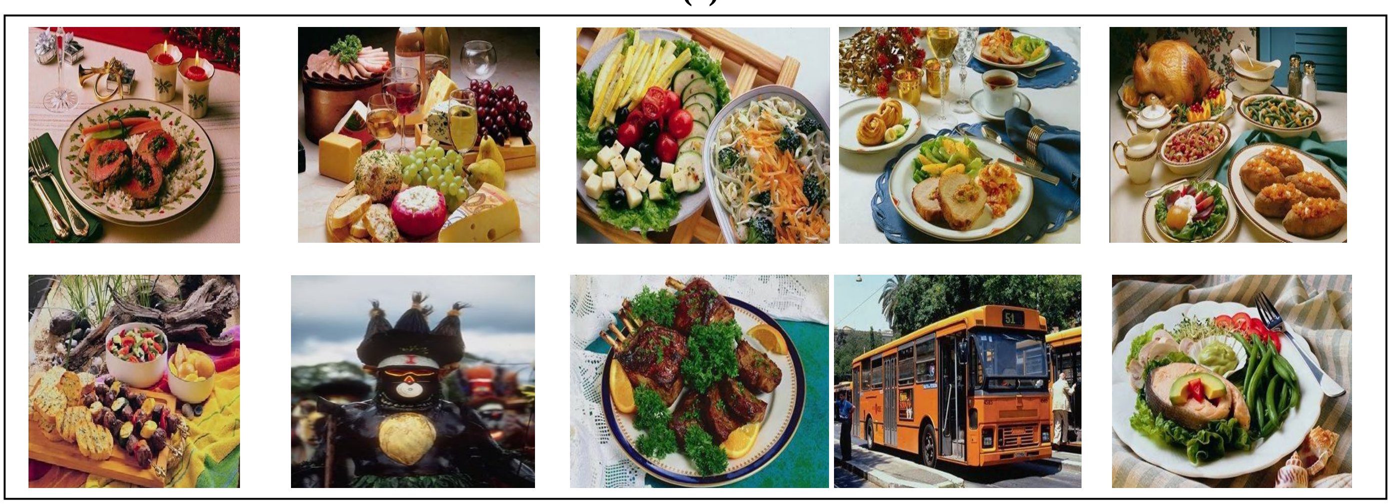
Table 4: Retrieval Results based on different retrieval methods

	Based on color		**Based on texture**		**Based on fusion**	
Class name	**Top 10**	**Top 20**	**Top 10**	**Top 20**	**Top 10**	**Top 20**
Africans	0.48	0.47	0.4	0.36	0.6	0.52
Beaches	0.3	0.21	0.18	0.14	0.12	0.12
Building	0.24	0.23	0.38	0.26	0.44	0.36
Buses	0.42	0.42	0.78	0.75	0.68	0.58
Dinosaurs	1	0.99	0.92	0.86	1	0.98
Elephants	0.5	0.47	0.44	0.35	0.8	0.62
Flowers	0.66	0.53	0.44	0.46	0.72	0.76
Horses	0.76	0.52	0.32	0.31	0.76	0.68
Mountains	0.44	0.42	0.22	0.24	0.6	0.46
Foods	0.66	0.54	0.62	0.43	0.84	0.68
Shaded cells	**2**	**0**	**2**	**0**	**7**	**1**
Mean Similarity	**0.546**	**0.48**	**0.47**	**0.416**	**0.656**	**0.576**

Taking into account the mean similarity in Table4, it is clear that our proposed method based on fusion of color and texture outperformed the other two methods based on color and texture, The mean similarity for fusion method are (0.656 and 0.576 for top 10 and top 20 respectively) while the mean similarity for color and texture methods are (0.546 and 0.47) for top 10 and (0.48 and 0.416) for top 20 respectively. In addition, some classes have high precision because it's images have simple contents while the other classes have low precision because it's images have complex contents. Furthermore, shaded cells show the high or maximum similarity value of each among all method in different top values, our proposed method has seven good values out of ten while color and texture have two out of ten.

Figure (8) below illustrates the top 10 images retrieved from class Ten based on fusion based image retrieval method. The figure shows that eight correct images out of total top 10 images were retrieved correctly.

(a)



(b)

Fig 8: (a) Query. (b) Result retrieval based on fusion methods.

4.3 Comparison between proposed method and previous study:

Table 5: Proposed method results compared with Ahmed j.Afifi et al. (2012) [11] on top 10 retrieval.

	Based on color		**Based on texture**		**Based on fusion**	
Class name	**Proposed method**	**j.Afifi et al (2012)**	**Proposed method**	**j.Afifi et al (2012)**	**Proposed method**	**j.Afifi et al (2012)**
Africans	0.48	0.301	0.4	0.212	0.6	0.6
Beaches	0.3	0.223	0.18	0.286	0.12	0.7
Building	0.24	0.215	0.38	0.311	0.44	0.8
Buses	0.42	0.276	0.78	0.269	0.68	0.7
Dinosaurs	1	0.656	0.92	0.361	1	0.7
Elephants	0.5	0.261	0.44	0.224	0.8	0.5
Flowers	0.66	0.317	0.44	0.386	0.72	0.7
Horses	0.76	0.42	0.32	0.244	0.76	0.5
Mountains	0.44	0.254	0.22	0.214	0.6	0.5
Foods	0.66	0.221	0.62	0.211	0.84	0.4
Shaded cells	**2**	**0**	**1**	**0**	**7**	**3**
Mean Similarity	**0.546**	**0.314**	**0.47**	**0.2718**	**0.656**	**0.61**

From Table 5 above, our proposed methods work well compared with the previous study, based on mean similarity, our proposed method (0.546, 0.47 and 0.656) for retrieve based on color, texture and fusion respectively. While the mean similarity of previous study (0.314, 0.2718 and 0.61) based on color, texture and fusion respectively. In addition, if we consider the shaded cells, our proposed method has seven high values out of ten.

Finally, there are some weak results appear in this study such as results of class beaches and buses because the dominant color of these classes is very similar of the dominant color of most of the database, and their texture features is very complex. To overcome these drawbacks other for features extraction can be used and tested, also other attributes can be considered such as shape to improve these results.

Chapter 5

Conclusion and Recommendation

Conclusion and Recommendation

5.1 Conclusion

Although CBIR has been a very active research area in the recently decades, many challenges are issued because of the complexity of images data. Many researches have been done to develop some algorithms that solve some problems and achieve the accuracy when retrieving images and distinguishing between them. Many proposed algorithms use images to extract features and use their features for similarity matching. However, most of the algorithms use the grayscales images.

This study implemented CBIR system that uses the combination of HSV color moment features and Gabor texture features. This method implemented on the WANG image database. Experimental results for ten class images showed the combination of color and texture features has higher retrieval accuracy than used only color or texture features.

Also this method approved the presented images by its features need size of storage media less than use the images itself.

5.2 Recommendation and future work

In this study the texture features extracted by Gabor function and color extracted by color moment, there are many other methods to extract color and texture. Those methods can be tested and used. Also the low mean values of some classes in this study can be improved by consider additional attribute such as shape.

In future work, in addition to color and texture, another attributes can be use such as shape which consider the special relationship between pixels. Lastly, GUI and web-based application can be developed and added to this work.

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