Available online at www.dergipark.org.tr/en

INTERNATIONAL ADVANCED RESEARCHES and ENGINEERING JOURNAL

e-ISSN: 2618-575X

Journal homepage: www.dergipark.org.tr/en/pub/iarej

International Open Access

Volume 05
Issue 01

April, 2021

*Review Article*

# An analysis of content-based image retrieval

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ARTICLE INFO

*Article history:*
Received 20 October 2020
Revised 02 February 2021
Accepted 12 February 2021

*Keywords:*
Content-Based Image Retrieval (CBIR)
Feature Eextraction
Performance measure
Shape
Texture
Tamura
Wavelet transform

ABSTRACT

Nowadays, working on digital images is gaining much popularity in multimedia systems, due to the rapid increase in the utilization of large image databases. Thus, the Content-Based Image Retrieval (CBIR) method has become the most valuable method for these databases. This study mainly focuses on content-based image retrieval; which uses image features like color, shape, texture, etc. by searching the user query image from a large image database based on user request. CBIR is the most widely used technique as its searching capability is faster than the other traditional methods, and it works well in retrieving images automatically. It is also a big alternative approach to traditional methods. The CBIR techniques are used in many applications like surveillance detection, crime avoidance, fingerprint identification, E-library, medical, historical monument and biodiversity information systems, and many more. A total of 38 CBIR articles were comparatively analyzed.



## 1. Introduction

Content-based image retrieval (CBIR) also known as Content-Based Visual Information Retrieval (CBVIR) or Query by Image Content (QBIC), is a method for solving image retrieval problems that employs computer vision methods. Content-based image retrieval is conflicting with conventional knowledge of conceptual approaches.

Content-based is searching and analysis of different image features. It is a kind of metadata that takes the information of the image with the help of different tags, keywords, or descriptions of the image. The word content of CBIR refers to color, shape, texture, or some other information that is useful for the image description. Searching on metadata depends on consequent choice and completeness. In other words, users manually search a query image by entering keywords in a very large database which takes a long time. The users are also not able to analyze the right query information about an image. This assessment for retrieving the effective information from an image is not well defined. So the CBIR method is used effectively and efficiently which faces similar challenges.

The content-based image retrieval system has two basic challenges: first is the intention gap and the second is the semantic gap. In the intention gap, related difficulties of users are the suffering to precisely express the image content by a query, like an image or a sketch map. The semantic gap is related to the origin of the problem which is used to describe the tall height image features with the semantic concept of short height image features [1 - 3].

Content-based image retrieval, introduced in 1992 by T. Kato, explains the experimental method to retrieve image features like color or shape features from the huge image database automatically. The content-based term used here describes the method of obtaining images from a image features database, with various methods, tools, and algorithms that are designed to develop the areas like statistical methods, object detection, pattern recognition, and computer vision, etc.

In the early 1920s, some new research methods in CBIR are introduced. Especially, two types of research are in progress to the present-day for retrieving the

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DOI: 10.35860/iarej.811927

images from the large multimedia databases. In the primary research, the local image feature of Scale Invariant Feature Transform (SIFT) is contented [4]. SIFT is an image feature detection algorithm that detects and describes local features. The "Bag of Visual Words" (BOW) model [5] is used in secondary studies. The BOW model makes a powerful summary of demonstration or illustration of images based on the quantization of the restricted local features and promptly modifies the characteristic of file indexing of an organization for image retrieval. A recent Literature survey on multimedia content-based image retrieval is presented as a reference in this study [6 - 29].The general contribution of this study was to explain and analyze the collection of CBIR works with their details for the readers.

The manuscript is organized as follows;section 2 is a literature review, sections 3and 4 explain Image Retrieval Techniques and Content-Based Image Retrieval Techniques, section 5 presents Content-Based Image Retrieval Methods. Section 6 and 7 explain Distance Measurements and Performance Evaluation. Finally, sections 8 and 9 present “Results and Discussions” and Conclusions.

## 2. Literature Review

The research by Yue et al. [30] focuses on color and texture low-level characteristics extracted from CBIR. These two types of features are based on a co-occurrence matrix to extract image features to form the feature vectors after being used in a global color histogram, local color histogram, and texture features which are examined by CBIR. After feature extraction, it calculates the Euclidean distance measurements to find the images. CBIR methods are designed by applying color and texture fused features with the help of weight constructions of feature vectors. The process of retrieving the experiments by showing the combination of features is retrieved by bringing an enhanced illustration of the single feature. This proceeds to a superior retrieve outcome. The whole work is done on Java Eclipse enlargement atmosphere and SQL server 2005 is used as the database system.

Singh et al. [31] in their study, solve the content-based image retrieval in energetic surroundings with address problems. It focuses on implementing a new structure that is capable of search and correct features to examine the new query images that improve retrieval accuracy and to make it more effective. It works on the Fuzzy C-Means (FCM) algorithm that generalizes the hard C algorithm. It is produced as a soft panel in a set database. The invariant array vector of images is extracted using a feature extraction tool such as Fast Fourier Transform in this research. Aside from the HSI component of the color image, the resulting array vector is used as a first feature vector after image segmentation, and then a second feature vector is used. The study proposed an algorithm on 100 tested different images and produce a better performance as compared to the traditional method of CBIR.

Alsmadi[32] developed in his study, a novel relationship between the evaluation of a heuristic algorithm known as a memetic algorithm (Genetic algorithm with a great deluge) to achieve features of the target image and the train image. It comprises of Gradient Descent (GD) algorithm with a Genetic algorithm (GA). It also increases the quality of weights (solution) by increasing the fitness function (number), which helps in the process of searching. Hence, it tests comparable images that are retrieved from a large image database and the calculated results work as a measure of average precision and recall rate performance. Filtering processes can be used in the CBIR in the future to provide more precise results.

Ahamed et al. [33] focus on accessible CBIR system limitations like bandwidth requirement, data security, and storage space, to defeat these limitations. A new technique, CBIS prediction Errors, (CBIR-PE), is presented that uses to rectify errors instead of actual images for storage, transmission, and retrieval. It proposes new techniques that are based on groupings like the clustering technique called WBCT-FCM, WBCT, and FCM. The performance of the proposed WBCT-FCM and CBIR-PE are evaluated using the COREL-1k database. After testing, results are much better as compare to the traditional clustering technique. It retrieves better accuracy as compared to the existing methods.

Saeed et al. [34] proposed a new technique of edifice feature vector to represent images for clustering. It consists of 140 elements which take different features such as color histogram, color moments, Gabor filters, GLCM matrix, etc. It works implicitly on the core database which contains 1000 colored images.

In the study of Joshia et al. [35], the results are deployed from binary and grayscale image retrieval. It is detected by descriptors for color IRS, while it does not detect perfect query. It uses the KCOLavg descriptor, which eliminates the combination given by three colors and considers the average color contribution in the background. Therefore, it does not give a better efficient descriptor in color images. Hence, the study of the intuitive descriptor gives a better output.

Sharma et al. [36] focus on feature extraction and homogeneous attribute measures, utilizing a pyramid that is prepared on wavelet decay and energy level calculations. These energy levels are equivalent to the manipulative distance between the target image and the training images. A substantially huge image database from the Brodatz album is applied for retrieval claims. The investigational report shows that the prep underrating of Canberra, Bray-Curtis, Square chord, and Square Chi-squared distances are more than the conservative Euclidean and Manhattan distance.

Mistry et al. [37] proposed a hybrid feature system for competent CBIR. It is based on spatial, frequency, Color, and Edge directivity Descriptor (CEDD), and BSIF feature descriptors. The proposed method uses the WANG database; it contains 1000 Corel images of 10 various types of .jpg images, of size 384 × 256 or 256 × 384. It combines 100 images in 10 various groups like animals, vehicles, objects, places, etc.

Khodaskaret al. [38] presented a study on CBIR use in the color feature. The likelihood of histograms for each color component is increased with this feature. These histograms are separated into different numbers of major coordinates and for each coordinate, different statistical features like standard deviation, skewness, mean, variance, kurtosis, etc are calculated. The processing rate is slow, and the proposed technique is deployed on average image databases achieving better results.

Pradeep et al. [39] demonstrated the CBIR approach by combining artificial neural networks, fuzzy logic, support vector machines, and other soft computing methods. The traditional CBIR system retrieves images by using low-level image features, and it gets the semantic gap. It suggests an advanced structure for CBIR that increases the accuracy of image retrieval by combining fundamental soft computing methods. The proposed system works with relevant feedback based on a Support vector machine (SVM). It gives an intelligent classification of images based on a relevant or irreverent query image, and later, it calculates the performance measures like precision, recall, and accuracy.

Katira et al. [40] presented the technique of CBIR, which is used with the ordered-dither block truncation coding, (ODBTC), for the image content descriptors. The encoding is done by using ODBTC that combines the image blocks into quantized and bitmap images, such as color co-occurrence features, (CCF) and bit pattern features, (BPF). This is converted into ODBTC encoded data streams without any decoding. The experimental result shows that the planned scheme is greater than the block processing coded image retrieving systems.

Gupta et al. [41] proposed some primitive features of an image that were utilized in the current scenario system. Some features are selected based on similarity identification between the images. The proposed algorithms are used for calculating the similarity between image features and then describe them. MATLAB tool is used for image verification in a database.

Wavelet-Based Color Histogram Image Retrieval was proposed by Bagri et al. [42] for feature selection such as color and texture (WBCHIR). In the path of wavelet transformation and color histogram, shape and shade features are often used for feature selection, making these features energetic and adaptable. In this study, the segmentation and grid information is used for the first time for feature extraction.

Giveki et al. [43] used the texture Gray Level Co-occurrence Matrix, Hue moments, and the grouping of Tamura texture features and shape invariant Hue moments to compare the combination of texture and shape features. The system's efficiency is measured using the accuracy and recall methods.

Selviet al. [44] presented experimentation on the effectiveness of choosing color space performance using CBIR for Wavelet decomposition. Hence, the efficiency increased in the results of CBIR representation using wavelet transform in color space and color moments.

Sasikala et al. [45] proposed three algorithms to increase the performance. In this study, the Heterogeneous Minimum Order k-SimRank (HMok-SimRank) algorithm is used which derives the corresponding algorithm using Integrated Weighted Similarity Learning (IWSL) to integrate the data for query images in an image database. A ranking algorithm is used for finding the rank of the images which increases both relevance and speed.

Singh et al. [46] introduce CBIR problems and challenges, by using an accurate image searching system. It is based on CBIR using Mpeg-7 descriptors, which works on low-level features and is extracted from the large database. it transforms between color spaces and quantization and uses color information for feature extraction. This proposed method achieves robustness and 92.4% accuracy.

Dharani et al. [47] proposed a survey study on the CBIR technique. The study searches the gigantic image database for the target image based on the user query using visual characteristics of an image such as color, shape, texture, and so on. It is based on labeled and unlabelled images to analyze the efficiency of an image using the method like D-EM, SVM, RF, etc.

Smeulders et al. [48] discuss the current state of content-based retrieval from various image formats, as well as the role of semantics, pattern, and the sensory gap. A special retrieval strategy, such as global features, object and shape, salient points, structural combinations, and signs, is used for image and object similarity searches.This is accomplished through the use of system engineering databases, system design, and evaluations.

Li et al. [49] focus on the number of digital images increasing from time to time and taking out from huge databases which is very complex. Indexing image data is based on the text. The indexing uses low-level features of the image that may diminish the workload and make mining to become more rapid. The indexing technique index the digital images in the database by the peak color proportion. The images will be routinely confidential by their low-level feature like color. Execution of this technique will benefit image mining.

Tarulatha et al. [50] work on advanced technologies to increase accuracy using CBIR systems. The study centers on the shifted design which is complicated for the low-level feature extract algorithms that reduce the semantic gaps among image features and databases. The authors carried out a literature survey on recent technologies to achieve an elevated level of semantic-based image retrieval.

Liu et al. [51] focused on Gabor wavelet proof texture analysis for image retrieval method based on the Gabor filter. The texture feature works on the mean and variance of statistical features for Gabor filtered image. In normalization, it is used by a spherical shift of the feature elements which override on points. The image indexing and retrieval are conducted on the image texture and standard images.

Siradjuddin et al. [52], in Content-based Image Retrieval, provided an autoencoder using a Convolutional Neural Network for feature extraction. In the convolutional autoencoder architecture, the encoder and decoder layers are used. The encoder layer reduces the image's dimension by applying the convolutional neural network's feature learning capability to it. The decoding layer rebuilds the autoencoder's output as closely as possible to the data input. The results found that the extracted features can be used to represent images and recover relevant images in content-based image retrieval.

Fadaei et al. [53] suggested a technique that extracts the Zernike moments from the query image and calculates an interval for that query. The retrieval process ignores images in the database that are beyond the interval. As a result, a database reduction happens before retrieval, resulting in increased speed. Relevant images for query images are stored in the reduced database, while irrelevant images are discarded.

Naoufal et al. [54] used a procedure based on color features coded as strings and genetic algorithms to create a content-based image retrieval system. The goal is to find the fittest people in a huge group of people. After that, they compare the results achieved by varying the size of the images at different intervals to see how the size affects their technique to reduce the computation time. This method claims to lower the cost of retrieving other features while also improving retrieval accuracy.

Rudrappa et al. [55] showed a system that uses ground-based imagery of clouds in the sky to determine if they are low, middle, or high-level clouds. For cloud classification, they use K-means clustering and Content-Based Image Retrieval (CBIR) approaches. The evolved system divides clouds into three categories: low, middle, and high-level clouds. The outcome of this cloud identification can then be used as an input to a system that determines rainfall dynamically.

Finally, in the commercial field, The CBIR method was implemented by IBM, known as QBIC (Query-based Image Content). QBIC works on networking and graphics-based approaches. It is a simple, well-understood, and attractive substitute to traditional methods. A CBIR system architecture is presented in Figure 1.

The offline stage and the online stage are the two steps of a common content-based image retrieval framework. In the offline stage, the image is captured and placed in the image database. Later on, images are represented, and data indexed. In the online stage, other query methods, image features, image feature advantages, and disadvantages of features are considered for image retrieval. CBIR Framework module is given in Figure 2.

## 3. Image Retrieval Techniques

The image retrieval system is a structure that allows you to search, discover, and retrieve images from a large image database. Figure 3 shows a block diagram of the image recovery system. Traditionally, image retrieval uses some common methods for adding metadata like capturing, keyword, or some other type of information that describes an image. Early research works on image retrieval techniques are summarized here for the reader's attention.

### *3.1 Text-Based Image Retrieval*

The text-based image retrieval method also known as the descriptive image-based system is used for retrieving XML documents that contain images.

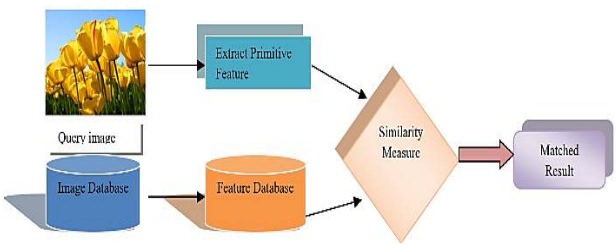



Figure 1. CBIR system architecture

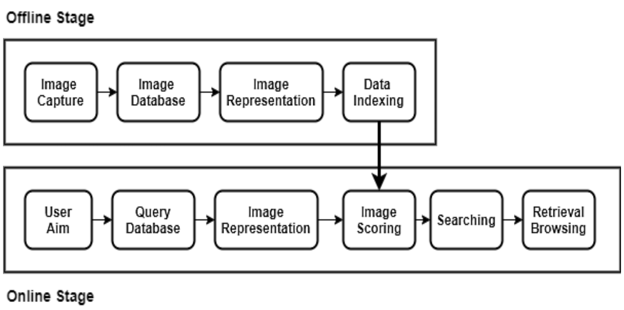



Figure 2. CBIR framework module (online/offline stages)

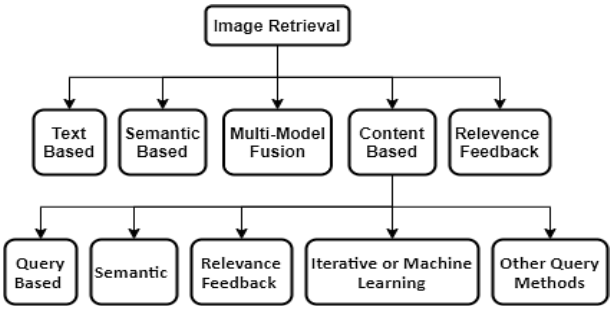



Figure 3. Block diagram of Image retrieval technique

It is based on textual information for an exact multimedia query in the database. Therefore, it overcomes the limitation of the CBIR system. It allows the users to present information according to the needs of textual query and finding the significant images which match with the textual query and the database [56-60].

*3.2 Multimodal Fusion Image Retrieval*

Multimodal fusion image retrieval is required for data synthesis and a machine learning algorithm, called, combination of evidence is deployed. This algorithm is used for merging multiple sources of evidence, which is based on multiple modalities, like the skimming effect, chorus effect, and dark horse effect [61].

*3.3 Semantic-Based Image Retrieval*

A semantic-based image retrieval system is used for current images. It is the method, that works to solve the semantic gap problem, which leads to two main approaches. The first is Annotating images and the second is image segmentation that uses automatic image explanation and adopting the semantic web initiatives [62, 63].

*3.4 Relevance Feedback Image Retrieval*

It is used to determine the distinction between user information and image representation, which determines the limit of nuclear retrieval systems' image retrieval accuracy. It's used to fill in important semantic gaps. The underlying concept behind relevance feedback is to incorporate the user's perception of the query and have them compute the retrieval results. For better results, user interaction is required [64 - 67].

## 4. Content-Based Image Retrieval Techniques

CBIR systems are projected on many techniques. But there are some problems withthe image retrieving system based on pixel contents [68-72]. Early research works on content-based image retrieval techniques are summarized here for the reader's attention.

*4.1 Query-Based Technique*

Query by example is based on a query technique, which works based on a searching algorithm. The searching algorithm is based on the functionality of the resulting image and shares common image information which is known as Reverse searching image. Some common examples of an image searching system are as follows:

- An existing image can supply by the users selected from a random set.
- The user draws a rough calculation of an image.

*4.2 Semantic Retrieval*

Semantic retrieval is used to start a user quest, for example, "find pictures of Abraham Lincoln". It is a sort of open-ended task, which is extremely complicated for computer operations. Lincoln cannot face the cameras and can't use the same poses. CBIR systems use low-level features such as texture, color, and shape features. These features are used in grouping and interfacing so that it is easy to input the databases which are qualified to match the features such as the face, fingerprint, or shape. Generally, image retrieval requires a human identification of the higher-level concept.

*4.3 Relevance Feedback (Human Interaction)*

The Combine CBIR system is a searching technique for the identification of the large variety of probable user images and the target can be a strong task. A CBIR system relies totally on the understanding ability of user queries.

*4.4 Iterative Or Machine Learning*

Machine learning and application is an iterative technique for the fitting of extra culpability in CBIR.

*4.5 Other Query Methods*

These methods are based on searching and browsing, for example, navigation of modified and hierarchical categories such as query by image type, query by a various instance of images, query by visual outline, query by the straight requirement of image features, and multimodal queries (e.g. combining touch, voice, etc.)

## 5. Content-Based Image Retrieval Methods

Content-based image retrieval (CBIR), which is used as a distance measure, is the most common technique for comparing two images. The distance is computed by comparing the two images' color, texture, and shape similarity.

*5.1 Color*

One of the most important features of a content-based image retrieval system is the color feature, which aids image recognition. Color features are a pixel property and these properties work on the reflection of light. Color tells about the variation between object, position, and time of day. There are many types of color model that describes the color information of an image, and it reduces image information about potential inequity to the single gray level values.

Color space is a method that represents pixel coordinates in 3D color space, in which the popular Red-Green-Blue (RGB) method is used for image retrieval. RGB method consists of three colors which are red, green, and blue, together with additive primaries, which are developed by combining all three colors. In contrast, the cyan-magenta-yellow (CMY) method is a subtractive color model and is used mostly for printing. It is developed for brightness inclusion.

Both the color models RGB and CMY are mechanism-based or perceptually non-uniform. The CIE (International Color Commission) measured the colors and perceptually standardized them. CIE is made for subtractive color mixtures and designed the color management [47].

The Hue, Saturation, and Value (HSV) space model is widely used in computer graphics. The invariant moment is used to change the light and camera direction, and it is an appropriate method for image retrieval. The invariant moment is represented by calculating the wavelength of light, and it expresses the pure spectrum color model which ranges from 0º to 360º. RGB coordinates are easily translated into HSV coordinates and are represented by using equations (1), (2) and (3). The conversion of the RGB space color model to the HSV space image model is shown in Figure 4. Example color conversions to a different color model are presented in Figure 5a and Figure 5b.

$$H = cos^{-1}\frac{1}{2}\frac{[(R-G)+(R-B)]}{\sqrt{[(R-G)^2+(R-B)(G-B)]}} \quad (1)$$

$$S = 1 - \frac{3[\min(R,G,B)]}{R+G+B} \quad (2)$$

$$V = \frac{R+G+B}{3} \quad (3)$$

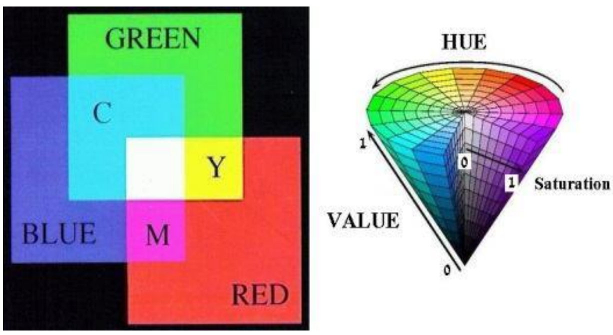
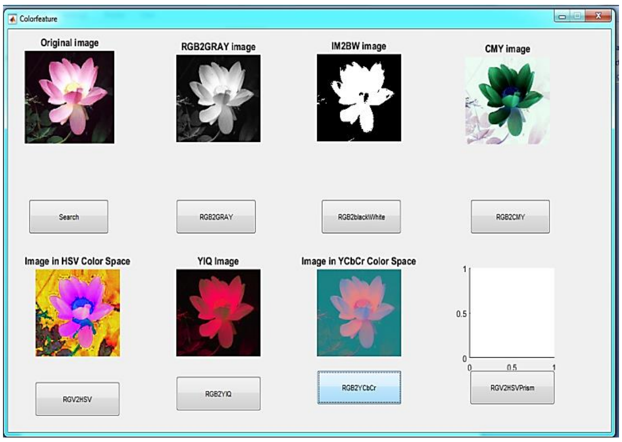
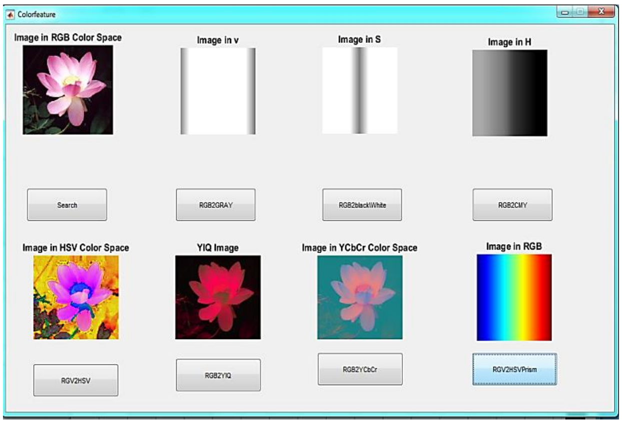



Figure 4. Block diagram of image retrieval technique




(a)




(b)

Figure 5. Color conversion to a different color model

Some common techniques used in the color feature are as follows:

### *5.1.1 Color moment*

The most popular color feature used for CBIR is the color moment. The color moment is a statistical measure that differentiates images using the feature extraction method and that image is recognized by the distribution of color moment (statistical measure) or features. There are some common statistical measures namely mean, variance, and skewness shown by equations (4), (5), and (6).

The color moment proves the efficiency and effectiveness of color statistical distribution of images. A sample of the image database used in calculations is presented in Figure 6.

$$\mu_{i=\frac{1}{N}\sum_{j=1}^{N} f_{ij}} \quad (4)$$

$$\sigma_i = (\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-\mu_i)^2)^{\frac{1}{2}} \quad (5)$$

$$s_i = (\frac{1}{N}\sum_{j=1}^{N}(f_{ij-}\mu_i)^3)^{\frac{1}{3}} \quad (6)$$

Table 1. The results of color moment calculations for the database in Figure 6

| No. | ColorMo1 | ColorMo2 | ColorMo3 | ColorMo4 | ColorMo5 | ColorMo6 |
|---|---|---|---|---|---|---|
| Image1 | 98.5513 | 150.7495 | 101.2073 | 85.5941 | 101.1767 | 77.3031 |
| Image2 | 95.9414 | 64.8982 | 58.3551 | 83.2036 | 57.7118 | 87.1210 |
| Image3 | 69.7427 | 111.2991 | 73.9050 | 84.5222 | 73.8894 | 48.2561 |
| Image4 | 77.0045 | 33.9630 | 50.8406 | 67.5750 | 50.2813 | 53.6986 |
| Image5 | 82.2800 | 125.5592 | 67.4838 | 67.3654 | 67.6743 | 60.8554 |
| Image6 | 84.2418 | 50.5414 | 43.1666 | 61.5602 | 42.4683 | 70.5261 |

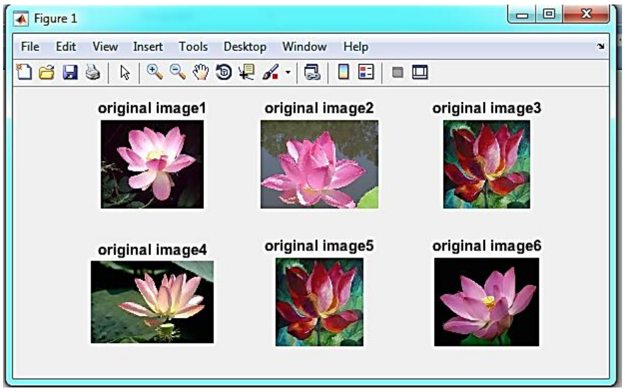



Figure 6. Sample of image database

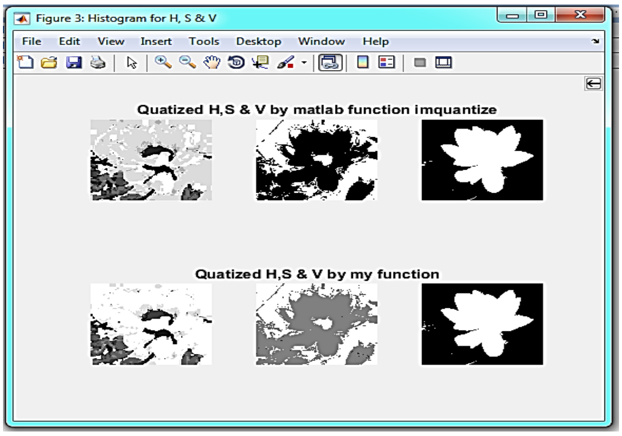



Figure 7. HSV histogram for color model

where $f_{ij}$ is the image value, $i^{th}$ is the color element of an image pixel, j and $N$ are the numbers of the pixel images.

Color moment calculations are carried out for the 6 original images in Figure 6 and the results are presented for the color moments in Table 1. The images were obtained from an online database atozflowers.com/. A custom software was written in Matlab to calculate the color moment presented in Table1.

### *5.1.2 Color Histogram*

A color histogram is an interpretation and identification of RGB image intensity. Color histogram defines a color vector, which is a set of pixels of all the images, coordinates which are denoted by the pixels, and the images considered individually as an RGB image. It is a way of viewing translation and rotation, by changing an image slowly with the help of scalar transformations and viewing angles. H is a color histogram vector for an image defined in equation (7) as:

$$H = \{H[1], H[2], H[3], \dots\dots H[i], \dots\dots H[N]\} \quad (7)$$

where i is a color histogram, H[i] is the number of pixelscolor, i is an image, and N is the number of the coordinate for a color histogram. An example HSV histogram for the color model is presented in Figure 7.

### *5.1.3 Color Correlogram*

The color correlogram is a color-based table indexing feature, with the $k^{th}$ entry for (i, j) indicating the possibility of indexing color j coordinates at a distance of k from a pixel of color I in the image.

The mathematical representation of color correlogram is shown in equation (8).

$$\gamma_{(i,j)}{}^{(k)} = Pr_{p1\epsilon c(I), p2\epsilon I}[P2\epsilon I_{c(j)} |P1-P2| = K] \quad (8)$$

where i, j ∈ {1, 2, …, N}, k∈ {1, 2, …, d}, and | p1 – p2 | is the distance between pixels p1 and p2.

### *5.1.4 Color Coherence Vectors*

The color coherence vector is divided into two categories namely coherent histogram and non-coherent pixel. Pixels are measured to be coherent if they are part of a continuous equally colored area and the size of this area exceeds some threshold. This area is usually defined as 1% of the image area. Finally, the general advantages and disadvantages of color models are summarized as shown in Table 2.

Table 2. Advantages and disadvantage of color models

| Models | Advantages | Disadvantages |
|---|---|---|
| RGB (Red, Green, Blue) | The transformation method is not used for displaying information, as it is measured as the basis of color space for the different methods, it uses video display because of its stabilizer properties. | It is not used in object identification and recognition of colors. |
| CMY (K) | It is normally used for the production of printer color. | It is a subtractive model so inks are not given as color output. |
| HSV | HSV color model can be simply identified by individual observation as compare to CMY or RGB. | Hue coordinates are receptive to derivations because of their sharp nature features. |

### *5.2 Texture*

The texture of an image is its most important feature. It is a set of the matrix which calculates the spatial collection of color intensities of an image and selects the region of an image. It can be synthetically created, and it identifies natural scenes that are captured in an image. Segmentation, classification, pattern recognition, and machine vision all use the texture feature. Some of the most prevalent approaches are directionality, contrast, coarseness, roughness, regularity, and line-likeness. These are divided into three approaches: structural, statistical, and spectral.

***Structural approach:*** It is an image texture, a set of primitive texture elements (pixel or texels), in morphological operators and adjacency graph. It is based on a regular subpattern.

***Statistical approach:*** It is a quantitative measure, like co-occurrence matrices, Tamura feature, Fourier power spectra, and shift-invariant principal component analysis (SPCA), etc.

***Spectral approach:*** It is a property used for the Fourier spectrum, which explains the global periodicity of a gray level image by the identification of high energy coordinates in the Fourier spectrum.

The commonly used techniques in the statistical approach are:

#### *5.2.1 Gray Level Co-Occurrence Matrix*

It is developed by R.M. Haralick, and it is the most important and popular method for representing image textures. It is the second-order statistical method in which 14 statistical measures are used for feature extraction. See Table 3. GLCM Texture Analysis examples with different pixel distances are given in Figures 8,9 and 10.

GLCM Texture feature analysis is carried out with the images in the image database in Figure 6. The results are presented in Table 4.

Table 3. Advantages and disadvantage of color models

| No. | Feature | Formula | Remark |
|---|---|---|---|
| 1 | Contrast | $\sum_{n=0}^{Nn-1} n^2\{\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P(i,j)\}, \|i-j\| = n$ | Have a discriminating ability. Rotationally variant |
| 2 | Entropy | $-\sum i \sum j\, P(i,j) \log(P(i,j))$ | Have a strong discriminating ability. Almost rotational invariant. |
| 3 | Correlation | $\frac{\sum i \sum j P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$ | Have a strong discriminating ability. Rotational dependent feature. |
| 4 | Sum average | $\sum_{i=2}^{2N} i p_{z+y}(i)$ | Characteristics are similar to variance. Rotation is invariant. |
| 5 | Sum of squares: Variance | $\sum i \sum j\,(i-\mu)^2 P(i,j)$ | Computationally expensive Rotation variant. |
| 6 | Info. The measure of Correlation 1 | $\frac{HXY - HXY}{\max\{HX, HY\}}$ | Similar to the Correlation |
| 7 | Info. The measure of Correlation 2 | $(1-\exp[-2(HXY2 - HXY)])^{\frac{1}{2}}$ | Similar to the Correlation |
| 8 | Inverse Different Moment | $\sum i \sum j \frac{1}{1+(i-j)^2} P(i,j)$ | Similar to the angular second moment. |
| 9 | Sum Variance | $\sum_{i=2}^{2N} (i - f_{s)})^2 P_{(x+Y)}\,(i)$ | Similar to variance |
| 10 | Sum Entropy | $-\sum_{i=2}^{2N} P_{(x+y)}(i) \log\{P_{(x+y)}\,(i)\} = f_s$ | Similar to entropy |
| 11 | Angular second moment / Energy | $\sum i \sum j\, P(i,j)^2$ | No distinguishing ability |
| 12 | Difference variance | $\sum_{i=0}^{N-1} i^2\, P_{(x-y)}(\mathrm{i})$ | Similar to Variance |
| 13 | Difference Entropy | $-\sum_{i=0}^{N-1} P_{(x-y)} \log\{\, P_{(x-y)}(\mathrm{i})\}$ | Similar to Entropy |
| 14 | Max. Correlation coeff./ Mean | $Q(i,j) = \sum k \frac{P(i,j)P(j,k)}{p_x(i)p_y(k)}$ | The square root of the second-largest Eigenvalue |

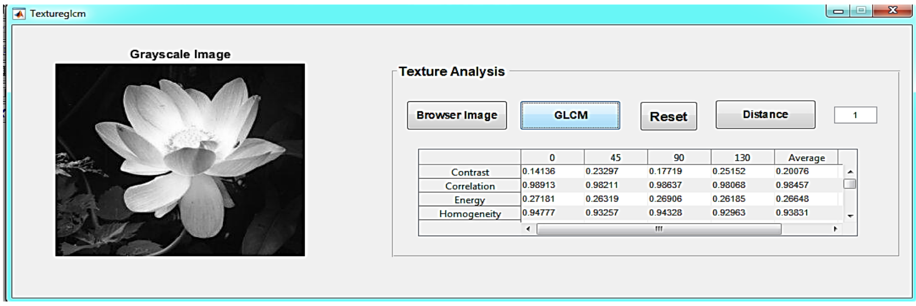



Figure 8. Texture Analysis for 1-pixel distance

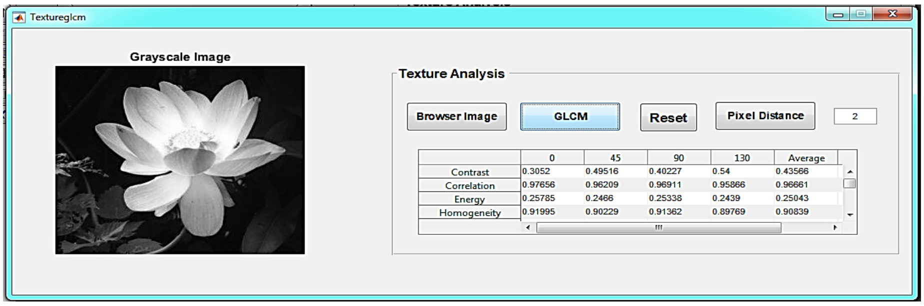



Figure 9. Texture Analysis for 2-pixel distance

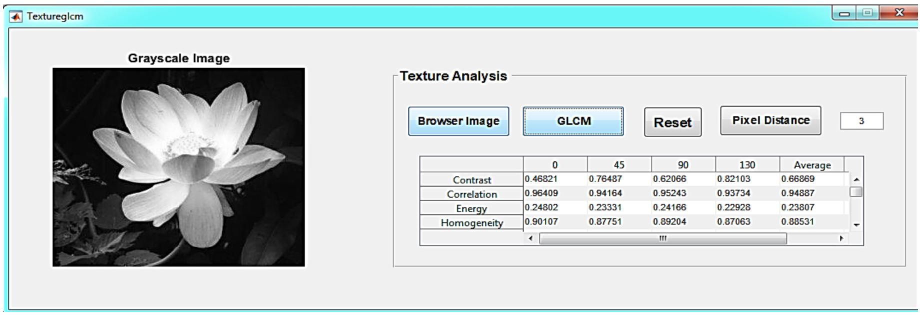



Figure 10. Texture Analysis for 3-pixel distance

### *5.2.2 Tamura texture*

Tamura feature is designed by studying the human perceptual experience of texture features. There are some perceived texture feature types which are as follows:

a) Coarseness
b) Contrast
c) Directionality
d) Linelikeness
e) Regularity

***Coarseness:***

It is a distance measure related to the spatial variation of a gray-level image. Hence it is easy to find the size of the primitive element (pixels) from the texture feature. Coarseness is the quantitative measure of a scalar image with a fixed window size. The smaller value of the texture element is known as coarser.

***Contrast:***

It is a measure to check the image whether is black or white based on distribution.

***Directionality:***

It is the information of edge strength and directional angle. It uses the pixel-wise differential for computing an image.

***Linelikeness:***

It describes the average conjunction of edge directions, so it defines the isolated pixels by using distance and with the direction α.

***Regularity:***

It defines coarseness, contrast, and direction. It is denoted by users as a normalization factor and σ defines the standard deviation of the texture features of each sub-image.

### *5.2.3 Wavelet transform*

Wavelet transforms offers the multiresolution method that describes texture analysis and classification. It explains the basic function of a superposition in the family called wavelets. It uses a multi-resolution approach to calculate the 2D image. It employs recursive filtering and sub-sampling, which divides the image into sub-levels. Every level is decomposed into sub-bands of four frequencies which are, LH, LL, HH, and HL. L represents low frequency and H denotes the high frequency. Haar, Coiflet, Mexican Hat, Morlet, and Daubechies are some examples of wavelets. The most common and basic wavelets is Haar wavelet, and Daubechies is a fractal structure application.

Table 4. Texture features of GLCM

| No. | Feature | Image1 | Image2 | Image3 | Image4 | Image5 | Image6 |
|---|---|---|---|---|---|---|---|
| 1 | Autocorrelation 1 | 15.6346 | 15.6346 | 15.6346 | 15.6346 | 15.6346 | 15.6346 |
| 2 | Autocorrelation 2 | 15.6675 | 15.6675 | 15.6675 | 15.6675 | 15.6675 | 15.6675 |
| 3 | correlation 1 | 0.9691 | 0.9691 | 0.9691 | 0.9691 | 0.9691 | 0.9691 |
| 4 | correlation 2 | 0.9765 | 0.9765 | 0.9765 | 0.9765 | 0.9765 | 0.9765 |
| 5 | Cluster Prominence 1 | 1303.913 | 1303.913 | 1303.913 | 1303.913 | 1303.913 | 1303.913 |
| 6 | Cluster Prominence 2 | 1311.307 | 1311.307 | 1311.307 | 1311.307 | 1311.307 | 1311.307 |
| 7 | Cluster Shade 1 | 100.7474 | 100.7474 | 100.7474 | 100.7474 | 100.7474 | 100.7474 |
| 8 | Cluster Shade 2 | 101.3129 | 101.3129 | 101.3129 | 101.3129 | 101.3129 | 101.3129 |
| 9 | Dissimilarity 1 | 0.2155 | 0.2155 | 0.2155 | 0.2155 | 0.2155 | 0.2155 |
| 10 | Dissimilarity 2 | 0.1883 | 0.1883 | 0.1883 | 0.1883 | 0.1883 | 0.1883 |
| 11 | Max Probability 1 | 0.4785 | 0.4785 | 0.4785 | 0.4785 | 0.4785 | 0.4785 |
| 12 | Max Probability 2 | 0.4827 | 0.4827 | 0.4827 | 0.4827 | 0.4827 | 0.4827 |
| 13 | Sum of Square 1 | 15.7321 | 15.7321 | 15.7321 | 15.7321 | 15.7321 | 15.7321 |
| 14 | Sum of Square 2 | 15.7321 | 15.7321 | 15.7321 | 15.7321 | 15.7321 | 15.7321 |
| 15 | Sum of Average 1 | 6.10709 | 6.10709 | 6.10709 | 6.10709 | 6.10709 | 6.10709 |
| 16 | Sum of Average 2 | 6.10288 | 6.10288 | 6.10288 | 6.10288 | 6.10288 | 6.10288 |
| 17 | Sum of Variance 1 | 42.8879 | 42.8879 | 42.8879 | 42.8879 | 42.8879 | 42.8879 |
| 18 | Sum of Variance 2 | 43.0304 | 43.0304 | 43.0304 | 43.0304 | 43.0304 | 43.0304 |
| 19 | Sum of Entropy 1 | 1.9545 | 1.9545 | 1.9545 | 1.9545 | 1.9545 | 1.9545 |
| 20 | Sum of Entropy 2 | 1.9435 | 1.9435 | 1.9435 | 1.9435 | 1.9435 | 1.9435 |
| 21 | Diff of Variance 1 | 0.4022 | 0.4022 | 0.4022 | 0.4022 | 0.4022 | 0.4022 |
| 22 | Diff of Vari2nce 1 | 0.3051 | 0.3051 | 0.3051 | 0.3051 | 0.3051 | 0.3051 |
| 23 | Diff of Entropy 1 | 0.5566 | 0.5566 | 0.5566 | 0.5566 | 0.5566 | 0.5566 |
| 24 | Diff of Entropy 2 | 0.5135 | 0.5135 | 0.5135 | 0.5135 | 0.5135 | 0.5135 |

### *5.3 Shape*

The shape, which is used to extract information from images, is the most important feature. Because of noise, occlusion, and arbitrary distortion, the object recognition problem becomes more complicated. Shape representation is focused on the shape features and it is a boundary-based or region-based shape. To be more effective, a shape feature must have the following properties: identifiability, translation, occultation invariance, noise resistance, affine invariance, reliability, and statistical independence.

#### *5.3.1 Boundary-based shape*

This feature mainly focuses on the outer boundaries of an image that defines the important region by using the external characteristic of an image, in each pixel (or coordinate) along the image boundary. See Figure 11. Some representations of Boundary-based shapes are as follows:

1. Polygonal Models, or Boundary partitioning
2. Fourier Descriptors
3. Spines, higher-order constructions
4. Curvature Models

#### *5.3.2 Region-based shape*

This feature focuses on the shape region of the whole image by using a complete image internal description. some representations of Region-based shapes are as follows:

1. Super quadrics
2. Fourier Descriptors
3. Implicit Polynomials
4. Blum's skeletons

#### *5.3.3 Fourier descriptor*

Fourier descriptor describes the shape feature of an object in an image, in which it uses Fourier transform for boundaries and considers the shape (contour) of a two-dimensional image. Contour representations are divided into three types:

***Curvature:*** Curvature K(s) is a method that changes the rate of the tangent direction of the curve, it is represented as s, s is the point of the curve. It can be represented as:

$$K(s) = \frac{d}{ds}\theta(s) \tag{9}$$

where θ(s) represent the turning function of the curve.

***Centroid distance:*** Centroid distance is a method that calculates the distance function between the boundary pixel and the centroid ($x_c$, $y_c$) of an image object, It's defined as:

$$R(s) = \sqrt{(x_s - x_c)^2 + (y_s - y_c)^2} \tag{10}$$

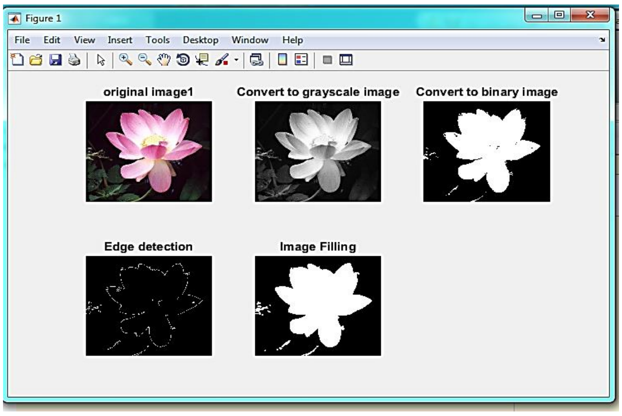



Figure 11. Edge detection

***Complex Coordinate:*** Complex coordinates describe the coordinates of boundary pixels and the complex number is defined as:

$$Z(s) = (x_s - x_c) + j(y_s - y_c) \tag{11}$$

### *5.3.4 Fourier transforms*

Contour representation is used to generate the complex coefficient representation of the object shape in the frequency domain. It can be divided into three groups. The first one is the low frequency coefficients that express the shape property.The second one is the higher frequency coefficients that reproduce the shape information. The third one is the complex frequency coefficients which achieve the rotation invariant, scalar invariance, amplitude coefficients separated by the amplitude of the DC component, and non-zero coefficients. The transformation invariance is based on the contour illustration.

### *5.3.5 Moment invariant*

It is based on conventional shape representation. It is a set of moment invariants. The main reason to propose the moment invariant is to calculate the region-based moment. if the object R is represented as the binary image, then the center moment order of p+q for the shape of object R is defined as:

$$\mu_{p,q} = \sum_{(x,y)\varepsilon R} (x - x_c)^p \, (y - y_c)^q \tag{12}$$

where ($x_c$, $y_c$) represents the center of the image. Invariants are independent of position, size, and orientation. Moment invariant is the basis of these moments. These are translation; rotation and scale and can be derived as:

$$\emptyset_1 = \mu_{2,0} + \mu_{0,2} \tag{13}$$

$$\emptyset_2 = (\mu_{2,0} - \mu_{0,2})^2 + 4(\mu^2)_{1,1} \tag{14}$$

$$\emptyset_3 = (\mu_{3,0} - \mu_{1,2})^2 + (3(\mu_{2,1}) - \mu_{0,3})^2 \tag{15}$$

$$\emptyset_4 = (\mu_{3,0} + \mu_{1,2})^2 + (\mu_{2,1} + \mu_{0,3})^2 \tag{16}$$

$$\begin{aligned}\emptyset_5 = (\mu_{3,0} - 3\mu_{1,2})(\mu_{3,0+\mu_{1,2}})[(\mu_{3,0} + \mu_{1,2})^2 \\ - 3(\mu_{2,1} + \mu_{0,3})^2] + (3\mu_{2,1} \\ - \mu_{0,3})(\mu_{2,1} \\ + \mu_{0,3})[3(\mu_{3,0} + \mu_{1,2})^2 \\ - (\mu_{2,1+\mu_{0,3}})^2]\end{aligned} \tag{17}$$

$$\begin{aligned}\emptyset_6 = (\mu_{2,0} - \mu_{1,2})[(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2 \\ + 4\mu_{1,1}(\mu_{3,0} + \mu_{1,2})(\mu_{2,1} \\ + \mu_{0,3})]\end{aligned} \tag{18}$$

Hue moments for the 6 test images in Figure 6 are tabulated in Table 5.

### *5.3.6 Turing angles*

In contour representations of 2D images, the close sequence representation leads to successive boundaries of the pixel ($x_s$, $y_s$), where $0 \leq s \leq N-1$ and N define the total number of the element on the boundaries. The turning function is represented as *θ(s)*, which finds the angle of the counter. It uses a clockwise tangent for the functions of the curve length *s* according to the situation point on the image (curve). It is defined as

$$\theta(s) = \tan^{-1}\left(\frac{y'_s}{x'_s}\right) \tag{19}$$

$$y'_s = \frac{dy_s}{ds} \tag{20}$$

$$x'_s = \frac{dx_s}{ds} \tag{21}$$

A summary of various Feature techniques is presented in Table 6.

Table 5. Hue moments for 6 test images in Figure 6

| No. | Hue Moment | Image1 | Image2 | Image3 | Image4 | Image5 | Image6 |
|---|---|---|---|---|---|---|---|
| 1 | Moment 1 | 0.0037 | 0.0028 | 0.0034 | 0.0045 | 0.00343 | 0.0051 |
| 2 | Moment 2 | 1.1320 | 6.5133 | 7.9582 | 1.8011 | 7.9544 | 2.2833 |
| 3 | Moment 3 | 6.6040 | 2.0469 | 1.6069 | 2.3019 | 1.5979 | 2.8695 |
| 4 | Moment 4 | 6.0669 | 2.0748 | 1.7688 | 2.3844 | 1.7525 | 2.8935 |
| 5 | Moment 5 | 3.8165 | 4.2588 | 2.9822 | 5.5861 | 2.9328 | 8.3352 |
| 6 | Moment 6 | 2.0412 | 5.2940 | 4.9287 | 1.0061 | 4.8795 | 1.3779 |
| 7 | Moment 7 | -4.2586 | 3.8194 | 1.6999 | -2.2187 | 1.5708 | -2.0836 |

Table 6. A summary of various feature techniques

| Types of feature | Methods | Characteristics |
|---|---|---|
| Color Features | Conventional color Histogram(CCH), Fuzzy Color histogram (FCH), [20,21] Color Correlogram | Simple to calculate. It cannot instruct the spatial info. It cannot instruct by color coordinates seminaries. It considers the degree of color relationship between the coordinates. It is strong to quantize fault. Here, the robustness changes the brightness intensity. |
| Texture Features | Steerable pyramid, Contourlet transform, Complex directional filter bank (CDFB) | In this, we use basic filters for translation and rotation. These filters are the linear combination of basic functions. Only the rotation invariants are the use of texture retrieval. Combining the Laplacian pyramid function with a directional filter requires less computation and difficulty. Optimally, it achieves the joint resolution of space and spatial frequency which is computationally intensive. So, it gives the highest result of texture retrieval. It compares the retrieval outcome with the Gabor wavelet output and it is Shift Invariant. |
| Shape Features | Fourier Descriptor, Moment Invariants, Directional Histograms | The shape feature is a phase of understanding and implementing the shapes. |

## 6. Distance Measurements

CBIR searches for similarities between the target image and the training images. As a result, the image retrieval method displays the results based on the image list. Many distance measurements are developed for the CBIR feature in recent years. Distance measurements are carried out to locate the connections of feature vectors. In the CBIR system, it is used to compare the relationship between the images. They are briefly summarized as follows:

### *6.1 Euclidean Distance*

It's the measurement of the distance between the image's two coordinates. Euclidean distance is identified as the line segment between 2D Euclidean coordinates X ($x_1$, $x_2$) and Y ($y_1$, $y_2$). The distance between two coordinates X and Y is defined as shown in equation (22);

$$D(p,q) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{22}$$

where, X = ($x_1$,$x_2$,$x_3$,……….,$x_n$) and Y = ( $y_1$,$y_2$,$y_3$,……….$y_n$) , n is the number of points.

### *6.2 Standard Euclidean Distance*

Standardized data is used to determine standard Euclidean distance. This data can be defined as Standardized Data= (original mean value)/Standard deviation shown in equation (23);

$$d = \sqrt{\sum (\frac{1}{{s_i}^2})(x_i - y_i)^2} \tag{23}$$

### *6.3 Manhattan Distance*

It uses a lattice that is purely based on a diagonally opposite horizontal or vertical path to determine the distance between two points. The Manhattan distance is computed using Pythagoras Theorem, while the diagonal distance is calculated using the sum of the horizontal and vertical components. Mathematically, it is defined as

$$Mh(p,q) = (x_1 - x_2) + (y_1 - y_2) \tag{24}$$

### *6.4 Minkowski Distance*

It's a popular image retrieval metric in which each image element's feature vector is independent of the others and all features are valued equally. Minkowski distances are used to calculate the distance between two images. Mathematically, it can be defined as

$$D(p,q) = (\sum_i (f_i(x) - f_i(y))^p) \tag{25}$$

### *6.5 Mahalanobis Distance*

The distance metric is applied to each dimension of the image feature, which is a vector that is unrelated to the others and is applicable in this distance measurement.It can be defined as

$$D(p,q) = \sqrt{(F_p - F_q)^T C^{-1} (F_p - F_q)} \tag{26}$$

where C is representing the covariance matrix of the image feature vector.

### *6.6 Chebyshev Distance*

It calculates the distance between the two points p and q. Chebyshev distance represents the standard coordinates pi and qi and it is a metric of the uniform norm. It can be represented as

$$D_{chess}(p,q) = \max(p_i - q_i) \tag{27}$$

where p and q are two points, Cartesian coordinates are ($x_1$, $y_1$) and ($x_2$, $y_2$).

$$D(i,j) = \sqrt{(F_i - F_j)^T A (F_i - F_j)} \tag{28}$$

where A(Fi-Fj) defines a similar matrix where Fi and Fj are vector lists.

## 7. Performance Evaluation

Performance measures are used to calculate the results and use image retrieval measures such as precision and recall, which work on feature extraction and give positive stability outcomes. These features extract information without any interpretation problems. It can be categorized as Precision, Recall, and F score.

### 7.1 Precision

Precision is the performance measure that retrieves the related images to the query image from the total retrieved database images.

$$\text{Precision} = \frac{\text{No. of the relevant retrieved image}}{\text{Total No. of retrieved image}} \quad (29)$$

### 7.2 Recall

The retrieval of related images to the image database is measured by the recall performance measure.

$$\text{Recall} = \frac{\text{No. of relevant retrieved}}{\text{Total No. relevant in the database}} \quad (30)$$

### 7.3 F-Score

The accuracy of an image retrieval of the corresponding query image is computed from the database image with precision and recall measurements, and the calculated values indicate the success of image retrieval. These two measurements aren't always enough to maximize the capable image retrieval's correct accuracy.As a result, they were combined into a single value that represents image retrieval accuracy. The F-Score of F-measure is the name for this arrangement. The score is computed using a combination of precision and recall measurements. The weighted average, or harmonic, is what it's called.

$$F = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \quad (31)$$

Finally, comparisons of Feature extraction methods are summarized in Table 7 for the reader's attention.

## 8. Results and Discussions

Various systematic approaches and general structure of the CBIR scheme are discussed in this review. Techniques for image retrieval are extensively explored and contrasted with the retrieval of content-based images. Content-based methods of retrieval including color structure and form are provided. The important points obtained from the detailed survey carried out in this study are summarized, in Appendix (Table A.1). The survey shows that CBIR is still a very interesting area for research. Different work is undergoing in this field to develop or modernize the CBIR system. It lessens the gaps between the high and low level features. Most of the studies are deployed to optimize retrieval performance. Some recent work on the CBIR system is done by combining two or more areas simultaneously to achieve better results in terms of performance.

## 9. Conclusions

In this study, various comprehensive approaches are investigated. The discussion of the general framework of the CBIR system is carried out. The important points of extraction from the encompassing survey are summarized. The survey shows that CBIR is still a very interesting area for research. Different work is undergoing in this field to develop or modernize the CBIR system. It lessens the gaps between the low-level and high-level features. Most of the studies are deployed to optimize retrieval performance. Some recent work on the CBIR system is done by combining two or more areas simultaneously to achieve better results in terms of performance.

Table 7. Comparison of feature extraction methods

| No. | Feature Extraction Method | Performance Evaluation Parameter | Advantage | Disadvantage |
|---|---|---|---|---|
| 1 | Color Histogram, Standard Wavelet | Retrieving Accuracy | It improves the retrieval accuracy. | Insufficient feature set |
| 2 | Color Moment, Gabor Filter GVF | Retrieving Efficiency | It creates a vigorous feature set. | elevated semantic gap |
| 3 | Color Moment, Gabor Filter, Co-occurrence Matrix | Precision | It reduces the semantic gaps via the RF and SVM | It is time overriding to the label negative. |
| 4 | Color Histogram, Tamura, Zenike Moment & Edge | Precision and Recall | Reduce the size of the dataset. All images with correlated features that are similar are retrieved. | Similarity measurement and image retrieval perform two times so it increases calculation. |
| 5 | Daubechies Wavelet | Precision, classifi-cation accuracy | Reduce the size of the search area. Manage a comprehensive image database. | The feature set not sufficient |

## Declaration

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

## Author Contributions

The authors H. Koyuncu, M. Dixit and B. Koyuncu carried out the investigation. H. Koyuncu and M. Dixit did the literature review. H. Koyuncu, M. Dixit and B. Koyuncu performed the analysis. M. Dixit performed the data curation. H. Koyuncu and M. Dixit performed the writing original draft preparation. B. Koyuncu performed the writing review, and editing.

## Acknowledgment

We gratefully appreciate the contributions received at every stage of the study from Devshri Satyarthi working as a lecturer in Dr. B.R.A. Polytechnic College, Gwalior, India.

## Nomenclature

*CBIR* : Content-Based Image Retrieval
*SIFT* : Scale Invariant Feature Transform
BOW : Power Bag of Visual Words
QBIC : Query by Image Content
CBVIR : Content-Based Visual Information Retrieval
*FCM* : Power Fuzzy C-Means

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## Appendix

Table A.1. Comparative analysis of CBIR techniques

| No. | Author and Year | Technique used for feature extraction/ indexing/ matching / relevance feedback/ database used | Comment |
|---|---|---|---|
| 1 | Chahooki et al. [25] | Shape-based indexing: contour-based and region-based method. Manifold learning is used for dimension reduction the MPEG-7 is the part B and fish shape dataset | Retrieval accuracy is increased due to the combination of four different characteristics of shape features. Isomap manifold learning method increases the retrieval precision |
| 2 | Tiakas et al. [80] | Multi sort indexing (MSINX) is high dimensional image descriptor Image Clef Wikipedia Retrieval 2010, Flickr 1 M, IRISA datasets | The system gives a more accurate retrieval result in less time. Mean average precision is calculated. It can handle energetic operations of insertion and deletion in real-time. |
| 3 | Batko et al. [12] | Automatic image annotation and classification(semantic search). Precision and response time of Proof media photo bank and proof media search log Annotation is calculated | Focused on web annotation Combines image and text processing techniques Annotation quality can be significantly improved due to various expansion and reduction techniques. |
| 4 | Raveaux et al. [16] | The image is segmented into regions. Graph-based image representation (region adjacency graph) is calculated to show spatial relationships From each region color (color histogram), texture (co-occurrence matrices), and shape (Zernike Moments) features are computed K-means clustering is used for cluster regions Coil-100 dataset is used. | This approach gives good results as compare to the tree-based approach. |
| 5 | Chu et al. [75] | Partial Duplicate Image Retrieval (PDIR) using SIFT features. Combined orientation position (COP) consistency Graph model for similarity matching, calculates the mean average precision and Average Retrieval Time. It uses Holodays/1000k, Sub-Dupimage/1000k, Dupimage 1000k, IPDID/1000k, and mobile data set | It enables us to accurately match visual Words. It is between two partial duplicate images. As PDIR is a system factor, it improves the strength of dealing with different data, as it is based on SIFT feature extraction. The method is proved as effective in retrieving near-duplicate images. |
| 6 | Samanta et al. [74] | Image indexing and retrieval using Line Edge Binary Pattern (LEBP) Brodatz image dataset Performance is measured using the Average Retrieval Rate (ARR) | DLEBP extracts eight directional line edge values as well as line edge information. Image retrieval performance significantly improves known as Average retrieval rate (ARR) |
| 7 | Bakar et al. [22] | Scale-invariant feature transform is based on the feature extraction method. Experimentation was done on the MPEG-7 dataset | Mostly suited and provide outstanding retrieval results for images with many good alternatives to traditional CBIR system as it is invariant to scale rotation and translation |
| 8 | An et al. [6] | Descriptor works on color features and finds salient objects. A binary map (spatial distribution of dominant color) roughly describes object shape and relative location. Testing is done on the Corel 1k and Corel 10k dataset. | It provides better retrieval performance according to conventional color-based methods. A binary map of dominant color matches the shapes well, Therefore, it is most suitable for object-based color image retrieval |
| 9 | Cheng et al. [13] | Color (color histogram, colorcorrelogram) and texture (Gabor, Tamura, and Edge histogram) visual features textual information (social-tag based) retrieval method relevance feedback NUS-WIDE and MIRFLICKR dataset | Retrieval system using the textual feature can achieve much better performance than only visual features |
| 10 | Zhang et al. [14] | Tries to reduce the Semantic gap used Hybrid, feedback mechanism to refine search result | The method can be used to distinguish the semantic gap, the resemblance with image accuracy. user search images quickly. |
| 11 | Pedronette et al. [77] | Image re-ranking using BP-tree etc., Result (MAP) evaluated with different feature includes ACC, BIC, CCV, GCH and LCH, ALOI dataset with 72000 images and 1000 classes of objects | The rank list is produced by an efficient indexing structure. It is scalable and well suited to a large dataset |
| 12 | Shrivastava et al. [27] | Region-based on segmentation of overriding color and local binary pattern features extraction of each region MPEG7 CCD and Corel image dataset. Average Normalized Modified the Retrieval Rank of employed calculate the performance | ROI is also used to specify the spatial location of regions It improves efficiency through the feature set containing a dominant color and LBP. It also consumes less computation time |
| 13 | Sokic et al. [17] | Fourier descriptor-based feature extraction MPEG-7 CE-1 set B, Swedish leaf dataset is used. | The method outperforms both the effectiveness and efficiency, Not suitable for region-based approaches. This descriptor is essentially a contour-based |

Table A.1. Comparative analysis of CBIR techniques (continue)

| | | | |
|---|---|---|---|
| 14 | Seetharaman et al. [28] | Multi-resolution-based features extraction Vistex texture DB and Brodatz texture image dataset are used. The average precision and recall rate is calculated. | The system is theoretically easy and memory-efficient.It lowers the computing difficulty. It's ideal for image databases with a lot of data. |
| 15 | Xiao et al. [81] | Relevance feedback Combines are high-level semantic and low-level visual features. Datasets used are: COREL images, Flickr Images, NUS-WIDE images | Features Datasets used are: COREL images, Flickr Images, NUS-WIDE images |
| 16 | Alzu'bi et al. [1] | Semantic image retrieval to reduce the semantic gap is discussed. Various relevant feedback schemes are explained. | It is explained how the system's performance in terms of accuracy and speed is affected. |
| 17 | Bai et al. [18] | Color and texture features are used to construct a Multiresolution feature vector. For the classification of the number of histograms, K-means histograms are used. Widely used texture databases are selected: VisTex, A LOT and Stex | Easy implementation Improves retrieval performance compare to state-of-art techniques. |
| 18 | Lakshmi et al. [82] | Relevance feedback by axis re-weighting scheme is proposed Caltech and Corel dataset is used for testing | An approach that leads to better convergence reduces the digit of iterations to reach superior retrieval accuracy. |
| 19 | Papushoy et al. [15] | Defining salient regions at local and global level Earthmovers distance is used for similarity comparison Benchmark. Dataset used are Simplicity and Corel 1K | It can produce a similar outcome to relevance feedback-based retrieval, and the system provides a stable outcome for a large variety of image categories |
| 20 | Hamouchenel et al. [8] | Texture segmentation using neighbors-based binary pattern method Brodatz dataset is used. | Research textures have been well recognized, produces better segmentation results compare to the classical decomposition method Improve accuracy of segmentation. |
| 21 | Barrena et al. [73] | Color, texture, and shapes feature extraction Classification using automated learning is used, Indexing and relevance feedback is used to increase the retrieval performance | Three spaces in combination improve results for recall and precision Relevance feedback enhances the quality of the retrieval process. Query finding are listed and sorted |
| 22 | Sun et al. [9] | Region identification with generic object detection Fusion of CNN and VLAD features Benchmark dataset: Holidays and UK Bench dataset | Promising accuracy is achieved. The system developed is scalable. Image demonstration of competent to the memory visual projection of the retrieval process gives the time efficiency. |
| 23 | Balaet al. [19] | Local text on the XOR patterns features descriptor Corel dataset is used in experimentation. | The feature vector is built using LTxXORPs, and the HSV histogram shows a major increase in recall and precision. |
| 24 | Matsui et al. [23] | Fine multi-scale edge orientation histogram-based feature extraction is proposed. Magna dataset is used for comparison | A proposed good solution to sketch-based image retrieval Could retrieves images from the MANGA database (not for other sketches) |
| 25 | Khodaskaret al. [26] | CBIR system using Ontology, Tries to reduce Semantic Gap using shared vocabulary (semantic features) | Bridges the semantic gap between the low and high-level features Improves semantic image retrieval with high accuracy, precision, and recall |
| 26 | Rahimi et al. [29] | Color ton distribution descriptors based on color co-occurrence matrices Classification using self-organizing map Corel and VisTex dataset | It chooses and extracts appropriate visual features with rich content. The low convolution of the feature extraction method is used in the SOM classifier. It can be used as a structural and signal processing feature description system which fails to supply satisfactory result in an image with the strong color distribution. |
| 27 | Kundu et al. [83] | Feature extraction using Multi-scale geometric analysis (MGA) of non-sub sampled contourlet transform (NSTC) Graph-based relevance feedback for ranking simplicity dataset, OLIVA dataset, and Caltech dataset is used for testing purposes. | User representation would process retrieval loop to eliminate the semantic gap by reducing the dimensionality of features. The ranking mechanism successfully uses user input to enhance the retrieval process' quality. |
| 28 | Irtaza et al. [84] | CBIR using Genetic Algorithm and SVM. Assures effective retrieval by taking user considerations into an account (i.e. Relevance feedback) Corel set A, Corel set B dataset are used. | Genetically optimized SVM overcomes the limitations of regular SVM like classifier instability, hyperplane bias. Image retrieval results show superiority in terms of recall and precision |
| 29 | Xuet al. [76] | Gabor wavelets, Grid color time, local binary pattern, edge histogram, and GIST features were used to extract features. The graph-based ranking is used as experimentation on Corel and MNIST dataset | Supports scalable grap reconstruction Significantly reduces the computational time |

Table A.1. Comparative analysis of CBIR techniques (continue)

| | | | |
|---|---|---|---|
| 30 | Jenni et al. [10] | Color string coding and string comparison-based feature extraction use SVM as a classifier, Corel photo collection is used. | Decreases computational complexity Significantly increases accuracy in image retrieval |
| 31 | Yu et al. [78] | The user's input is used to extract visual characteristics (color, shape, and texture). The dataset is sourced from the Microsoft Bing image search engine. | A more precise and robust ranking model is being developed. Visual contents can reduce noise in clicked features. |
| 32 | Montazer et al. [24] | Scale-invariant feature transform (SIFT) is based on the K-means clustering algorithm and its classification is Tested on Caltech 101 dataset | Using k-means clustering two main drawbacks of SIFT i.e. memory usage and matching time are overcome which shows high performance in searching images with objects |
| 33 | Guo et al. [20] | Error Diffusion Block Truncation Coding was used to extract features (EDBTC). To create feature vectors (BHF), color histogram feature (CHF) and bit pattern histogram feature (BPHF) are used . Image feature descriptors are computed using vector quantization. For the Corel 1000 and Corel 10000 datasets, the APR is determined. | The method is superior to former BTC methods. Due to the added indexing scheme, it achieves higher retrieval accuracy Feature vector are computed by incorporating vector quantization |
| 34 | Huang et al. [21] | Color moment (color), Zernikmoments (Shape), and co-occurrence matrix (texture) based feature extraction on Corel image dataset | A combination of three features solves the shortcoming (i.e. partly express and description of the image) of the method as a single feature Retrieval result is better than Contrary retrieval because it takes more time |
| 35 | Liu et al. [11] | Feature extraction based on (Chroma) color (graycolor co-occurrence matrices, Tamura and wavelet) texture features | Gives better performance with traditional luminance texture images |
| 36 | Hsiao et al. [79] | EMR (efficient manifold ranking) and the Pareto front procedure are capable of handling multiple queries with queries belonging to various image semantics. | Linear combination of ranking results is suitable for real-world datasets |
| 37 | Liu et al. [85] | An IND-CPA secure CBIR framework was suggested and introduced, which allows users to retrieve images from the cloud without having to interact with them constantly. | The CBIR framework is effective and reliable, according to the findings. |
| 38 | Ahmed [86] | This study proposes a novel relevance feedback retrieval technique(RFRM) for CBMIR . The feedback is applied using the voting values obtained from each class in the image repository. | The suggested RFRM approach outperforms all others in terms of recall and accuracy. |