A Comparative Study of Content Based Image Retrieval Trends and Approaches

Satish Tunga *satish.tunga@msrit.edu*
Dept. of Telecommunication Engineering, MSRIT, Bengaluru,
& Research Scholar, Jain Univ., Bengaluru, India

D. Jayadevappa *devappa22@gmail.com*
Dept. of Electronics & Inst. Engineering,
JSS Academy of Technical Education, Bengaluru,
VTU, Belgavi, India

C. Gururaj *gururaj.c@gmail.com*
Dept. of Telecommunication Engineering, BMSCE, Bengaluru,
& Research Scholar, Jain Univ., Bengaluru, India

Abstract

Content Based Image Retrieval (CBIR) is an important step in addressing image storage and management problems. Latest image technology improvements along with the Internet growth have led to a huge amount of digital multimedia during the recent decades. Various methods, algorithms and systems have been proposed to solve these problems. Such studies revealed the indexing and retrieval concepts, which have further evolved to Content-Based Image Retrieval. CBIR systems often analyze image content via the so-called low-level features for indexing and retrieval, such as color, texture and shape. In order to achieve significantly higher semantic performance, recent systems seek to combine low-level with high-level features that contain perceptual information for human. Purpose of this review is to identify the set of methods that have been used for CBR and also to discuss some of the key contributions in the current decade related to image retrieval and main challenges involved in the adaptation of existing image retrieval techniques to build useful systems that can handle real-world data. By making use of various CBIR approaches accurate, repeatable, quantitative data must be efficiently extracted in order to improve the retrieval accuracy of content-based image retrieval systems. In this paper, various approaches of CBIR and available algorithms are reviewed. Comparative results of various techniques are presented and their advantages, disadvantages and limitations are discussed. .

Keywords: Content-based Image Retrieval, Semantics, Feature Extraction.

1. INTRODUCTION

Content Based Image Retrieval (CBIR) is a challenging task. Current research works attempt to obtain and use the semantics of image to perform better *retrieval.* Image database management and retrieval has been an active research area since the 1970s [1]. The term Content-based image retrieval was originated in 1992, when it was used by T. Kato to describe experiments into automatic retrieval of images from a database, based on the colors and shapes present. Since then, this term has been used to describe the process of retrieving desired images from a large collection on the basis of syntactical image features. With the rapid increase in computer speed and decrease in memory cost, image databases containing thousands or even millions of images are used in many application areas [2] such as medicine, satellite imaging, and biometric databases, where it is important to maintain a high degree of precision. With the growth in the number of images, manual annotation becomes infeasible both time and cost-wise. Content-based image retrieval (CBIR) is a powerful tool since it searches the image database by utilizing visual cues alone. CBIR systems extract features from the raw images themselves and calculate an association measure (similarity or dissimilarity) between a query image and database images based on these features. CBIR is becoming very popular because of the high demand for searching image databases of ever-growing size. Since speed and precision are important, we need to develop a system for retrieving images that is both efficient and effective.

Image retrieval has been an extremely active research area over the last 10 years, but first review articles on access methods in image databases appeared already in the early 80s [3]. CBIR systems retrieve images from that database which are similar to the query image. Primarily research in Content Based Image Retrieval has always focused on systems utilizing color and texture features [4]. There has also been some work done using some local color and texture features. These account for Region Based Image Retrieval (RBIR) [5]. There are three important feature components for content based image retrieval [6]. The most common are color [7, 8], texture [9, 10]and shape [11, 12] or combinations of these. These features are combined to achieve higher retrieval efficiency [8]. In content-based image retrieval (CBIR), the image databases are indexed with descriptors derived from the visual content of the images. Most of the CBIR systems are concerned with approximate queries where the aim is to find images visually similar to a specified target image. In most cases the aim of CBIR systems is to replicate human perception of image similarity [13].The outline of the content based image retrieval system is shown in Figure 1.

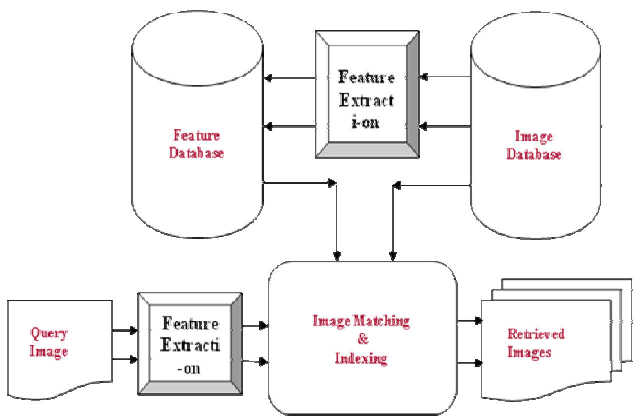


FIGURE 1: CBIR System and Its Various Components.

The process of CBIR consists of the following stages:

Image acquisition: It is the process of acquiring a digital image.

Image Database: It consists of the collection of n number of images depends on the user range and choice.

Image preprocessing: To improve the image in ways that increases the chances for success of the other processes. The image is first processed in order to extract the features, which describe its contents. The processing involves filtering, normalization, segmentation, and object identification. Like, image segmentation is the process of dividing an image into multiple parts. The output of this stage is a set of significant regions and objects.

Feature Extraction: Features such as shape, texture, color, etc. are used to describe the content of the image. The features further can be classified as low-level and high-level features. In this step visual information is extracts from the image and saves them as features vectors in a features database .For each pixel, the image description is found in the form of feature value (or a set of value called a feature vector) by using the feature extraction .These feature vectors are used to compare the query with the other images and retrieval.

Similarity Matching: The information about each image is stored in its feature vectors for computation process and these feature vectors are matched with the feature vectors of query image (the image to be search in the image database whether the same image is present or not or how many are similar kind images are exist or not) which helps in measuring the similarity. This step involves the matching of the above stated features to yield a result that is visually similar with the use of similarity measure method called as Distance method. Here is different distances method available such as Euclidean distance, City Block Distance, Canberra Distance.

Retrieved images: It searches the previously maintained information to find the matched images from database. The output will be the similar images having same or very closest features [14] as that of the query image.

User interface: This governs the display of the outcomes, their ranking, and the type of user interaction with possibility of refining the search through some automatic or manual preferences scheme [15].

1.1. *Challenges of CBIR Systems*

There could be many challenges faced by a CBIR system such as:

- The issue related to the Semantic gap where it means the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation. The user wants to seek semantic similarity, but the database can only provide similarity by data processing.
- The expectation of users for huge amount of objects to search among.
- Sometimes incompleteness query specification seems to be a challenge.
- Incomplete image description is also a source of challenge to an efficient CBIR system.

1.2. Search Options for CBIR Systems

Since the early 1990s, content-based image retrieval has become a very active research area. Both commercial and research image retrieval systems, have been built. Most image retrieval systems support one or more of the following options:

- Random browsing
- Search by example
- Search by sketch
- Search by text (including key word or speech)
- Navigation with customized image categories.

Today, there is the provision of a rich set of search options, but in practical applications which involves actual users still need systematic studies to explore the trade-offs among the different options mentioned above. Here, we will select a few representative systems and highlight their distinct characteristics. [15]

1.3. Real World Requirements

Building real-world systems involve regular user feedback during the development process, as required in any other software development life cycle. Not many image retrieval systems are deployed for public usage, save for Google Images or Yahoo! Images (which are based primarily on surrounding meta-data rather than content). There are, however, a number of propositions for real-world implementation. For brevity of space we are unable to discuss them in details, but it is interesting to note that CBIR has been applied to fields as diverse as Botany, Astronomy, Mineralogy, and Remote sensing [16, 17, 18, 19]. With so much interest in the field at the moment, there is a good chance that CBIR based real-world systems will diversify and expand further. Implementation of an IRM-based [20] publicly available similarity search tool on an on-line database of over 800,000 airline-related images [21] etc. Screen-shots can be seen in Fig. 2 and Fig. 3 respectively Based on our experience with implementing CBIR systems on real- world data for public usage, we list here some of the issues that we found to be critical for real-world deployment.

Performance: The most critical issue is the quality of retrieval and how relevant it is to the domain-specific user community. Most of the current effort is concentrated on improving performance in terms of their precision and recall.

Semantic learning: To tackle the problem of semantic gap faced by CBIR, learning image semantics from training data and developing retrieval mechanisms to efficiently leverage semantic estimation are important directions.

Volume of Data: Public image databases tend to grow into unwieldy proportions. The software system must be able to efficiently handle indexing and retrieval at such scale.

Heterogeneity: If the images originate from diverse sources, parameters such as quality, resolution and color depth are likely to vary. This in turn causes variations in color and texture features extracted. The systems can be made more robust by suitably tackling these variations.

Concurrent Usage: In on-line image retrieval systems, it is likely to have multiple concurrent users. While most systems have high resource requirements for feature extraction, indexing etc., they must be efficiently designed so as not to exhaust the host server resources. Alternatively, a large amount of resources must be allocated.

Multi-modal features: The presence of reliable meta- data such as audio or text captions associated with the images can help understand the image content better, and hence leverage the retrieval performance. On the other hand, ambiguous captions such as “wood” may actually add to the confusion, in which case the multi-modal features together may be able to resolve the ambiguity.

User-interface: As discussed before, a greater effort is needed to design intuitive interfaces for image retrieval such that people are actually able to use the tool to their benefit.

Operating Speed: Time is critical in on-line systems as the response time needs to be low for good interactivity. Implementation should ideally be done using efficient algorithms, especially for large databases. For computationally complex tasks, off-line processing and caching the results in parts is one possible way out. System Evaluation: Like any other software system, image retrieval systems are also required to be evaluated to test the feasibility of investing in a new version or a different product. The design of a CBIR benchmark requires careful design in order to capture the inherent subjectivity in image retrieval. One such proposal can be found in [22].

The machine learning algorithm predicts the category of the query image which is nothing but the semantic concept of the query image. Hence instead of finding similarity between the query image and all the images in database, it is found between the query image and only the images belonging to the query image category. Also when the entire database is searched, the retrieval result contains images of various categories.

1.4. Existing CBIR Systems

Some of the existing CBIR systems [16] are as follows:

1. QBIC or Query by Image Content It is the first commercial content based retrieval system. This system allows users to graphically pose and refine queries based on multiple visual properties such as color, texture and shape. It supports queries based on input images, user-constructed sketches, and selected colour and texture patterns.
2. VisualSEEK and WebSEEK VisualSEEk is visual feature search engine and WebSEEk is a World Wide Web oriented text/image search engine, both of which are developed at Columbia University.
3. Virage Virage is content based image search engine developed at Virage Inc.It supports color and spatial location matching as well as texture matching.
4. NeTra This system uses color, shape, spatial layout and texture matching, as well as image segmentation.
5. MARS or Multimedia Analysis and Retrieval System, this system makes use of colour, spatial layout, texture and shape matching.
6. Viper or Visual Information Processing for Enhanced Retrieval .This system retrieves images based on color and texture matching.
7. The img (Anaktisi) is a CBIR system on the web based on various descriptors which includes powerful color and texture features. The img (Anaktisi) provides different ways to search and retrieve them.

FIGURE 2: (a) Searching Image on COIL-20 Database (b) Searching Aircraft Images on Airlines.net database

2. CURRENT CBIR TECHNIQUES

Existing general-purpose CBIR systems roughly fall into three categories depending on the approach to extract features i.e., histogram, color layout, and region-based search. There are also systems that combine retrieval results from individual algorithms by a weighted sum matching metric [23], or other merging schemes [24].

2.1. Global Feature Based CBIR Systems

Some of the existing CBIR systems extract features from the whole image not from certain regions in it; these features are referred to as Global features. Histogram search algorithms [25] characterize an image by its color distribution or histogram. Many distances have been used to define the similarity of two color histogram representations. Euclidean distance and its variations are the most commonly used. The drawback of a global histogram representation is that information about object location, shape and texture is discarded. Color histogram search is sensitive to intensity variations, color distortions, and cropping. Color histogram search is sensitive to intensity variations, color distortions, and cropping. In simple color layout indexing [25], images are partitioned into blocks and the average color of each block is stored. Thus, the color layout is essentially a low resolution representation of the original image. However, as with pixel representation, although information such as shape is preserved in the color layout representation, the retrieval system cannot perceive it directly. Color layout search is sensitive to shifting, cropping, scaling, and rotation because images are described by a set of local properties [24]. Image retrieval using color features often gives disappointing results, because in many cases, images with similar colors do not have similar content. This is due to the fact that global color features often fails to capture color distributions or textures within the image.

D. Zhang [26] proposed a method combining both color and texture features to improve retrieval performance. By computing both the color and texture features from the images, the database images are indexed using both types of features. During the retrieval process, given a query image, images in the database are firstly ranked using color and features. Then, in a second step, a number of top ranked images are selected and re-ranked according to their texture features. Two alternatives are provided to the user, one is the retrieval based on color features, and the other is retrieval based on combined features. When the retrieval based on color fails, the user will use the other alternative which is the combined retrieval. Since the texture features are extracted globally from the image.

2.2. Region Based CBIR Systems

Region-based retrieval systems attempt to overcome the deficiencies of global feature based search by representing images at the object-level. A region-based retrieval system applies image segmentation to decompose an image into regions, which correspond to objects if the decomposition is ideal [27]. The object-level representation is intended to be close to the perception of the human visual system (HVS). Since the retrieval system has identified what objects are in the image, it is easier for the system to recognize similar objects at different locations and with different orientations and sizes. Region- based retrieval systems include the Natra system [28], and the Blobworld system [29].

The Natra and the Blobworld systems compare images based on individual regions. The motivation is to shift part of the comparison task to the users. To query an image, a user is provided with the segmented regions of the image and is required to select the regions to be matched and also attributes, e.g., color and texture, of the regions to be used for evaluating similarity. Such querying systems provide more control to the user. However, the user's semantic understanding of an image is at a higher level than the region representation.

Natsev et al. considered the similarity model WALRUS [30], which is a robust model for scaling and translation of objects within an image. Each image is first decomposed into regions. The similarity measure between two images is then defined as the fraction of the area of the two images covered by matching regions. However, WALRUS focuses on the development of a fast and effective segmentation method instead of an image-to-image similarity measure. Consequently, region matching should be necessary before image matching. The authors proposed a greedy heuristic for computing the similar region pair set with the maximum area. The basic idea is to iteratively choose the best pair of matching regions that maximizes the area covered by the regions. In [31], the mean shift algorithm is used for segmentation of images and interested regions are indexed using cluster-based tree to increase the efficiency of the retrieval process. However, this system uses only color as image signature, which is sensitive to shifting, cropping, scaling, and rotation. Region based image retrieval [32] uses low-level features including color, texture, and edge density. For color, the histogram of image regions are computed, for texture co- occurrence matrix based entropy, energy, etc, are calculated, and for edge density it is Edge Histogram Descriptor (EHD) that is found. To decrease the retrieval time of images, an idea is developed based on greedy strategy to reduce the computational complexity.

Li and Wang et al [33], proposed the Integrated Region Matching (IRM) algorithm, which allows matching a region of one image to several regions of another image to measure the similarity between images i.e. the region mapping between any two images is a many-to-many relationship. As a result, the similarity between two images is defined as the weighted sum of distances in the feature space, between all regions from different images. Compared with retrieval systems based on individual regions, such as Blobworld, the IRM approach decreases the impact of inaccurate segmentation by smoothing over the imprecision in distances.

Fuzzy Club [34] addresses the issue of effective and efficient content based image retrieval by presenting an indexing and retrieval system that integrates color, texture, and shape information for the indexing and retrieval, and applies these region features obtained through unsupervised segmentation, as opposed to applying them to the whole image domain. Fuzzy Club emphasizes improving on a color feature “inaccuracy” problem in the region based literature that is color histogram bins are not independent. Fuzzy Club first segments an image into regions of 4x4 blocks and extracts color and texture features on each block. The k-means algorithm is used to cluster similar pixels together to form a region. The Lab color space is used to extract color features and Haar wavelet transform is used to extract three texture features. A secondary clustering is performed to reduce query processing time. Regions with similar features are grouped together in the same class.

3. FEATURE EXTRACTION

Feature extraction is a means of extracting compact but semantically valuable information from images. This information is used as a signature for the image. Similar images should have similar signatures. If we look at the image shown in Figure 4, the white color and the texture of the building are characteristic properties. In a similar way, the sky can be described by its blue color. Furthermore, we can take the size of the objects in the image into account. Representation of images needs to consider which features are most useful for representing the contents of images and which approaches can effectively code the attributes of the images. Feature extraction of the image in the database is typically conducted off-line so computation complexity is not a significant issue. This section introduces three features: texture, shape, and color, which are used most often to extract the features of an image.

3.1. Colour

One of the most important features visually recognized by humans in images is color. Humans tend to distinguish images based mostly on color features. Because of this, color features are the most widely used in CBIR systems and the most studied in literature. Color is a powerful descriptor that simplifies object identification, and is one of the most frequently used visual features for content-based image retrieval. To extract the color features from the content of an image, a proper color space and an effective color descriptor have to be determined. The purpose of a color space is to facilitate the specification of colors. Each color in the color space is a single point represented in a coordinate system. Several color spaces, such as RGB, HSV, CIE L*a*b, and CIE L*u*v, have been developed for different purposes [35]. Although there is no agreement on which color space is the best for CBIR, an appropriate color system is required to ensure perceptual uniformity.

FIGURE. 3. (a) Image Properties (b) Sample Image (c) Colour Histogram of Sample Image

Therefore, the RGB color space, a widely used system for representing color images, is not suitable for CBIR because it is a perceptually non-uniform and device-dependent system [36]. After selecting a color space, an effective color descriptor should be developed in order to represent the color of the global or regional areas. Several color descriptors have been developed from various representation schemes, such as color histograms [37], color moments [38], color edge [39], color texture [40], and color correlograms [41].

3.2. Colour Histogram

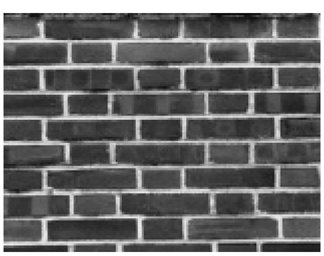
The most commonly used method to represent color feature of an image is the color histogram. A color histogram is a type of bar graph, where the height of each bar represents an amount of particular color of the color space being used in the image [35]. The bars in a color histogram are named as bins and they represent the x-axis. The number of bins depends on the number of colors there are in an image. The number of pixels in each bin denotes y-axis, which shows how many pixels in an image are of a particular color. The color histogram can not only easily characterize the global and regional distribution of colors in an image, but also be invariant to rotation about the view axis.

In color histograms, quantization is a process where number of bins is reduced by taking colors that are similar to each other and placing them in the same bin. Quantizing reduces the space required to store the histogram information and time to compare the histograms. Obviously, quantization reduces the information regarding the content of images; this is the tradeoff between space, processing time, and accuracy in results [41]. Color histograms are classified into two types, global color histogram (GCH) and local color histogram (LCH). A GCH takes color histogram of whole image and thus represents information regarding the whole image, without concerning color distribution of regions in the image. In the contrary, an LCH divides an image into fixed blocks or regions, and takes the color histogram of each of those blocks. LCH contains more information about an image, but when comparing images, it is computationally expensive. GCH is known as a traditional method for retrieving color based images. Since it does not include color distribution of the regions, when two GCHs are compared, one might not always get a proper result when viewed in terms of similarity of images [42]. An example of a color histogram in the HSV color space can be seen with the image in Figure 6.

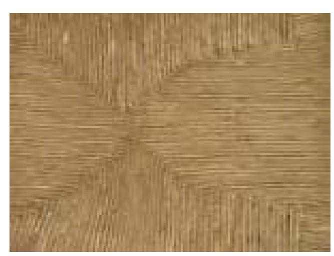
3.3. Texture

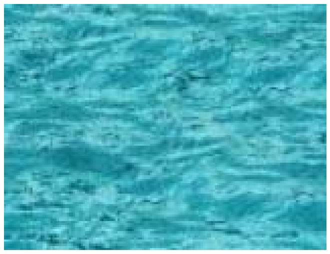
Texture definitions are based on texture analysis methods and the features extracted from the image. However, texture can be thought of as repeated patterns of pixels over a spatial domain, of which the addition of noise to the patterns and their repetition frequencies results in textures that can appear to be random and unstructured. Texture properties are the visual patterns in an image that have properties of homogeneity that do not result from the presence of only a single color or intensity. The different texture properties as perceived by the human eye are, for example, regularity, directionality as shown in figures (a) to (d).

In real world scenes, texture perception can be far more complicated. The various brightness intensities give rise to a blend of the different human perception of texture as shown in figures (e) & (f). Image textures have useful applications in image processing and computer vision. They include: recognition of image regions using texture properties, known as texture classification, recognition of texture boundaries using texture properties, known as texture segmentation, texture synthesis, and generation of texture images from known texture models. Since there is no accepted mathematical definition for texture, many different methods for computing texture features have been proposed over the years. Unfortunately, there is still no single method that works best with all types of textures. According to Manjunath and Ma [44], the commonly used methods for texture feature description are statistical, model-based, and transform-based methods. The texture feature description categories are explained below.


(a)Regular


(b) Irregular


(c) Directional


(d) Non Directional


(e) Complex texture 1


(f) Complex texture 2

FIGURE. 4. (a) to (d): Simple Textures Images; (e) to (f): Complex Textures Images

(i) Statistical Methods:
Statistical methods analyze the spatial distribution of grey values by computing local features at each point in the image, and deriving a set of statistics from the distribution of the local features. They include co- occurrence matrix representation, statistical moments, gray level differences, autocorrelation function, and grey level run lengths. The most commonly used statistical method is the Gray-level Co-occurrence Matrix (GLCM) [45]. It is a two-dimensional matrix of joint probabilities between pairs of pixels, separated by a distance, d, in a given direction, r. It is popular in texture description and is based on the repeated occurrence of some gray level configuration in the texture; this configuration varies rapidly with distance in fine textures and slowly in coarse textures. Haralick [45] defined 14 statistical features from gray-level co-occurrence matrix for texture classification, such as energy, entropy, contrast, maximum probability, autocorrelation, and inverse difference moment. Gray-level co-occurrence matrix method of representing texture features has found useful applications in recognizing fabric defects and in rock texture classification and retrieval [46].

(ii) Model Based Approaches:
Model-based texture methods try to capture the process that generated the texture. By using the model-based features, some part of the image model is assumed and an estimation algorithm is used to set the parameters of the model to yield the best fit [47]. To describe a random field, assume the image is modeled as a function f (r, ω), where r is the position vector representing the pixel location in the 2-D space and ω is a random parameter. Once a specific texture ω is selected, f (r, ω) is an image, which is a function over the 2-D grid indexed by r. Function f (r, ω) is called as a random field. There are currently three major model based methods: Markov random fields by Dubes and Jain [48], fractals by Pentland [49], and the multi-resolution autoregressive features introduced by Mao and Jain [50].

(iii) Transform Domain Features:
The word transform refers to a mathematical representation of an image. There are several texture classifications using transform domain features in the past, such as discrete Fourier transform, discrete wavelet transforms, and Gabor wavelets. On the other hand, wavelet analysis breaks up a signal into shifted and scaled versions of the original wavelet (mother wavelet), which refers to decomposition of a signal into a family of basis functions obtained through translation and dilation of a special function. Moments of wavelet coefficients in various frequency bands have been shown to be effective for representing texture [46]. Gabor filter (or Gabor wavelet) has been shown to be very efficient. Manjunath and Ma [44] have shown that image retrieval using Gabor features outperforms that using other transform features.

3.4. Shape
One of the common used features in CBIR systems is the shape. Shape of an object is the characteristic surface configuration as represented by the outline or contour. Shape recognition is one of the modes through which human perception of the environment is executed. It is important in CBIR because it corresponds to region of interests in images. Shape feature representations are categorized according to the techniques used. They are boundary-based and region-based [50]. In region based techniques, all the pixels within a shape are taken into account to obtain the

shape representation. Common region based methods use moment descriptors to describe shape [51]. Region moment representations interpret a normalized gray level image function as a probability density of a 2-D random variable. The first seven invariant moments, derived from the second and third order normalized central moments, are given by Hu [52]. Comparing with region based shape representation; contour based shape representation is more popular. Contour based shape representation only exploits shape boundary information. Simple contour-based shape descriptors include area, perimeter, compactness, eccentricity, elongation, and orientation. Complex boundary-based descriptors include Fourier descriptors, grid descriptors, and chain codes [42]. In our proposed system, we do not consider shape features during similarity distance computation. Including shape feature in the proposed system is one of our future works.

3.5. Shape Features

Shape information can be 2D or 3D in nature, depending on the application. The three shape descriptors are: Region Shape, Contour Shape and Shape 3D. 2D shape descriptors, the Region Shape and Contour Shape descriptors are intended for shape matching. They do not provide enough information to reconstruct the shape nor to define its position in an image. These two shape descriptors have been defined because of the two major interpretations of shape similarity, which are contour-based and region-based. Region Shape and Contour Shape descriptors as well as the Shape 3D descriptor are described in more detail below.

(i) Region Shape

The shape of an object may consist of a single region or a set of regions as well as some holes in the object. Since the Region Shape descriptor, based on the moment invariants [53], makes use of all pixels constituting the shape within a frame, it can describe any shape. The shape considered does not have to be a simple shape with a single connected region, but it can also be a complex shape consisting of holes in the object or several disjoint regions. The advantages of the Region Shape descriptor are that in addition to its ability to describe diverse shapes efficiently it is also robust to minor deformations along the boundary of the object. The feature extraction and matching processes are straightforward. Since they have low order of computational complexities they are suitable for shape tracking in the video sequences [54].

(ii) Contour Shape

The Contour Shape descriptor captures characteristics of a shape based on its contour. It relies on the so-called Curvature Scale-Space (CSS) [55] representation, which captures perceptually meaningful features of the shape. The descriptor essentially represents the points of high curvature along the contour (position of the point and value of the curvature). This representation has a number of important properties, namely, it captures characteristic features of the shape, enabling efficient similarity-based retrieval. It is also robust to non-rigid motion [53, 54].

3.6. Similarity Measure

The similarity between two images is defined by a similarity measure. Selection of similarity metrics has a direct impact on the performance of content-based image retrieval. The kind of feature vectors selected determines the kind of measurement that will be used to compare their similarity [23]. If the features extracted from the images are presented as multi-dimensional points, the distances between corresponding multi-dimensional points can be calculated. Euclidean distance is the most common metric used to measure the distance between two points in multi-dimensional space [56]. For other kinds of features such as color histogram, Euclidean distance may not be an ideal similarity metric or may not be compatible with the human perceived similarity. Histogram intersection was proposed by Swain and Bllard [57] to find known objects within images using color histograms.

3.7. Indexing Structures

When manipulating massive databases, a good indexing is a necessity. Processing every single item in a database when performing queries is extremely inefficient and slow. When working with text-based documents, creating good indexes is not very difficult. Next, in-depth processing only needs to be done with these documents. When searching for images, however, this approach is much more difficult. Raw image data is non-indexable as such, so the feature vectors must be used as the basis of the index. Popular multi-dimensional indexing methods include the R-tree and the R*-tree algorithms [23]. The Self Organizing Map (SOM) is also one of the indexing structures [58]. The SOM is trained to match the shape of the data in the feature space. After the training, the closest node in the SOM is calculated for every image in the database. When a query is done, the first thing to be done is to calculate the closest SOM node, also known as the best matching unit (BMU), to the query image's feature vector. When this is done, we know which images in the database are the closest to the query image.

4. IMAGE REGION MOMENTS

Image moments and their functions have been utilized as features in many image processing applications, viz., pattern recognition, image classification, target identification, and shape analysis. Moments of an image are treated as region-based shape descriptors. Among region-based descriptors, moments are very popular. These include invariant moments, Zernike moments and Legendre moments.

4.1. Invariant Moments

Invariant moments or geometric moments are the simplest moment functions with the basis $\varphi_{pq}(x,y) = x^p y^q$. The geometric moment function m_{pq} of order $(p+q)$ is defined by

$$m_{pq} = \sum_x \sum_y x^p y^q f(x,y);\ p,q = 0,1,2,.. \tag{1}$$

The geometric central moments that are invariant to translation are defined by

$$\mu_{pq} = \sum_x \sum_y (x-\overline{x})^p (y-\overline{y})^q f(x,y);\ p,q = 0,1,2,.. \tag{2}$$

The seven invariant moments are given by the following equations

$$I_1 = \eta_{20} + \eta_{02} \tag{3}$$

$$I_2 = (\eta_{20} + \eta_{02})^2 + (2\eta_{11})^2 \tag{4}$$

$$I_3 = (\eta_{20} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{02})^2 \tag{5}$$

$$I_4 = (\eta_{20} + 3\eta_{12})^2 + (\eta_{21} + \eta_{02})^2 \tag{6}$$

$$\begin{aligned} I_5 &= (\eta_{20} - 3\eta_{12})(\eta_{20} + \eta_{12})[(\eta_{20} + \eta_{12})^2 \\ &-3(\eta_{21} + \eta_{02})^2] + (3\eta_{21} - \eta_{02})(\eta_{21} + \eta_{02}) \\ &[3(\eta_{20} + \eta_{12})^2 - (\eta_{21} + \eta_{02})^2] \end{aligned} \tag{7}$$

$$\begin{aligned} I_6 &= (\eta_{20} - \eta_{02})[(\eta_{20} + \eta_{12})^2 - (\eta_{21} + \eta_{02})^2] \\ &+4\eta_{11}(\eta_{20} + \eta_{12})(\eta_{21} + \eta_{02}) \end{aligned} \tag{8}$$

$$\begin{aligned} I_7 &= (3\eta_{21} - \eta_{02})(\eta_{20} + \eta_{12})[(\eta_{20} + \eta_{12})^2 - \\ &3(\eta_{21} + \eta_{02})^2] - (\eta_{20} - 3\eta_{12})(\eta_{21} + \eta_{02}) \\ &[3(\eta_{20} + \eta_{12})^2 - (\eta_{21} + \eta_{02})^2] \end{aligned} \tag{9}$$

$n_{p,q} = \frac{\mu_{pq}}{y}, \gamma = 1 + \frac{p+q}{z}$, for $p+q = 2,3,...$

Invariant moments are invariant to translation, rotation and scaling [59, 60].

4.2. Zernike Moments

Zernike Moments (ZM) is orthogonal moments and can be used to represent shape content of an image with minimum amount of information redundancy [69, 70]. Orthogonal moments allow for accurate reconstruction of the image, and makes optimal utilization of shape information. Zernike Moments (ZM) are widely used in CBIR as shape descriptors [18, 19]. Z Zernike moments are derived from the orthogonal Zernike polynomials. Hence, it is an orthogonal moment. The Zernike moments are given by

$V_{nm}(x,y)=V_{nm}(r\cos\theta, r\sin\theta)=R_{mn}(\gamma)\exp(jm\theta)$ (10)

$R_{mn}(\gamma)$ is the orthogonal radial polynomial, and is given by

$$R_{mn}(\gamma)=\sum_{z=0}^{(n-|m|)/2}(-1)^2\frac{(n-s)!}{s!x\frac{(n-2s+1|m|)!(n-2s-|m|}{2}}\gamma^{n.2s} \tag{11}$$

$n=0,1,2,...0\le|m\le n;|\ n-|m|$ is even.

The Zernike moments for the image $f(x,y)$ are defined by equation

$$Z_{nm}=\frac{n+1}{\pi}\sum_r\sum_\theta f(r\cos\theta, r\sin\theta)$$
$$R_m(\gamma)\exp(jm\theta)r\le 1 \tag{12}$$

Zernike moments are invariant to rotation, translation and scaling. Also they are robust to noise and minor variations in shape. But the computational complexity of Zernike moments is high [59,61].

4.3. Legendre Moments

Legendre moments use Legendre polynomials as the kernel function. The two-dimensional Legendre moments of order $(p+q)$ for an image $f(x,y)$ are defined by equation

$$L_{pq}=\frac{(2p+1)(2q+1)}{4}\int_{-1}^{1}\int_{-1}^{1}P_p(x)XP_q(y)f(x,y)dxdy\quad x,y\in[-1,1] \tag{13}$$

where the Legendre polynomial $P_p(x)$ of order $'p'$ is given by the equation

$$P_p(x)=\sum_{k=0}^{p}\left((-1)^{\frac{p-k}{z}}\frac{1}{zp}\frac{(p+k)x^k}{\left[\frac{p-k}{z}\right]!\left[\frac{p+k}{z}\right][k]}\right) \tag{14}$$

The Legendre moments described in equation (11) can be expressed in discrete form by

$$L_{pq}=\lambda_{pq}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}P_p(x_i)P_q(y_j)f(i,j) \tag{15}$$

Where $\lambda_{pq}=\frac{(2p+1)(2q+1)}{N^2}$; x_i & y_i are the normalized pixel coordinates and are given by

$$x_i=\frac{2_i}{N-1}-1\,\&\,y_i=\frac{2_j}{N-1}-1 \tag{16}$$

4.4. Exact Legendre Moments

Legendre Moments (LM) are continuous and orthogonal moments, they can be used to represent an image with minimum amount of information redundancy. Many algorithms are developed for the computation of LM [71, 72, 73], but these methods focus mainly on 2D geometric moments. When they are applied to a digital image, a numerical approximation is necessary. Error due to approximation increases as the order of the moment increases. An accurate method for computing the Exact Legendre Moments (ELM) proposed by Hosney [74].

5. DISTANCE MEASURES

Distance measures are used for comparing the similarity of two images. There are different kinds of similarity measurements like Euclidean distance, histogram intersection, Bhattacharya distance and Mahalanobis distance for CBIR applications.

5.1. Euclidean Distance

Let p be the query image and t be the target image and let $p_q(z_q)$ and $p_t(z_t)$ be their respective probability densities. The Euclidean distance between the query image and the target image is given by equation

$$D_{Ece}(q_i, t_i) = \sum_{i=1}^{n} (q_i - t_i)^2 \tag{17}$$

In Euclidean distance, the least value of distance measure indicates the similarity [62, 63, 64].

5.2. Histogram Intersection

It is a distance measure for comparing histograms. It calculates the common part of the two histograms, and neglects the features occurring in a single histogram. The histogram intersection of two histograms [65] H and $H^{'}$ is calculated using equation

$$d_{\cap}(H, H^{'}) = \sum_{m=1}^{M} \min((H_{m^{'}}, H^{'}_{m}) \tag{18}$$

5.3. Bhattacharya Distance

The Bhattacharya Distance measures the similarity between two discrete or continuous probability distributions. A popular distance of similarity between two Gaussian distributions is the Bhattacharya distance. The Bhattacharya distance [66] between the query image q and the target image t in the database is given by equation

$$D_{Bhat}(q,t) = \frac{1}{g}(\mu_q - \mu_t)^T \left[\frac{\sum_q - \sum_t}{2}\right]^{-2}(\mu_q - \mu_t) + \frac{1}{2} l_n \frac{\left|(\sum_q - \sum_t \ / 2\right|}{\sqrt{\left|\sum_q\right| \left|\sum_t\right|}} \tag{19}$$

Where μ_q and μ_t are the mean vectors $\sum_q$ and $\sum_t$ are the covariance matrices of the query image q and the target image t, respectively [67, 68].

5.4. Mahalanobis Distance

The Mahalanobis Distance is based on the correlations between variables, and is used to analyze various patterns. It is useful in determining the similarity between an unknown sample set and a known one. The unknown sample set is the query image, and the known set is the images in the database. The Mahalanobis distance between the query image q and the target image t is given by equation following equation [66].

$$D_{Maha}(q,t) = (\mu_q - \mu_t)^T \sum{}^{-2} (\mu_q - \mu_t) \tag{20}$$

6. MACHINE LEARNING TECHNIQUES

The high level semantic features are derived from the image database with the help of machine learning techniques. There are two types of machine learning techniques i.e. supervised machine learning technique and unsupervised machine learning technique.

6.1. Supervised Machine Learning Techniques

Neural networks, Decision trees, and Support Vector Machines (SVMs) are some of the supervised machine learning techniques, which learn the high level concepts from low-level image features. The supervised machine learning techniques perform the classification process with the help of the already categorized training data. For the training data, the input (low level image features) and the desired output is already known. Hence, given a query image, the low level features are extracted and it is given as input to any one of the machine learning algorithms which is already trained with the training data. The machine learning algorithm predicts the category of the query image which is nothing but the semantic concept of the query image. Hence instead of finding similarity between the query image and all the images in database, it is found between the query image and only the images belonging to the query image category. Also when the entire database is searched, the retrieval result contains images of various categories. But when the machine learning techniques are used, since the query image‘s category (semantic concept) is predicted, the retrieval results will contain the images belonging to that category alone.

6.1.1. Neural Network

Neural networks are also useful in concept learning. The low level features of the segmented regions of the training set images are fed into the neural network classifiers, to establish the link between the low level image features and high level semantics. The disadvantage of this method is that it requires a large amount of training data, and is computationally intensive [75, 76, 77]. When the query image feature vector is presented to the neural network, it gives its semantic concept.

6.1.2. Support Vector Machine

Support Vector Machines (SVMs) are supervised learning methods [78, 79] used for image classification. It views the given image database as two sets of vectors in an ‘ n ’ dimensional space and constructs a separating hyper plane that maximizes the margin between the images relevant to query and the images not relevant to the query. SVM is a kernel method and the kernel function used in SVM is very crucial in determining the performance.

The basic principle of SVMs is a maximum margin classifier. Using the kernel methods, the data can be first implicitly mapped to a high dimensional kernel space. The maximum margin classifier is determined in the kernel space and the corresponding decision function in the original space can be non-linear [80]. The non-linear data in the feature space is classified into linear data in kernel space by the SVMs. The aim of SVM classification method is to find an optimal hyper plane separating relevant and irrelevant vectors by maximizing the size of the margin (between both classes).

Image classification or categorization is a machine learning approach and can be treated as a step for speeding-up image retrieval in large databases and to improve retrieval accuracy. Similarly, in the absence of labelled data, unsupervised clustering is also found useful for increasing the retrieval speed as well as to improve retrieval accuracy. Image clustering inherently depends on a similarity measure, while image classification has been performed by different methods that neither require nor make use of similarity measures [81].

6.1.3. SVM-Binary Decision Tree

The SVM-BDT takes advantage of the efficient computation of the binary tree architecture, and the high classification accuracy of the SVMs. Here, (N-1) SVMs are needed to train an N class problem. For the construction of the SVM-BDT, first, the semantic template of each of the categories or classes is found. The Euclidean distance between the semantic templates of each of the N classes is the N × N distance matrix. Two classes that have the largest Euclidean distance are assigned to each of the two clustering groups. The semantic template of these two classes is the cluster center of the two groups. The cluster center is updated to the semantic template of the newly added class. All the classes are assigned to one of the two possible groups of classes. The process continues, until there is only one class per group. The SVM binary classifier is used to train the samples in each non leaf nodes of the decision tree [68]. During the testing time, the feature vector of the query image is given as input to the SVM-BDT, and only $[\log_2 N]$ classifiers are consulted during the testing time.

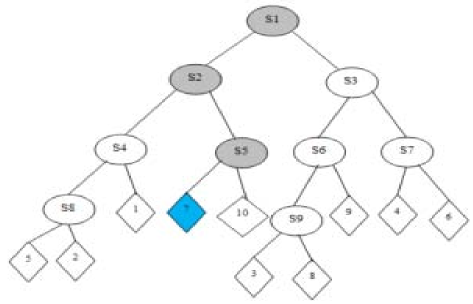


FIGURE 8: SVM-BDT for 10 Category Image Set.

The SVM-BDT predicts the label (semantic category) of the query image. Hence, the similarity distance between the query image and the predicted category images are computed and the images with least distance are retrieved. An example of a 10- class SVM-BDT is shown in Figure 8. For SVM-based image classification, recent work shows that the radial basis kernel function (RBF) works well, when the relation between the class labels and attributes is nonlinear [62].

6.1.4. Bayes Classifiers

Bayes classifiers are used in text retrieval systems. Since ten years, CBIR community is transposing them to image retrieval [85, 66]. Bayes binary classifiers use the class-conditional likelihood associated with class $cP(X \mid c)$ to compute the mapping function $g(x)$ of an input vector x.

$$g(x) = \arg\max_{c \in (-1,1)} P(X \mid c) P(c) \tag{21}$$

Because we have no prior assumption on the size of a class, we assume that $p(1) = p(-1) = \frac{1}{2}$ once $g(x)$ is computed the relevance function $f(x)$ may be expressed as follows.

$$f(x) = p(x \mid c) = g(x) \tag{22}$$

To estimate the probability density function, we use a kernelized version of Parzen windows:

$$p(x \mid c) = \frac{1}{\left|\{i(y_i = c\}\right| \sum_{i \in \{i|y_i \in c\}} k(x, x_i)} \tag{23}$$

where K(., .) is a kernel function.

6.1.5. k-Nearest Neighbors

This classification method has been used successfully in image processing and pattern recognition. For instance, in competition with neural networks, linear discriminant analysis (and others), kNearest Neighbors performed best results on pixel classification tasks [87]. The k-NN algorithm is one among the simplest of all machine learning algorithms. K-nearest neighbor algorithm (KNN) is also involved into our CBIR system. Based on the training result, KNN is applied for the query data images. KNN helps to classify the input data; also it fixes the code book which means the training result can be self-adapted. k-Nearest Neighbors classifiers attempt to directly estimate $f(x)$ using only the k nearest neighbors of x. In a small database ,a simple sequential scan is usually employed for k nearest – neighbor (KNN) search. But for large data set, efficient indexing algorithms are imperative. High dimensional data is increasingly in many common fields. As the number of dimensions increase, many clustering techniques begin to suffer from the curse of dimensionality, degrading the quality of the results.

6.2. Unsupervised Machine Learning Techniques

Unsupervised learning refers to the problem of trying to find hidden structure in the unlabeled data. It has no measurements of outcome, to guide the learning process. Image clustering is a typical unsupervised learning technique. It groups the sets of image data in such a way, that the similarity within a cluster should be maximized, and the similarity between different clusters must be minimized [82].

K-means clustering aims to partition the given n observations into k clusters. The mean of each cluster is found and the image is placed in a cluster, whose mean has the least Euclidean distance with the image feature vector. Parallel techniques for K-means are developed that can largely accelerate the algorithm [89], [90], [91]. In high dimensions, data becomes very sparse and distance measures become increasingly meaningless. Paper [88] reviewed the literature on parsimonious models and Gaussian models from the most complex to simplest which yields a method similar to the K Means approach. N Cut clustering is used to cluster the database images into different semantic classes. A set of n images is represented by a weighted undirected graph represents image.

CBIR based on Visual Contents				
Sl. No.	Papers	Features	Approaches	Limitations
1	W. Niblack et al. [92]	Colour	Histogram and colour moments	Query image is an unknown image, then the retrieval performance is poor
2	Chad Carson et al. [93]		Region Histogram	Result in the mismatch of the retrieval process when the image's orientation, and position or scales are altered.
3	J. Sawhney & Hefner et al. [94]		Colour Histogram	Similarity measure is extended to retrieve the texture regions from a database of natural images.
4	Stricker & Orengo [95]		Colour Moment	Semantically relevant images will be retrieved with amount of time
5	Michel Orega et al. [96]	Shape	Fourier Transform	The user gives feedback and the query image information becomes a new cluster
6	F. Mokhtarian et al. [97]		Curvature Scale Space	Given a query image, the user has to select the region of interest from the query image
7	Sougata Mukherjea et al. [98]		Template Matching	Images from the history of the user access patterns, and the access frequencies of the images in the database.

8	Furnikaza Kanehara et al. [99]	Shape	Convex Parts	The feedback can be got from the user again and again, till the user is satisfied with the results.
9	Pentland et al. [100]		Elastic Deformation of Templates	The similarity distance is found between the query image and the images belonging to the predicted cluster alone.
10	J. R. Smith et al. [101]	Texture	Wavelet Transform	All the classes are assigned to one of the two possible groups of classes.
11	S. Michel et al. [102]		Edge Statistics	Due to the complex distribution of the image data, the k-means clustering often cannot separate images
12	B. S Manjunath et al. [103]		Gabor Filters	The machine learning predicts the category of the query image
13	George Tzaglarakis et al. [104]		Statistical	The query image belongs to the class for which the membership is very large
The Semantic Gap In Image Retrial				
Sl. No.	Papers	Techniques	Approaches	Limitations
14	S. F Chang et al. [109]	Semantic Template	Semantic Visual Template	Texture descriptors contain features derived from co-occurrence matrices
15	Yang et al. [105]	Relevance Feedback	Semantic Feedback Mechanism	Lower retrieval precision by introducing the semi-supervision to the non-linear Gaussian-shaped RBF relevance feedback
16	Rege et al. [106]		Multiuser relevance feedback (User centered semantic hierarchy)	System is said to be efficient if semantic gap is minimum.
17	Liu et al. [107]		Semantic manifold	Bridging the semantic gap between the low-level features and the high-level semantics
18	Janghy Yoon & Nikil Jayant et al. [108]	Relevance Feedback	Multimedia model feedback	Descriptors based on color representation might be effective with a data set containing black and white images.
19	I notes [110]	Manual	User Annoted region	Retrieval application is

				specialized for a certain, limited domain, the smaller the gap can be made by using domain knowledge.
20	Face book [111]		User Annoted region/object	The resulting segments can be described by shape features
21	Google user labella [112]		User Annoted whole image	Often, the performance of a retrieval system with feedback
22	Brad Shaw et al. [113]	Semiautomatic	Bayer Probability	Probabilistic retrieval form is the use of support vector machines
23	Ghoshot [114]		Co-occurrence model	Background complication and independent of image size and orientation
24	Ilaria et al. [115]		Graph based link	Cannot be used to differentiate objects with different sizes or shapes.
25	Huang et al. [116]	Automatic	Decision tree	Line contents of images can be used to represent texture of the image.
26	Feng & Chan [117]		Bootstrapping	Statistical approaches do not exploit the sensitivity of the human visual system to textures.
27	Gao et al. [118]		Latent Semantic analysis	The characterization consists of local autocorrelation of coefficients in each subband.
28	Mori et al. [119]		Hidden Markov model	descriptor can tackle not only rotation but also small non-rigid deformation
29	P. L Standchey et al. [120]	Object Ontology	Colour representation ontology	It is extremely difficult to describe high level semantic concepts with image features only
30	V. Mezaris [121]	Object Ontology	High level concept ontology	A query system integrating multiple query seeds
31	Huan Wang [122]		Multimodality ontology	Could accommodate any number of features in a modular and extensible way.

TABLE 1: Performance Comparison of Various CBIR Techniques.

$G=(v,E), V=\{1,2,...,n\}$ and edges $E=\{(i,j)/i,j\in V$

$E=\{(i,j)/i,j\in V$ are formed between every pair of nodes. The weight w_{ij} of an edge (i,j) is an image. The system displays the image clusters and adjusts the model of similarity measure according to user feedbacks [83].

Fuzzy clustering models provide a promising solution to the clustering problem. The Fuzzy c-means (FCM) clustering is the most widely used fuzzy clustering algorithm. This algorithm is based on an iterative optimization of a fuzzy objective function. The degree of membership of a data item to a cluster is between [0, 1]. For a given query image, the output of the FCM is the membership value of the image with each of the K classes. The query image belongs to the class for which the membership value is high [62, 63, 84].

Hence the unsupervised learning algorithms takes the uncategorized image data as input and clusters those data into a number of categories by finding the hidden structure in the unlabelled data. The clustering algorithms divide the given data into n clusters and give cluster centers of each cluster. When a query image features are given to the clustering algorithm, it finds the distance between the query image and the entire cluster centers.

7. COMPARISON OF VARIOUS CBIR METHODS

The field of Content Based Image Retrieval has been an active research area for several decades and has been paid more and more attention in recent years as a result of the dramatic and fast increase in the volume of digital images. Many novel techniques have been proposed to tackle the challenges. However; all current CBIR systems suffer from insufficient generalization performance and accuracy as they are not able to establish a robust link or between image features and high-level concepts. In this section Table I summarize performance comparison of various CBIR techniques with respect to various components such as visual contents and semantic gaps. Table II gives comparison of various CBIR components used in various techniques with appropriate image data sets.

Sl. No.	Papers	Data Set	Distance measures	Machine Learning
1	Rahman M.H. et al. [123]	Brodatz database	Normalized Euclidean distance	Random walk with relevance feedback
2	Saptadi et al. [61]	MRI images	Error tolerance distance	R-Tree Data Structure
3	Felci Rajam et al. [63]	COREL dataset	Euclidean, Bhattacharya-Mahalanobis	SVM Binary Decision Tree
4	Lining et al. [124]	COREL dataset	Mahalanobis distance	Generalized Biased Discriminant Analysis (GBDA)
5	Imtnan et al. [125]	Vistex database, Outex database	Kullback–Leibler(KL) divergence	Parametric Spectral Analysis
6	[Hatice et al.[126]	Follicular Lymphoma, Neuroblasto ma	Correlation distance measure	SVM, Nearest neighbor search
7	Ja-Hwung et al. [127]	COREL dataset	Weighted KNN search	Navigation Pattern based Relevance Feedback
8	Yu-Gang et al. [128]	NUS-WIDE TRECVID	Canberra distance	Semantic graph
9	Kuldeep et al. [129]	Data set of MRI, CT-scan and X-ray	Euclidean Distance	Parallel implementation feature extraction and feature matching
10	Felci et al. [68]	Caltech	Euclidean, Bhattacharya, Mahalanobis	SVM-BDT, SCM
11	Wang Xing Yuan, [129]	Public sources	Weighted KNN search	Navigation Pattern based Relevance Feedback
12	Samuel et al., [130]	Oliva dataset, Caltech dataset	l^1- norm	Random walk with relevance feedback

TABLE 2: Comparison of Various CBIR Components used in Various Components.

8. CONCLUSION

This paper presents a brief survey on work related to the exciting fields of content-based image retrieval and provides a detailed review of the works carried out in this field. This paper also discusses the various methodologies used for extracting the salient low level features and various distance measures to find the similarity between images in reducing the semantic gap between the low level features and the high level semantic concepts. A discussion of various approaches of CBIR and comparison of various techniques with respect to data are also made.

9. FUTURE RESEARCH

This paper presents a comparative study of Content Based Image Retrieval Trends and the various approaches towards resolving some of the problems encountered in CBIR. One alternative is to use more sophisticated feature representations. Instead of using a purely data-driven evaluation using basic image features, higher-level information about regions could be used. Since an image epitome provides a composite description of shape and appearance, it is possible to achieve a better measure of homogeneity/heterogeneity of the segments. One of the steps towards resolving the semantic information problem, when possible, prior knowledge, especially application-dependent knowledge, should be incorporated into an evaluation method so that the evaluation method knows the preferred characteristics of a segment. Different methods can be applied to include prior knowledge about a preferred features.

10. REFERENCES

[1] T. Huang, Y. Rui, Image retrieval: Past, present, and future, in: Proceedings of the International Symposium on Multimedia Information Processing, 1997, pp. 1–23.

[2] Ch. Srinivasa Rao , S. Srinivas Kumar and B. Chandramohan," Content Based Image Retrieval using Exact Legendre Moments and Support Vector Machine", The International Journal of Multimedia and its Applications (IJMA), Vol.2, No.2, pp: 69-79, May 2010.

[3] S.K. Chang, T. Kunii, “Pictorial Database Applications”, IEEE Computer, Vol. 14, No. 11, 1981.

[4] C.Gururaj, D.Jayadevappa, Satish Tunga, “ Novel Algorithm for Exudate Extraction from Fundus Images of the Eye for a Content Based Image Retrieval System”, 4th IEEE International Conference on Control System, Computing and Engineering (ICCSCE – 2014), ISBN- 978-1-4799-5685-2, 28th – 30th November 2014, pp 460 – 465, Penang, Malaysia, DOI: 10.1109/ICCSCE.2014.7072763

[5] J. Li, J.Z. Wang, G. Widerhold, “IRM: Integrated Region Matching for Image Retrieval”, 8th ACM International Conference on Multimedia, pp. 147-156, October 2000.

[6] H.J. Lin, et al. “A Study of Shape Based Image Retrieval”,24th IEEE International Conference on Distributed Computing Systems Workshops, 2004.

[7] Y. Rui, T.S. Huang, S.F. Chang SF, “Image Retrieval: Current Techniques, Promising Directions and Open Issues”, J. Vis. Commun. Image Rep., Vol. 10, No. 4, pp.39-62, 1999.

[8] P. Hiremath, J. Pujari, “Content Based Image Retrieval Using Color, Texture and Shape Features”, IEEE International Conference on Advanced Computing and Communications, ADCOM, 2007M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 989.

[9] M.M. Islam, D. Zhang, G. Lu, “Automatic Categorization of Image Regions Using Dominant Colour Based Vector Quantization”, Digital Image Computing: Techniques and Applications, Canberra, Australia, pp.191-198, December 1-3, 2008.

[10] N. Rasiwasia, N. Vasconcelos, P.J. Moreno, "Query by Semantic Example", 15th International Conference on Image and Video Retrieval, Lecture Notesin Computer Science, Vol. 4071, Springer, Berlin, pp. 51-60, 2006.

[11] V.A. Tanase, "Content Based Image Retrieval Systems: A Survey", Dept. of Computing Science, Utrecht University, Technical Report, 2000.

[12] W. Zhang, et al., "Shape Based Indexing in a Medical Image Database", IEEE Workshop on Biomedical Image Analysis, 1998.

[13] Ville Viitaniemi, "Image Segmentation in Content-Based Image Retrieval", Helsini University of Technology, Department of Electrical and Communications Engineering, Master Thesis, Finland 24th May 2002.

[14] H.B. Kekre, "Survey of CBIR Techniques and Semantics", International Journal of Engineering Science and Technology (IJEST), ISSN: 0975-5462 Vol. 3 No. 5, May 2011.

[15] Kanchan Saxena, Vineet Richaria, Vijay Trivedi, "A Survey on Content Based Image Retrieval using BDIP, BVLC AND DCD", Journal of Global Research in Computer Science, Vol.3, No. 9, Sep. 2012, ISSN-2229-371X.

[16] Z. Wang, Z. Chi, and D. Feng, "Fuzzy integral for leaf image retrieval," Proc. IEEE Intl. Conference on Fuzzy Systems, 2002.

[17] A. Csillaghy, H. Hinterberger, and A.O. Benz, "Content Based Image Retrieval in Astronomy," Information Retrieval, 3(3):229–241, 2000.

[18] T. H. Painter, J. Dozier, D. A. Roberts, R. E. Davis, and R. O. Green, "Retrieval of sub-pixel snow-covered area and grain size from imaging spectrometer data," Remote Sensing of Environment, 85(1):64–77, 2003.

[19] M. Schroder, H. Rehrauer, K. Seidel, M. Datcu, "Interactive learning and probabilistic retrieval in remote sensing image archives," IEEE Trans. Geosciences and Remote Sensing, 38(5):2288–2298, 2000.

[20] J.Z. Wang, J. Li, and G. Wiederhold, "Simplicity: Semantics-Sensitive Integrated Matching for Picture Libraries," IEEE Trans. Pattern Analysis and Machine Intelligence, 23(9), 947–963, 2001.

[21] Airliners.net, http://www.airliners.net.

[22] H. Muller, W. Muller, D. M. Squire, S. Marchand-Maillet, and T. Pun, "Performance evaluation in content-based image retrieval: Overview and proposals," Pattern Recognition Letters, 22(5):593-601, 2001.

[23] F. Long, H. Zhang, H. Dagan, and D. Feng, "Fundamentals of content based image retrieval," in D. Feng, W. Siu, H. Zhang (Eds.): "Multimedia Information Retrieval and Management. Technological Fundamentals and Applications," Multimedia Signal Processing Book, Chapter 1, Springer-Verlag, Berlin Heidelberg New York, 2003, pp.1-26.

[24] M. Ghahroudi, M. Sarshar, and R. Sabzevari, "A Novel Content-Based Image Retrieval Technique Using Tree Matching," Proceedings of The World Congress on Engineering, pp1797-180, May 2008.

[25] M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, and P. Yanker, "Query by image and video content: The QBIC system," IEEE Computer, vol. 28, no 9, pp.23-32, Sep. 1995.

[26] D. Zhang, "Improving Image Retrieval Performance by Using Both Color and Texture Features," In Proc. of IEEE 3rd International Conference on Image and Graphics (ICIG04), Hong Kong, China, Dec.18-20, 2004, pp.172-175.

[27] J. Wang, J. Li, G. Wiederhold, “Simplicity: semantics-sensitive integrated matching for picture libraries,” IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 23, no. 9, pp. 947–963, Sep. 2001.

[28] W. Ma and B. Manjunath, “Natra: A Toolbox for Navigating Large Image Data bases,” Proc. IEEE Int'l Conf. Image Processing, Santa Barbara, 1997, pp. 568- 571.

[29] C. Carson, M. Thomas, S. Belongie, J.M. Hellerstein, and J. Malik, “Blob world: A System for Region-Based Image Indexing and Retrieval,” Proc. Visual Information Systems, pp. 509-516, June 1999.

[30] A. Natsev, R. Rastogi, and K. Shim, “WALRUS: A Similarity Retrieval Algorithm for Image Databases,” IEEE Trans. On Knowledge and Data Engineering, vol.16, pp. 301-318, Mar. 2004.

[31] M. Sudhamani, and C. Venugopal, “Image Retrieval from Databases: an Approach using Region Color and Indexing Technique,” International Journal of Computer Science and Network Security, vol.8 no.1, pp. 54-64, January 2008.

[32] S. Nandagopalan, B. Adiga, and N. Deepak, “A Universal Model for Content-Based Image Retrieval,” Proc. of world academy of science, engineering and technology, vol. 36, pp. 659-662, DEC. 2008.

[33] J. Li, J. Wang, and G. Wiederhold, “Integrated Region Matching for Image Retrieval,” In Proceedings of the 2000 ACM Multimedia Conference, Los Angeles, October 2000, pp. 147-156.

[34] R. Zhang, and Z. Zhang, “A Clustering Based Approach to Efficient Image Retrieval,” Proceedings of the 14th IEEE International Conference on Tools with Artificial Intelligence (ICTAI’02), Washington, DC, Nov. 2002, pp. 339-346.

[35] R. Gonzales, R. E. Woods, “Digital Image Processing,” 2nd Ed., New Jersey Prentice Hall, 2002.

[36] T. Gevers and A. Smeulders, “Pictoseek: Combining color and shape invariant features for image retrieval,” IEEE Trans. Image Processing, vol. 9, no. 1, pp.102– 119, Nov. 2000

[37] A. Ouyang, and Y. Tan, “A novel multi-scale spatial-color descriptor for content-based image retrieval,” Proceedings of the 7th International Conference on Control, Automation, Robotics and Vision, Mexico, August 2002, vol. 3, pp. 1204-1209.

[38] H. Yu, M. Li, H. Zhang, and J. Feng, “Color texture moments for content-based image retrieval,” Proceedings of the International Conference on Image Processing, Rochester, New York, USA, September 22-25, 2002, vol. 3, pp. 929-932.

[39] T. Gevers, and H. Stokman, “Classifying color edges in video into shadow-geometry, highlight, or material transitions,” IEEE Transactions on Multimedia, vol. 5, no. 2, pp. 237-243, Sep. 2003.

[40] H. Guan, and S. Wada, “Flexible color texture retrieval method using multi-resolution mosaic for image classification,” Proceedings of the 6th International Conference on Signal Processing, vol. 1, pp. 612-615, Feb. 2002.

[41] H. Moghaddam, T. Khajoie, and A. Rouhi, “A new algorithm for image indexing and retrieval using wavelet correlogram,” Proceedings of the International Conference on Image Processing, vol. 3, pp. 497-500, May 2003.

[42] M. Lew, N. Sebe, C. Djeraba and R. Jain, “Content-Based Multimedia Information Retrieval: State of the Art and Challenges,” ACM Transactions on Multimedia Computing, Communications and Applications, vol. 2, no. 1, pp. 1-19, February 2006.

[43] J. Fuertes, M. Lucena, N. Perez, and J. Martinez, “A Scheme of Color Image Retrieval from Databases,” Pattern Recognition Letters, vol. 22, pp.323–337, June 2001.

[44] B. Manjunath and W. Ma, “Texture features for Browsing and retrieval of image data,” IEEE transactions on pattern analysis and machine intelligence, vol. 18. No. 8, pp. 837-842, August 1996

[45] R. Haralick, K. Shanmugam, and I. Dinstein. “Texture Features for Image Classification,” IEEE Trans. on Systems, Man and Cybernetics, SMC, vol.3, no 6, pp. 610–621, Nov. 1973.

[46] R. Datta, J. Li, and J. Wang, “Content-based image retrieval - approaches and trends of the new age,” ACM Computing Surveys, vol. 40, no. 2, Article 5, pp. 1-60, April 2008.

[47] M. Chantler, and J. Wu, “Rotation Invariant Classification of 3D Surface Textures using Photometric Stereo and Surface Magnitude Spectra,” Proceedings of British Machine Vision Conference, Vol.2, pp 486-495, Jan. 2002.

[48] R. Dubes, and A. Jain, “Random field models in image analysis,” Journal Applied Statistic, vol. 16, no. 2, pp.131-164, Nov. 1989.

[49] A. Pentland, “Fractal-Based Description of Natural Scenes,” IEEE Transaction on Pattern Analysis Machine Intelligence, vol. 6, no. 6, pp. 661-674, 1984.

[50] J. Mao, and A. Jain, “Texture Classification and Segmentation using Multi-Resolution Simultaneous Autoregressive Models,” Pattern Recognition, vol. 25, no. 2, pp. 173-188, 1992.

[51] C. Teh and T. Roland, “On image analysis by the methods of moments,” IEEE Trans. On Pattern Analysis and Machine Intelligence, vol. 10, no. 4, pp. 496-513, 1988.

[52] M. Hu. “Visual Pattern Recognition by Moment Invariants,” IEEE Transactions on Information Theory, IT, vol. 8, pp. 179-187, Feb. 1962.

[53] M. Bober, “MPEG-7 Visual Shape Descriptors”, IEEE Trans. on Circuits and Systems for Video Technology, vol. 11, no. 6, pp. 716-719, June 2001.

[54] http://mpeg.telecomitalialab.com/standards/mpeg-7/mpeg-7.htm

[55] F. Mokhtarian, and R. Suomela, “Robust Image Corner Detection Through Curvature Scale Space”, IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 20, no. 12, pp. 1376-1381, December 1998

[56] G. Qian, S. Sural, Y. Gu, and S. Pramanik, “Similarity between Euclidean and cosine angle distance for nearest neighbor queries,” Proceedings of ACM Symposium on Applied Computing, vol. 12, no. 22, pp. 1232-1237, 2004.

[57] M. Swain, D. Ballard, “Color indexing,” International Journal of Computer Vision vol. 7, no 1, pp 11-32, Nov. 1991.

[58] J. Laaksonen, M. Koskela, S. Laakso, and E. Oja, “Picsom-content-based image retrieval with self-organizing maps,” Pattern Recognition Letters, vol. 21, pp. 1199– 207, Feb. 2000.

[59] Yang Mingqiang, Kpalma Kidiyo, Ronsin Joseph. A survey of shape feature extraction techniques, Pattern Recognition, Peng-Yeng Yin (Ed.) pp. 43-90, 2008.

[60] Asmatullah Chaudhry, Javed Ullah, M. Arfan Jaffar, Jin Young Kim, Tran Anh Tuan. Human Activity Recognition System: Using Improved Crossbreed Features and Artificial Neural Network. Life Sci J, vol. 9, no. 4, pp. 5351-5356, 2012.

[61] Saptadi Nugroho and Darmawan Utomo. Rotation Invariant Indexing For Image Using Zernike Moments and R–Tree. TELKOMNIKA, Vol.9, No.2, pp. 335-340, 2011.

[62] Rahman M.M., Bhattacharya M.P. and Desai B.C. A framework for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback. IEEE Trans. Inform. Technol. Biomed., Vol. 11, No. 1, pp.58–69, 2007.

[63] Felci Rajam I. and Valli S. SRBIR: semantic region based image retrieval by extracting the dominant region and semantic learning. Journal of Computer Science, Vol. 7, No. 3, pp.400–408, 2011.

[64] Felci Rajam I. and Valli S. Region-based image retrieval using the semantic cluster matrix and adaptive learning. International Journal of Computational Science and Engineering, Vol. 7, No. 3, pp.239–252, 2012.

[65] Deselaers T, Keysers D, Ney H. Features for image retrieval: an experimental comparison. Inf. Retr. 11(2), pp. 77–107, 2007.

[66] Md. Mahmudur Rahman, Bipin C. Desai, and Prabir Bhattacharya. Supervised Machine Learning Based Medical Image Annotation and Retrieval in Image CLEF med 2005. Proceedings of the CLEF 2005, LNCS 4022, pp. 692–701, 2006.

[67] Felci Rajam I. and Valli S. SRBIR: semantic region based image retrieval by extracting the dominant region and semantic learning. Journal of Computer Science, Vol. 7, No. 3, pp.400–408, 2011.

[68] Felci Rajam I. and Valli S. Region-based image retrieval using the semantic cluster matrix and adaptive learning. International Journal of Computational Science and Engineering, Vol. 7, No.3, pp.239–252, 2012.

[69] M. Zhenjiang, “Zernike moment - based image shape analysis and its application”, Pattern Recognition Letters, Vol. 21, pp. 169-177, 2000.

[70] A. Khotanzad, Y.H.Hong, “Invariant image recognition by Zernike moments”, IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(5), pp. 489-498, 1990.

[71] J. D. Zhou, H. Z. Shu, L. M. Luo, W. X. Yu, “Two new algorithms for efficient computation of Legendre moments”, Pattern Recognition, Vol.35(5), pp. 1143-1152, 2002.

[72] P. T. Yap and R. Paramesaran, “An Efficient Method for the Computation of Legendre Moments,” IEEE Transactions on Pattern Recognition and Machine Intelligence, Vol.27, No.12, pp.1996-2002.

[73] S. X. Liao, M. Pawlak, “On image analysis by moments,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 18(3), pp. 254-266, 1996.

[74] Khalid M. Hosney, “Exact Legendre moments computation for gray level images”, Pattern Recognition, Vol. 40, pp. 3597-3605, 2007.

[75] Liu Y., Zhang D., Lu G. and Ma W.Y. A survey of content-based image retrieval with high-level semantics. Patt. Recog. 40, pp. 262-282, 2007.

[76] Aymn E.Khedr and Abd El-Ghany A. M. Mohmed. A proposed image processing framework to support early liver Cancer Diagnosis. Life Sci J, vol. 9, no. 4, pp. 3808-3813, 2012.

[77] Thenmozhi. S, Balasubramanie. P, Venkatesh. J, Aarthy. C. Detection of reflection in iris images using back propagation. Life Sci J, vol. 9, no. 3, pp. 2446-2450, 2012.

[78] C. Campbell, "Algorithmic Approaches to Training Support Vector Machines: A Survey, ESANN, D-Facto Publications, pp. 27- 36, 2000.

[79] C. J. C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition," Data Mining and Knowledge Discovery, Vol. 2, pp. 121-167, 1998.

[80] K. K. Seo, "An application of one-class support vector machines in content-based image retrieval," Expert Systems with Applications, Vol. 33(2), pp.491-498. 2007.

[81] R. Datta, D. Joshi, J. Li, and J. Z. Wang,"Image Retrieval: Ideas, Influences, and Trends of the New Age", ACM Computing Surveys, Vol. 40, No.2, Article 5, 2008.

[82] Liu Y., Zhang D., Lu G. and Ma W.Y. A survey of ontent-based image retrieval with high-level semantics. Patt. Recog. 40, pp. 262-282, 2007.

[83] Zakariya S. M., Rashid Ali and Nesar Ahmad. Content Based Image Retrieval by Combining Visual Features of an Image with A Threshold. Special Issue of IJCCT Vol. 2, No. 2, 3, 4, pp. 204-209, 2010.

[84] Celia B, Felci Rajam I. An efficient content based image retrieval framework using machine learning techniques. Proceedings of the Second international conference on Data Engineering and Management (ICDEM ‗10), Springer LNCS, Vol. 6411, pp 162- 169, 2010.

[85] N. Vasconcelos. Bayesian models for visual information retrieval. Ph.D thesis, Massachusetts Institute of Technology, 2000.

[86] N. Vasconcelos and M. Kunt. Content-based retrieval from image databases: current solutions and future directions. In International Conference in Image Processing (ICIP'01), volume 3, pages 6–9, Thessaloniki, Greece, October 2001.

[87] D. Michie, D. J. Spiegelhalter, and C. C. Taylor, editors. Machine Learning, Neural and Statistical Classification. Ellis Horwood, 1994.

[88] C.Fraley and A. Raftery, "Model based clustering discriminate analysis and density estimation", journal of American statistics association, 97, 611-631 ,2002.

[89] E. Dahlhaus, "Parallel algorithms for hierarchical clustering and applications to split decomposition and parity graph recognition," J. Algorithms, vol. 36, no. 2, pp. 205–240, 2000.

[90] C. Olson, "Parallel algorithms for hierarchical clustering," Parallel Comput., vol. 21, pp. 1313–1325, 1995.

[91] K. Stoffel and A. Belkoniene, "Parallel K-means clustering for large data sets," in Proc. EuroPar'99 Parallel Processing, 1999, pp.1451–1454.

[92] W. Niblack, R. Barber, W. Equitz, M. Flickner, E. Glasman, D. Petkovic, P. Yanker, C. Faloutsos, and G. Taubin. "The qbic project: Quering images by content using color,

texture, and shape.” In Proceedings of the SPIE Conference on Storage and Retrieval for Image and Video Databases, 2□3 February ’93, San Jose, CA, pages 173–187, 1993.

[93] Chad Carson and Virginia E. Ogle. “Storage and retrieval of feature data for a very large online image collection”. IEEE Computer Society Bulletin of the Technical Committee on Data Engineering, 19(4):19–27, December 1996.

[94] J. Hafner, H. S. Sawhney, W. Equitz, M. Flickner, and W. Nib□ lack. “Effcient color histogram indexing for quadratic form dis□ tance functions.” IEEE Transactions on Pattern Analysis and Ma□ chine Intelligence, 17(7):729-736, 1999

[95] M. Stricker and M. Orengo. “Similarity of color images”. In W. Niblack and R. Jain, editors, Storage and Retrieval for Image and Vid□ eo DatabasesIII (SPIE), volume 2420, pages 381{392, San Diego/La Jolla, CA, USA, February 1995.

[96] MichaelOrtega,Yong Rui, Kaushik Chakrabarti, Sharad Mehro□ tra, and Thomas S. Huang. “Supporting similarity queries in MARS”. In Proceedings of the 5th ACM International Multimedia Conference, Seattle, Washington, 8□14 Nov. ’97, pages 403–413, 1997.

[97] F. Mokhtarian, S. Abbasi, and J. Kittler. “Efficient and robust retrieval by shape content through curvature scale space”. In Smeulders and Jain, pages 35–42

[98] Sougata Mukherjea, Kyoji Hirata, and Yoshinori Hara. “To□ wards a multimedia world wide web information retrieval en□ gine.” In Sixth International WWW Conference, 7□11 April ’97, San□ ta Clara, CA, USA, 1997.

[99] Fumikazu Kanehara, Shin’ichi Satoh, and Takashi Hamada. “A flexible image retrieval using explicit visual instruction.” In Proceedings of the Third International Conference on Document Analysis Recognition, Montreal, Canada, August ’95, pages 175– 178, 1995.

[100] Pentland A et al (1996) “Photobook: tools for content□based manipulation of image databases” International Journal of Computer Vision 18(3), 233□254

[101] J. R. Smith and S. F. Chang, “Transform features for texture classification and discrimination in large image databases”, in Proc. IEEE Int. Conf. on Image Proc., 1994

[102] S. Michel, B. Karoubi, J. Bigun, and S. Corsini. “Orientation radiograms for indexing and identification in image databases” In Proceedings Eusipco□96, European conference on signal processing, pages 1693–1696, 1996.

[103] B. S. Manjunath and W. Y. Ma. “Texture features for browsing and retrieval of large image data” IEEE Transactions on Pattern Analysis and Machine Intelligence, (Special Issue on Digital Libra□ ries), Vol. 18 (8), August 1996, pp. 837□842.

[104] George Tzagkarakis and Panagiotis Tsakalides. “A Statistical approach to texture image retrieval via alpha□stable modeling of wavelet decompositions”. in Proc. 5th International Workshop on Image Analysis for Multimedia Interactive Services (WIAMIS □04), Lisbon, Portugal, April 21□23, 2004.

[105] C. Yang, M. Dong, and F. Fotouhi. “S□iras: An interactive se□ mantic image retrieval and annotation system”. International Journal on Semantic Web and Information Systems, 2(3):37{54, 2006.

[106] M. Rege, M. Dong, and F. Fotouhi. “Building a user□centered semantic hierarchy in image databases”. Multimedia Systems, 12(45):325{338, March 2007.

[107] Y. Y. Lin, T.L. Liu and H.T. Chen. “Semantic manifold learning for image retrieval.” In Proceedings of the ACM International Conference on Multimedia, 2005

[108] Janghyun Yoon and Nikil Jayant. “Relevance Feedback for semantics based Image retrieval”

[109] S.F. Chang, W. Chen, H. Sundaram, “Semantic visual templates: linking visual features to semantics”, International Conference on Image Processing (ICIP), Workshop on Content Based Video Search and Retrieval, vol. 3, October 1998, pp. 531–534.

[110] http://www.iath.virginia.eduinote

[111] http://www.facebook.com

[112] http://images.google.com/imagelabeler/

[113] Bradshaw B. “Semantic based image retrieval: a probabilistic approach” Proceedings of the ACM International Conference on Multimedia, Los Angeles, California, Oct. 30Nov.4, 2000; 167-176.

[114] Ghoshal A, Ircing P, Khudanpur S. “Hidden Markov models for automatic annotation and contentbased retrieval of images and video”. Proceedings of the 28th International ACM SIGIR Conference on Research and Development in Information Retrieval, Salvador, Brazil, Aug 2005; 1519: 544551.

[115] Ilaria Bartolini and Paolo Ciaccia. “Towards an Effective Semi Automatic Technique for Image Annotation”

[116] Huang J., Kumar SR., Zabih R. “An automatic hierarchical image classification”. Proceedings of the ACM International Conference on Multimedia, Bristol, UK, Sep. 1216, 1998; 219228.

[117] H. Feng and T.S. Chua. “A bootstrapping approach to annotating large image collection.” Proceedings of the Fifth ACM SIGMM international workshop on Multimedia information retrieval (MIR 03), pages 55{62, Berkeley, California, USA, November 2003.

[118] S. Gao, D.H. Wang, and C.H. Lee. “Automatic image Aannotation through multitopic text categorization”. Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2006), volume 2, pages II{377{II{380, Toulouse, France, May 2006.

[119] Y. Mori, H. Takahashi, and R. Oka. “Imagetoword transformation based on dividing and vector quantizing images with words”. In Proceedings of the First International Workshop on Multimedia Intelligent Storage and Retrieval Management, Orlando, Florida, October 1999.

[120] P.L. Stanchev, D. Green Jr., B. Dimitrov, “High level color similarity retrieval”, Int. J. Inf. Theories Appl. 10 (3) (2003) 363–369.

[121] V. Mezaris, I. Kompatsiaris, M.G. Strintzis, “An ontology approach to objectbased image retrieval”, Proceedings of the ICIP, vol. II, 2003, pp. 511–514.

[122] Huan Wang, Song Liu Liangtienchia. “Image retrieval with a multimodality ontology”. Multimedia System (2008).

[123] Rahman M.H., Pickering M.R., Frater M.R. Scale and Rotation Invariant Gabor Features for Texture Retrieval. IEEE International Conference on Digital Image Computing Techniques and Applications (DICTA), pp. 602-607, 2011.

[124] Lining Zhang, Lipo Wang and Weisi Lin. Generalized Biased Discriminant Analysis for Content-Based Image Retrieval. IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics, Vol. 42, No. 1, pp. 282-290, 2012.

[125] Imtnan-Ul-Haque Qazi, OlivierAlata, Jean-Christophe Burie, Ahmed Moussa, ChristineFernandez-Maloigne. Choice of a pertinent color space for color texture characterization using parametric spectral analysis. Pattern Recognition 44, pp. 16–31, 2011.

[126] Hatice Cinar Akakin and Metin N. Gurcan. Content-Based Microscopic Image Retrieval System for Multi-Image queries. IEEE Transactions on Information Technology.

[127] Ja-Hwung Su, Wei-Jyun Huang, Philip S. Yu, Fellow, and Vincent S. Tseng. Efficient Relevance Feedback for Content-Based Image Retrieval by Mining User Navigation Patterns. IEEE Transactions on Knowledge and Data Engineering, Vol. 23, No. 3, pp. 360-372, 2011.

[128] Yu-Gang Jiang, Qi Dai, Jun Wang, Chong-Wah Ngo, Xiangyang Xue and Shih-Fu Chang. Fast Semantic Diffusion for Large-Scale Context-Based Image and Video Annotation. IEEE Transactions on Image Processing , Vol. 21, No. 6, pp. 3080 – 3091, 2012.

[129] Wang Xing-Yuan, ChenZhi-feng, YunJiao-jiao. An effective method for color image retrieval based on texture. Computer Standards & Interfaces 34, pp. 31–35, 2012.

[130] Samuel Rota Bul_o, Massimo Rabbi and Marcello Pelillo. Content-Based Image Retrieval with Relevance Feedback using Random Walks. Pattern Recognition, Vol. 44, No. 9, pp. 2109-2122, 2011.