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Review on Image Search Engines

Ms. Kshitija A. Upadhyay Mrs. Gyankamal J. Chhajed Ms. Jyoti D. Gavade

Abstract— In this paper we have reviewed and analyzed different techniques to search images from database. We have reviewed different techniques like text based image retrieval (TBIR), content based image retrieval (CBIR), CBIR with relevaeedback.We also reviewed different Generic CBIR systems (QBIC,Virage,Photobook,andFourEyes,Mars,VisualSeek,Netra) and World Wide Web Image search engines(Alta Vista photo and media finder WebSeek,ImageRover,WebSeer) that are available today .Variety of features used by these content-based image retrieval are also overviewed in this paper. We have also represented analysis of these systems by considering different factors like number of reference images,relevance feedback, user provided reference images, sketch support, implementation.

Index Terms— Image search, text based image retrieval (TBIR), content based image retrieval (CBIR), CBIR with relevance feedback,relevance feedback ,Generic CBIR,World wide web image search engines,reference image.

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1 INTRODUCTION

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Text based image retrieval (TBIR) and Content-based image retrieval (CBIR) in particular are well-known fields of research in information management in which a large number of methods have been proposed and investigated but in which still no satisfying general solutions exist. The need for adequate solutions is growing due to the increasing amount of digitally produced images in areas like journalism, medicine, and private life, requiring new ways of accessing images. For example, medical doctors have to access large amounts of images daily [1],home-users often have image databases of thousands of images [2], and journalists also need to search for images by various criteria [3, 4]. In the past, several CBIR systems have been proposed and all these systems have one thing in common: images are represented by numeric values, called features or descriptors, that are meant to represent the properties of the images to allow meaningful retrieval for the user.

2 IMAGE RETRIEVAL TECHNIQUES

2.1 Text based image search

Text based image search engines use only keywords as queries. Users type query keywords in the hope of finding a certain type of images.

- *Kshitija is currently pursuing masters degree program in computer engineering at VPCOE Baramati ,Pune University,Maharashtra, India,. E-mail: kshitija20@gmail.com*
- *Mrs. Gyankamal is currently Assistant Professor and Head in computer engineering at VPCOE Baramati ,Pune University,Maharashtra, India, E-mail:gjchhajed@gmail.com*
- *Jyoti is currently pursuing masters degree program in computer engineering at VPCOE Baramati ,Pune University,Maharashtra, India,. E-mail: jyotiatole@gmail.com*

The search engine returns thousands of images ranked by the keywords extracted from the surrounding text. Text based image search engines rely on text for indexing of images**.** As a consequence of this, the quality of an engine's image results depends on the quality of the textual information that surrounds or associated with the images (e.g. filename, nearby text, page title, or picture tags within the HTML code).

Advantages:

Text based image search is easy to implement.TBIR doesn't require user to have a similar image to search.TBIR is user-friendly, but not developer-friendly.TBIR is easy to conceptualize as everything is done manually.

Limitation:

Text-based image search suffers from the ambiguity of query keywords. The keywords provided by users tend to be short. Also sometime it is hard for users to describe the visual content of target images using keywords accurately. Thus text based image search results are noisy and consist of images with quite different semantic meanings.So the user gets relevant images by Text based image search engine only if it is annoted correctly.Manual annotation is needed and in order to fully describe content of images human annotator must provide description of every objects characteristics.A comprehensive description of images is usually impossible as images contain much detail.This method becomes impractical as database grows in size.If database is large then annotation are not probably made by single indexer and interpretation of images may vary.The user must know exact terms the annotator used in order to retrieve images he wants.

2.2 Content based image retrieval:

Content-based image retrieval (CBIR), is a technique for retrieving images on the basis of automatically-derived features such as color, texture and shape. "Content-based" means that the search will analyze the actual contents of the image. The term 'content' in this context might refer colors, shapes, textures, or any other information that can be derived from the image itself. The user can either browse an image from the hard disk or he can also select the example images provided by us to search the image of that kind.

Content based image retrieval (CBIR) is based on the automating matching of feature of query image with that of image database through some image-image similarity evaluation. Therefore images will be indexed according to their own visual content such as color, texture, shape or any other feature or a combination of set of visual features.

Advantages: One of the main advantages of the CBIR approach is the automatic retrieval process, instead of the traditional keyword-based approach, which usually requires very laborious and time-consuming previous annotation of database images.CBIR retrieves relevant images fastly and doesn't need of manual annotation of images.

Limitation: High feature similarity may not always correspond to semantic similarity .Different users at different time may give different interpretations for the same image.

CBIR systems can be classified into two categories:

a) General Content Based Image Retrieval System.
b) WWW Image Search Engine.

General Content Based Image Retrieval systems need to be locally installed. These systems also operate on fixed and predetermined image databases as opposed to the WWW image search engines. In this section, a few representative CBIR systems are introduced.

2.2.1 General Content Based Image Retrieval System:

i) QBIC:

The best-known system for content-based image retrieval is probably IBM's QBIC Query By Image Content (Niblack et al. 1993, Flickner et al. 1995, Niblack et al. 1997), developed at the IBM Almaden Research Center.QBIC was the first commercial CBIR application .QBIC supports queries based on example images, user-constructed sketches and drawings, and selected color and texture patterns, etc. The color feature used in QBIC are the average (R,G,B), (Y,i,q), (L,a,b), and MTM (mathematical transform to Munsell) coordinates,and a *k*-element color histogram[5] . Its texture feature is an improved version of the Tamura texture representation [6] i.e. combinations of coarseness, contrast, and directionality. Its shape feature consists of shape area, circularity, eccentricity, major axis orientation, and a set of algebraic moment invariants[5]. QBIC is one of the few systems which takes into account the high dimensional feature indexing. The image query is based on one reference image and one feature at a time. The visual queries can also be combined with textual keyword predicates. The QBIC home page is available at [7].

ii) Virage:

Virage Image Engine (Bach et al. 1996, Gupta 1997) is a commercial content-based search engine developed at Virage Technologies Inc. Virage supports visual queries based on color, composition (color layout), texture, and structure (object boundary information). But Virage goes one step further than QBIC. It also supports arbitrary combinations of the above four atomic queries. The users can adjust the weights associated with the atomic features according to their own emphasis. In [8], Jeffrey *et al.* further proposed an open framework for image management. They classified the visual features ("primitive") as general (such as color, shape, or texture) and domain specific (face recognition, cancer cell detection, etc.). Virage is intended as a portable framework for different CBIR applications. The Virage Technologies Inc. home page is located at [9]. The Virage Image Engine has also been licensed into the AltaVista Photo & Media Finder.

iii) Photobook and FourEyes:

MIT Media Lab's Photobook [10] (Pentland et al. 1994) is a set of interactive tools for searching and querying images. Photobook is divided into three separate image descriptions, namely Appearance Photobook (face recognition), Texture Photobook, and Shape Photobook, which can also be combined. The features are compared using one of the matching algorithms that Photobook provides: Euclidean, Mahalanobis, divergence, vector space angle, histogram, Fourier peak, and wavelet tree distances, as well as any linear combination of these. The latest version of Photobook allows also user-defined matching algorithms via dynamic code loading. The photobook WWW home page is located a [11].

Photobook includes also FourEyes (Minka 1996), an interactive tool for image segmentation and annotation. The user selects some image regions and gives them labels, and FourEyes extrapolates the label to other regions on the image and in the database. As there exists no such label model which is suitable for all kinds of labels in all kinds of images, FourEyes contains a learning agent which selects and combines appropriate models among a society of models based on examples from the user to select the label model. In the FourEyes approach, relevance feedback techniques are applied in image retrieval, and the system tries to self-improve its responses to the queries.

iv) MARS:

MARS or Multimedia Analysis and Retrieval System (Huang et al. 1996) is an interdisciplinary research effort involving multiple research communities at the University of Illinois. The main focus of MARS is to develop methods to organize various features into adaptive retrieval architecture, instead of finding the best representations for any particular application area.MARS also includes relevance feedback architecture for image retrieval (Rui et al. 1997a). This technique presents users with a list of images and asks the users to select the one closest to the desired image. As this process is repeated and more images selected, the MARS engine improves its list of suggested images. The MARS home page is located at [12].

v) Visual Seek:

Visual Seek (Smith and Chang 1996c) is a content-based image and video query system developed at the Image and Advanced Television Lab of Columbia University. It integrates feature-based image indexing by color with region-based spatial query methods. This enables queries with multiple color regions in the sketch image. Queries may be conducted by sketching a layout of color regions, by providing the URL of a seed of Visual Seek is located at [13].

vi) NETRA:

NETRA[14] is a prototype image retrieval system that is currently being developed in the University of California, Santa Barbara (UCSB) (Ma and Manjunath 1997). NETRA uses the color, texture, shape, and spatial location information of segmented image regions to search and retrieve similar regions from the database. The used color indexing scheme for region-based image retrieval is presented in (Deng and Manjunath 1999).

The system incorporates an automated image segmentation algorithm that allows region-based search. Images are segmented into homogeneous regions at the time they are added to the database, and image attributes that represent each of these regions are computed. The user is then able to compose queries such as retrieve all images containing regions having the color of object A, texture of object B, shape of object C, and lie within the upper one-third of the image , in which the individual objects can be regions from different images. The NETRA WWW home page is available at [15].

2.2.2 WWW Image Search Engine:

Another important and related area is the retrieval of multimedia and visual information from the World Wide Web.WWW image search engines of efficiency comparable to their textual counterparts do not yet exist, but a number of experimental projects have been started. Image search engines face the same problems as the text-based search engines, such as the immense size, diversity, and dynamic nature of the WWW. In addition, these systems must cope with some unique difficulties as computer-based general image analysis is a very difficult task. The various issues on indexing and retrieval of images of the WWW have been discussed, for example, by Agnew et al. (1997) and La Cascia et al. (1998).

i) AltaVista Photo and Media finder:

The popular AltaVista WWW search engine currently incorporates an image retrieval engine called the AltaVista Photo & Media Finder (Swain 1999, Eberman et al. 1999) developed at the Compaq Cambridge Research Laboratory. The system contains technologies from the Virage Image Engine and from WebSeer . It can be found and used at [16].

The initial query is text-based, matching relevant text extracted from the WWW pages containing the images. Optionally, the query can be narrowed to include only photos or graphics, or to include only color or black & white images. In addition, images likely to be page decorations, i.e. small images, wide banners, and very tall and thin images, as well as objectionable images can be discarded from the query results. The system returns a set of images as the result of the initial query. These images can then be used as example images to search for visually similar images based on color and texture distributions, color layout, and image structure.

ii) WebSeek:

WebSEEk (Smith and Chang 1996a) is a WWW-oriented image search engine, developed at Columbia University along with the VisualSeek image query system. It uses both textual keywords, for example from the URL addresses and HTML tags, and color information to categorize images. WebSEEk consists of three modules which are the image collecting module, classification and indexing module, and image browsing and retrieval module. Currently, WebSEEk has catalogued over 665 000 images and videos in the WWW. The user interface of the search engine is available on-line at [17]

iii) Image Rover:

ImageRover combines textual and visual statistics in a single index for content-based search of a WWW image database. Textual statistics are captured in vector form using latent semantic indexing (LSI) based on text in the containing HTML document. Used visual statistics include color and texture.To begin a search with ImageRover, the user first enters a few keywords describing the desired images. After that, the user can refine this initial query through relevance feedback. During relevance feedback, both visual and textual cues are combined to gain better search performance.Image Rover home page is available at [18].

iv) WebSeer:

WebSeer (Frankel et al. 1996) was a World Wide Web image retrieval project at University of Chicago but it has been subsequently terminated. With WebSeer, one could search for images using keywords describing the contents of the image and also, optionally, by the visual content of the image. The content properties included whether or not the image is a photograph (Athitsos et al. 1997), or how many faces the image contains (Rowley et al 98).

2.3 CBIR with relevance feedback :

In CBIR, the user is an inseparable part of the process. As the retrieval systems are usually not capable of returning the wanted images in their first response to the user, the image query becomes an iterative and interactive process towards the desired image or images.The relevance feedback approach has been applied also to content-based image retrieval (Rui et al. 1997b, Taycher et al. 1997, Minka 1996).

Some visual features may be more effective for certain query images than others. In order to make the visual similarity metrics more specific to the query, relevance feedback [19]was widely used to expand visual examples. The user was asked to select multiple relevant and irrelevant image examples from the image pool. A query-specific similarity metric was learned from the selected examples.

Advantages : In CBIR with relevance feedback,user is allowed to interact with system to “refine” the results of query until he/she is satisfied.

Limitation : The requirement of more users effort makes it unsuitable for web-scale commercial systems like Bing image search and Google image search in which users feedback has to be minimized.

3. FEATURES USED IN EXISTING IMAGE RETRIEVAL TECHNIQUES

Image features refer to characteristics which describe the contents of an image. Visual feature extraction is the foundation for all kinds of applications of content-based image retrieval and, therefore, various types of features have been studied extensively. Different visual features can also be categorized as distinct feature types which include color, texture, shape, and structure.

3.1. Color Feature Extraction:

3.1.1 Color Histogram:

The *histogram* of an image is a plot of the gray level values or the intensity values of a color channel versus the number of pixels at that value. The shape of the histogram provides us with information about the nature of the image, or subimage if we are considering an object within the image. For example, a very narrow histogram implies a low contrast image, a histogram skewed toward the high end implies a bright image, and a histogram with two major peaks, called bimodal, an object that is in contrast with the background. The histogram features that we will consider are statistical based features, where the histogram is used as a model of the probability distribution of the intensity levels. These statistical features provide us with information about the characteristics of the intensity level distribution for the image.

The features based on the first order histogram probability are the mean, standard deviation, skew, energy, and entropy[20].

i) Mean:

The *mean* is the average value, so it tells us something about the general brightness of the image. A bright image will have a high mean, and a dark image will have a low mean. We will use L as the total number of intensity levels available, so the gray levels range from 0 to (L – 1). For example, for typical 8-bit image data, L is 256 and ranges from 0 to 255. We can define the mean as follows:

$$\bar{g} = \sum_{g=0}^{L-1} gP(g) = \sum_{r}\sum_{c}\frac{I(r,c)}{M}$$

Where,r is the number of rows, c is the number of columns, I(r,c) is the intensity of the pixel(r,c), M is total number of pixels, g is the gray level and $P(g)$ is histogram probability.

ii) Color Moments:

Color moments have been successfully used in many retrieval systems especially when the image contains just the object. The *first order* (*mean*), the *second* (*variance*) and the *third order* (*skewness*) color moments have been proved to be efficient and effective in representing color distributions of images.

Mathematically, the first three moments are defined as:

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij}, \qquad \sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-\mu_i)^2\right)^{\frac{1}{2}},$$

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

where,

f_{ij} is the value of the *i*-th color component of the image pixel *j* and

N is the number of pixels in the image.

Using the additional third-order moment improves the overall retrieval performance compared to using only the first and second order moments. However, this third-order moment sometimes makes the feature representation more sensitive to scene changes and thus may decrease the performance. Since only 9 (three moments for each of the three color components) numbers are used to represent the color content of each image, color moments are a very compact representation compared to other color features. Due to this compactness, it may also lower the discrimination power. Usually, color moments can be used as the first pass to narrow down the search space before other sophisticated color features are used for retrieval.

iii) Color Entropy:

The *entropy* is a measure that tells us how many bits we need to code the image data, and is given by

$$Entropy = -\sum_{g-0}^{L-1} P(g)\log_2[P(g)]$$

As the pixel values in the image are distributed among more intensity levels, the entropy increases. A complex image has higher entropy than a simple image. This measure tends to vary inversely with the energy.

3.2. Shape Feature Extraction:

Edge detection is useful for locating the boundaries of objects within an image. Any abrupt change in image frequency over a relatively small area within an image is defined as an edge. Image edges usually occur at the boundaries of objects within an image, where the amplitude of the object abruptly changes to the amplitude of the background or another object.

The shape representations can be divided into two general categories: boundary-based and region-based. Boundary-based methods utilize only information on the boundary of an object, whereas region-based methods describe the shape based on whole area of object.

Boundary based method may also contain description of inner boundaries .The difference between two representations is that boundary based methods model object as one dimensional curve whereas region based methods operate on two dimensional field. In the following sections, a number of both boundary and region-based shape descriptors suitable for content-based image retrieval are briefly introduced. A more detailed coverage on using shape features in CBIR can be found in the Master's Thesis of Brandt (1999). Further instance in(Sonka et al 1993)

3.2.1 Boundary-Based Shape Features

i) Chain code:

The chain code (a.k.a. Freeman-code or F-code) can be used to represent the boundary of any object (Freeman 1974). The boundary is traced in either direction and a code is assigned to each pixel depending on the direction of the next boundary pixel. Both 4 and 8-neighborhoods can be used in the construction of the chain code. The ordinary chain codes are sensitive to noise and not invariant to scaling and rotation and hence the chain codes need to be modified before used as shape descriptors.

ii) Fourier descriptor:

Another basic boundary-based shape representation is the Fourier descriptor (Zahn and Roskies 1972, Persoon and Fu 1977) in which the complex coefficients of the Fourier transform of the boundary trace are used as a shape features. The Fourier descriptor is invariant to scaling, rotation, and reflection. The UNL (Universidade Nova de Lisboa) Fourier descriptor (Rauber and Steiger Garcao 1992) is an extension to the Fourier descriptor which can handle also open curves. It is computed in two stages: First the image is transformed into polar coordinated by the UNL transform and then a Fourier transform is computed on the result. Furthermore, as a part of the MARS research project, Rui et al. (1996) proposed the Modified Fourier Descriptor (MFD) which is robust to a affine transformations and noise generated by spatial discretizations.

iii) Wavelet descriptor :

The wavelet transform can also be used to describe object boundaries analogously to the Fourier transform. Wavelets are effective in representing local properties of a boundary due to the localization properties of wavelet bases. Chuang and Kuo (1996) used wavelets to construct a descriptor which has many desirable properties like multiresolution representation, invariance, uniqueness, stability, and spatial localization.

3..2.2 Region based shape features [21] :

i) Heuristic region descriptors:

A simple shape feature can be constructed from a combination of heuristic region descriptors, such as area, Euler's number, circularity, eccentricity, elongatedness, rectangularity, and the orientation of the major axis (Sonka et al. 1993).

ii) Moment Invariants:

The moment invariant method (Hu 1962) is a common region-based shape representation. It is based on using such region-based moments which are invariant to transformations as shape features. Hu identified seven such moments and subsequently many improved versions have been proposed.

iii) Finite element method:

In Shape Photobook ,Pentland et al. (1995) used a shape representation based on the physical model of the object. The tool used was a standard engineering method called finite element method (FEM). In FEM, a positive definite symmetric matrix, called the stiffness matrix is defined. It describes how each point in an object is connected to other points in the object. The eigenvectors of the stiffness matrix is then used as shape feature.

iv) Keyimages:

Tegolo (1994) developed a method to locate subimages in the stored images of a database and match them with the query image. The used image characteristics were designed to allow image retrieval from a minimum set of image descriptors called key images. First, both the query image and stored images are segmented. Then, moments and geometrical features are computed from the segmented regions, and finally a matching process is run on the resulting features.

3.3. Texture Feature Extraction:

3.3.1 Tamura Features:

The Tamura features , including coarseness, contrast, directionality, linelikeness, regularity, and roughness[22] are designed in accordance with psychological studies on the human perception of texture. The computations of these three features are given as follows.

i) Coarseness:

Coarseness is a measure of the granularity of the texture. To calculate the coarseness, moving averages $Ak(x,y)$ are computed first using 2k × 2k (k = 0, 1, …, 5) size windows at each pixel (x, y), i.e.,

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

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

Then, the differences between pairs of non-overlapping moving averages in the horizontal and vertical directions for each pixel are computed, i.e.,

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

After that, the value of k that maximizes E in either direction is used to set the best size for each pixel, i.e., $S_{best}(x,y) = 2^k$

The coarseness is then computed by averaging S_{best} over the entire image, i.e.,

$$F_{crs} = \frac{1}{m*n} \sum_{i=1}^{m} \sum_{j=1}^{n} S_{best}(i,j)$$

Instead of taking the average of S_{best} , an improved version of the coarseness feature can be obtained by using a histogram to characterize the distribution of S_{best} . Compared with using a single value to represent coarseness, using histogram-based coarseness representation can greatly increase the retrieval performance. This modification makes the feature capable of dealing with an image or region which has multiple texture properties, and thus is more useful to image retrieval applications.

ii) Contrast:

The formula for the contrast is as follows:

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

where the kurtosis α4 = μ4/σ4, μ4 is the fourth moment about the mean, and σ2 is the variance. This formula can be used for both the entire image and a region of the image.

iii) Directionality

To compute the directionality, image is convoluted with two 3x3 arrays. These two arrays are as follows:

$$\begin{matrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{matrix} \quad \text{and} \quad \begin{matrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{matrix}$$

and a gradient vector at each pixel is computed. The magnitude and angle of this vector are defined as:

$$|\Delta G| = \frac{|\Delta H| + |\Delta V|}{2}$$

$$\theta = \tan^{-1}\left(\frac{\Delta V}{\Delta H}\right) + \frac{\pi}{2}$$

where ΔH and ΔV are the horizontal and vertical differences of the convolution. Then, by quantizing θ and counting the pixels with the corresponding magnitude |ΔG| larger than a threshold, a histogram of θ, denoted as *HD*, can be constructed. This histogram will exhibit strong peaks for highly directional images and will be relatively flat for images without strong orientation. The entire histogram is then summarized to obtain an overall directionality measure based on the sharpness of the peaks:

$$F_{dir} = \sum_{p}^{n_p} \sum_{\emptyset \in w_p} (\emptyset - \emptyset_p)^2 H_D(\emptyset)$$

In this sum *p* ranges over *np* peaks; and for each peak *p*, *wp* is the set of bins distributed over it; while ϕ*p* is the bin that takes the peak value.

iv) Linelikeness :

To catch the texture element composed of lines or linelikeness, a M × M -sized direction matrix P_{Dd} is defined. The element $P_{Dd}\,(i,j)$ of the matrix is the relative frequency of two pixels separated by a distance d, one with the direction code i and the other with j.The Linelikeness is defined as

$$F_{lin} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{M} P_{Dd}\,(i,j) \cos\frac{2\pi(i-j)}{M}}{\sum_{i=1}^{M} \sum_{j=1}^{M} P_{Dd}\,(i,j)}$$

v) Regularity :

The regularity of repeated patterns in a texture is calculated by taking the sum of the standard deviations of the measures F_{crs} , F_{con} , F_{dir} , and F_{lin}

$$F_{reg} = 1 - r\,(\sigma_{crs} + \sigma_{con} + \sigma_{dir} + \sigma_{lin})$$

vi) Roughness:

Roughness of image is calculated as sum of contrast and coarseness values.

$$F_{roug} = F_{con} + F_{crs}$$

3.3.2 Wold Decomposition :

According to a psychological study by Rao and Lohse (1993), the main components of texture perception can be described as periodicity, directionality, and randomness. Hence, it is justified to apply texture models which relate to these perceptual components in content-based image retrieval. To capture the properties of human texture feature of image retrieval a set of texture features based on two dimensional(2D) wold decomposition was proposed by (Liu and Picard 1996).

The Wold theory allows to represent a given 2D random field y (m, n) with three mutually orthogonal components by the following decomposition:

$$y(m,n) = w(m,n) + p(m,n) + g(m,n)$$

w(m, n) is indeterministic whereas the other fields p(m, n) and approximated y harmonic and evanescent fields. The perceptual properties of these components have been shown to closely agree with the components of human texture perception (Liu and Picard 1996).

IV ANALYSIS

Analysis of these systems by considering different factors like number of reference images, relevance feedback, and user provided reference images,sketch support,implementation is given in Table 1. The feature types used in these systems are summarized in Table 2.

Search engines / Factors	QBIC	Virage	Photo-book	Mars	Visual Seek	Netra	AltaVista	Web Seek	Image Rover	Web seer
No. of Ref. Images	1	1	1	Many	1	Many	1	Many	Many	None
Relevance feedback	No	No	Yes	Yes	No	No	No	Yes	Yes	No
User provided ref images	Yes	No	No	No	Yes	No	No	Yes	Yes	No
Sketch Support	Yes	No	No	No	Yes	No	No	No	No	No
Implementation	Both	Web	Local	Web	Web	Web	Web	Web	Web	Web

Table 1 : Analysis of image search engines based on factors.

Search engines / Features	QBIC	Virage	Photo-book	Mars	Visual Seek	Netra	AltaVista	Web Seek	Image Rover	Webseer
Color	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	
Color layout	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	
Texture	Yes	Yes	Yes	Yes		Yes	Yes		Yes	
Shape	Yes	Yes	Yes	Yes		Yes	Yes			
Keywords	Yes		Yes	Yes			Yes	Yes	Yes	Yes

Table 2: Analysis of image search engines based on features used.

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