Review Article a Review on Recent Advancement in Content-Based Image Retrieval

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Abstract: Multimedia databases growth is huge due to their requirement in network infrastructure and internet. Multimedia data means digital images, audio, video, animation and graphics together with text data. The acquisition, generation, storage and processing of multimedia data in computers and transmission over networks have grown tremendously in the recent past. Image retrieval is the field of study concerned with searching and retrieval of digital images from multimedia databases. Multimedia retrieval is the complex techniques which demand more effective system which can query the image as closely as possible to human perception. In this paper we address the challenges, techniques used in multimedia retrieval through the detailed look on the most recent work on multimedia retrieval.

Keywords- Content based image retrieval (CBIR), Multimedia Image Retrieval System (MIRS), CBIR search engines, Clustering techniques, Classification techniques.

I. INTRODUCTION

Availability of huge amount of digital data to user is possible due to increase in the computing power and electronic storage capacity. Digital data is also the basic component of many educational, entertainment and commercial applications [1] hence relevant information searching is becoming very necessary as well as challenging from a huge collection of image and video databases available. Many of the today's image retrieval systems rely on Content-based image retrieval CBIR having different techniques ranging from single feature vector to combined visual and conceptual image content descriptions . Images in CBIR are indexed according to their visual content, such as color, texture, and shapes.

Human interaction is an indispensable part of text-based retrieval systems which separate them from CBIR systems. Human mainly used high level features such as keywords, text descriptors to interpret images and matches their similarity. Even after several years of research due to the presence of semantic gap, expressing the discrepancy between the low level features that can be readily extracted from the images and the high level descriptions that are meaningful to the users [2], [3] satisfactory performance has not been achieved yet. It may regard perceptual features (also known as content dependent metadata) like color, texture, shape, structure and spatial relationship, or semantic primitives (also known as content-descriptive metadata) such as the identification of real-world objects and the meaning of the images [4] , and image retrieval using low-level visual features is a challenging and important issue in content-based image retrieval.

II. RECENT RESEARCH WORK IN CBIR

There are several research reviews which are based on image retrieval, representing different viewpoints. Enser [1995] [5] proposed a method for providing subject access to pictorial data, developing a four-category framework to classify different approaches. According to Cawkell [1993] [6] more dialogue between researchers into image analysis and information retrieval is needed. Aigrain et al [1996] [7] discuss the main principles of automatic image similarity matching for database retrieval, emphasizing the difficulty of expressing this in terms of automatically generated features. Eakins [1996] [8] proposes a framework for image retrieval classifying image queries into a series of levels, and discussing the extent to which advances in technology are likely to meet users' needs at each level. Idris and Panchanathan [1997a] [9] provide an in-depth review of CBIR technology, explaining the principles behind techniques for colour, texture, shape and spatial indexing and retrieval in some detail.. De Marsicoi et al [1997] [10] also review current CBIR technology, providing a useful feature-by-feature comparison of 20 experimental and commercial systems.

In addition to these reviews of the literature, a survey of "non-text information retrieval" was carried out in 1995 on behalf of the European Commission by staff from GMD (Gesellschaft für Mathematik und Datenverarbeitung), Darmstadt and Université Joseph Fourier de Grenoble [Berrut et al, 1995] [11]. This reviewed current indexing practice in a number of European image, video and sound archives, surveyed the current research literature, and assessed the likely future impact of recent research and development on electronic publishing. The report concluded that standard information retrieval techniques were appropriate for managing collections of non-text data, though the adoption of intelligent text retrieval techniques such as the inference-based methods developed in the

INQUERY project [Turtle and Croft, 1991] [12] could be beneficial.

III. MULTIMEDIA DATA RETRIEVAL

A. Metadata

The extra information added to the multimedia objects which helps in their description are called as metadata [13]. Multimedia Objects with their metadata definition are easy to retrieve. A metadata is said to be valuable in searching if it satisfy certain requirements:

1) A description of multimedia object should be as complete as possible.
2) Storage of metadata must be easier.
3) Comparison between two metadata should be fast.

Different types of metadata are described below.

B. Descriptive Data

It defines some format or factual information about the multimedia objects e.g. author name, creation date, length of multimedia object etc. Dublin Core is the standard for descriptive data that gives many possibilities to describe a multimedia object.

C. Features

The derived characteristics from the multimedia objects are called features. In order to describe features a certain kind of language is needed. The process in which features are captured from multimedia objects is known as feature extraction. This process is often performed automatically or with human support. There are two types of feature class low-level and high-level features.

D. Low-Level Features & High-Level Features

Low-Level feature grasp data pattern and statistics of a multimedia object and depend on the medium. A low-level description is one that describes individual components, detail rather than overview, rudimentary functions rather than complex overall ones, and is typically more concerned with individual components within the system and how they operate. Low-level features don’t have too much meaning for the end user. A high-level description is one that describes "top-level" goals, overall systemic features, is more abstracted, and is typically more concerned with the system as a whole, and its goals. There is a gap between low-level and high-level features. This gap is called the semantic gap [14].

IV. SCHEMATIC OVERVIEW OF MIRS SYSTEM

Multimedia Information Retrieval System (MIRS) are used for image retrieval. In Fig. 1 we give a schematic overview of MIRS. It shows that arriving multimedia objects are archived while metadata are extracted and stored in a metadata server. A user queries are answered with the help of index metadata. But sometime user not able to give exact query of the object which he wanted to search but able to find out the answer from the result obtained.

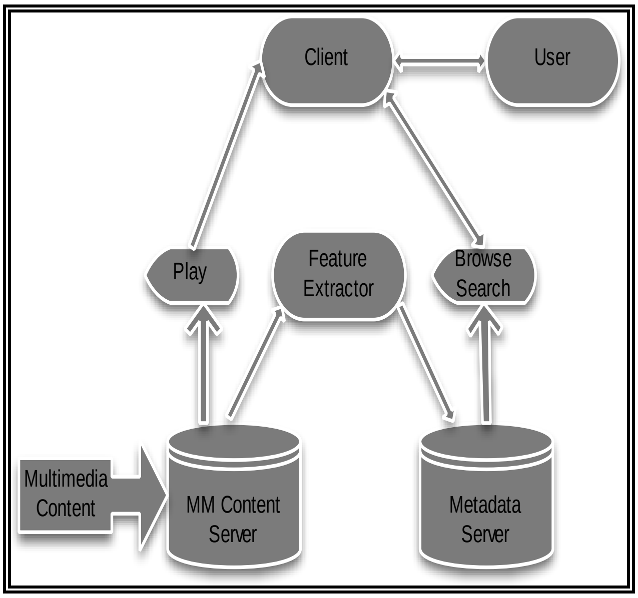


Fig.1 Typical MIRS System Architecture

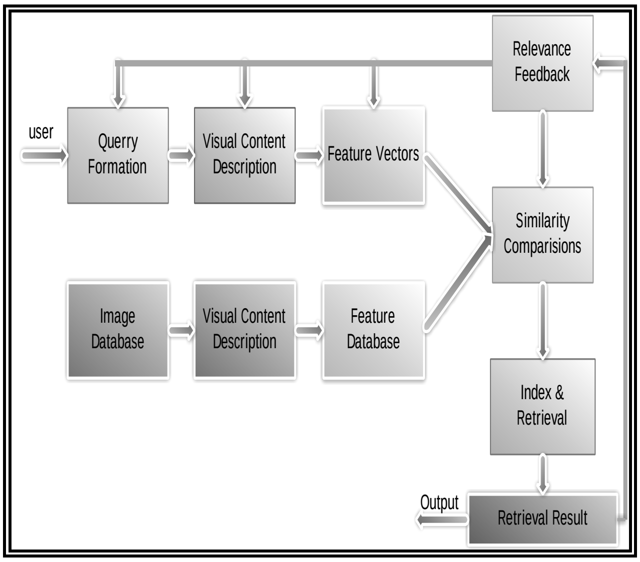
V. TEXT BASED IMAGE RETRIEVAL

In current commercial image databases, the images are search on the bases of annotations provided by the humans. These text annotations are then used as a basis for searching, using mature text search algorithms. Text based image retrieval is started since from 1970. For text-based image retrieval, the images are first annotated by text and then the text-based Database Management Systems are used to perform image retrieval. The query processing of such search engines is typically very fast due to the available efficient database management technology. In past, many keyword-based text information retrieval systems achieved great success for indexing image collections, especially on web sites and are still a common practice [15]. Kodak Picture Exchange System (KPX) [16], Press Link [17] and Time pictures archive collection (Time) [18] are examples of such systems.

A text-based image retrieval technique uses text to describe images due to which efficient image database search and query processing is not possible. The reason behind it is that specification of exact terms and phrases to describe the image is not sufficient for images which are much richer in content. Another drawback in text-based retrieval systems is that textual annotations used in text based retrieval systems is based on language, variations in annotation make difficult for efficient image retrieval.

VI. CONTENT-BASED IMAGE RETRIEVAL

Content-based image retrieval (CBIR) was introduced in the early 1980. Content-based image retrieval (CBIR) is the application of computer vision to the image retrieval problem that deals with the problem of searching for digital images in large databases. CBIR is a field of study that refers to the collection of techniques and algorithms which enable querying image databases using image content such as color, texture, objects and their geometries rather than textual attributes such as image name or other keywords [19], [20]. Content based Image Retrieval system is shown in Fig.3.



In CBIR, the visual features of image are firstly extracted, and the similarity between images is calculated using distance or similarity of visual features in visual feature space [21]. Various types of algorithm are developed and these algorithms may vary depending on the application, but result images should all share common elements with the provided example.

The various criteria used for searching for similar images include- Color, Texture and Shape. It is possible to return images with similar content. And this can be possible by determining the same in the provided image and searching for similar such features in the database of images using similarity measures. Although CBIR is still immature, there has been abundance of prior work.

CBIR is currently attracting significant research because of the availability of large image databases in various fields and easy access to large collections of images via the World Wide Web. Digital libraries - especially their visual content - may highly benefit from CBIR systems. Archaeologists may need visual comparisons of their archaeological finds at some stage of their examination. We used CBIR not only for retrieval reasons but especially to organize the content of general purpose image databases of a digital library e.g. to build clusters consisting of instruments or handwritings and letters.

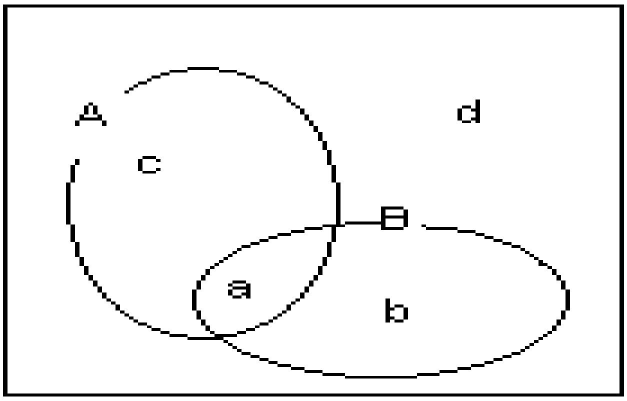
A. Performance Evaluation Of Cbir

There are two parameters to evaluate CBIR Precision and Recall

$$\text{Precision} := \frac{\text{Number of relevant images received}}{\text{Total Number of images received}}$$

$$\text{Recall} := \frac{\text{Number of relevant images retrieved}}{\text{Total Number of images in databases}}$$

Let A is set of relevant images, B is set of retrieved images and a, b, c are given in figure below



In the above, figure-4 ‘a’ stands for retrieved relevant images, b, c, d stands for retrieved irrelevant images.

B. Commercial Cbir Search Engines

This is a list of publicly available Content-based image retrieval (CBIR) engines, these image search engines look at the content (pixels) of their images in order to return results that match a particular query.

Name	Description
Bing Image Search	Microsoft's CBIR engine
Elastic Vision	Smart image searcher with content-based clustering in a visual network.
Gazopa Image Search	CBIR search engine, by Gazopa.
Google Image Search	Google's CBIR system, note: does not work on all images
Imense Image Search Portal	CBIR search engine, by Imense.
Imprezzeo Image Search	CBIR search engine, by Imprezzeo.
Incogna Image Search	CBIR search engine, by Incogna Inc.
Like.com	Shopping & fashion based CBIR engine
MiPai similarity search engine	Online similarity search engine
Piximilar	Demo engine, developed by Idee Inc.
Pixsta	Product comparison & shopping using CBIR for product images.
Shopachu	Shopping & fashion CBIR engine, by

	Incogna Inc.
TinEye	CBIR site for finding variations of web images, by Idee Inc.
Tiltomo	CBIR system using Flickr photos
eBay Image Search	Image Search for eBay Fashion

(Ref From http://en.wikipedia.org/wiki/List_of_CBIR_engines)

C. Content-Based Image Retrieval (Cbir) Systems

There are several excellent surveys of content-based image retrieval systems. We mention here some of the more notable systems. The first, QBIC (Query-by-Image-Content), was one of the first prototype systems. It was developed at the IBM Almaden Research Center and is currently folded into DB2. It allows queries by color, texture, and shape, and introduced a sophisticated similarity function. As this similarity function has a quadratic time-complexity, the notion of dimensional reduction was discussed in order to reduce the computation time. Another notable property of QBIC was its use of multidimensional indexing to speed-up searches. The Chabot system, developed at the University of California at Berkeley, brought text and images together into the search task, allowed the user to define concepts, such as that of a *sunset*, in terms of various feature values, and used the post-relational database management system Postgres. Finally, the MARS system, developed at the University of Illinois at Urbana-Champaign, allowed for sophisticated relevance feedback from the user.

D. The Need For Image Data Management

The process of digitization does not in itself make image collections easier to manage. Some form of cataloguing and indexing is still necessary – the only difference being that much of the required information can now potentially be derived automatically from the images themselves. One of the main problems they highlighted was the difficulty of locating a desired image in a large and varied collection. While it is perfectly feasible to identify a desired image from a small collection simply by browsing, more effective techniques are needed with collections containing thousands of items. Journalists requesting photographs of a particular type of event, designers looking for materials with a particular color or texture, and engineers looking for drawings of a particular type of part, all need some form of access by image content.

VII. TECHNIQUES FOR IMAGE RETRIEVAL

A. Visual Signature

The mathematical description of an image, for image retrieval purpose is called signature. Some systems design their own segmentations in order to obtain the desired region features during segmentation, be it color, texture, or both [22]. These algorithms are usually based on k-means clustering of pixel/block features.

In Ref. [23], firstly, an image is segmented into small blocks of size 4*4 from which color and texture feature are extracted. Then k-means clustering is applied to cluster the feature vectors into several classes .Blocks in same class are classified into same region. A so-called KMCC (k-means with connectivity constraint) is proposed in Ref. [24]. It is extended from the k-means algorithm. In this algorithm, the spatial proximity of each region is taken into account by defining a new center for the k-means algorithm and by integrating the k-means with a component labeling procedure.

B. Clustering

Clustering is methods in which we make cluster of objects that have similar in characteristics. The similarity between the clusters is dependent on the implementation. There is some difference between the Clustering and classification. In classification the objects are assigned to pre defined classes, whereas in clustering the classes are also to be defined. Clustering is a technique in which, the information that is logically similar is physically stored together [25]. Therefore to increase the efficiency in the database systems the number of disk accesses is to be minimized.

1. Hierarchical Clustering

i. Divisive Clustering - start by treating all objects as if they are part of a single large cluster, then divide the cluster into smaller and smaller clusters.
ii. Agglomerative Clustering - start by treating each object as a separate cluster and then group them into bigger and bigger clusters.
iii. Linkage Methods - cluster objects based on the distance between them.

A. Single Linkage Method
B. Complete Linkage Method
C. Average Linkage Method
D. Centroid Methods
E. Ward's Procedure

2. Non-Hierarchical Clustering

a. Sequential Threshold Method
b. Parallel Threshold method
c. Optimizing Partitioning method

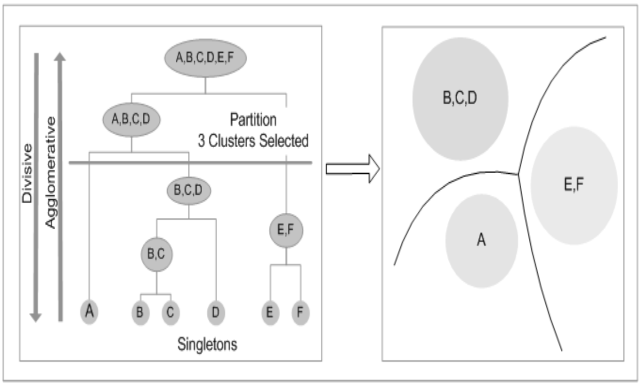
3. Clustering for a Large Database.

4. Other Approaches to Clustering

► Hierarchical Clustering

There is a concept of ordering involved in this approach. The clusters could be arrived at either from weeding out dissimilar observations (divisive method) or joining together similar observations (agglomerative method) [26]. The most popular agglomerative methods are:

a. single linkage (nearest neighbor approach)
b. complete linkage (furthest neighbor)
c. average linkage
d. Ward’s method
e. Centroid method.



A. The Single Link Method (Slink)

The single link method is probably the best known of the hierarchical methods and operates by joining, at each step, the two most similar objects, which are not yet in the same cluster. The name single link thus refers to the joining of pairs of clusters by the single shortest link between them.

B. The Complete Link Method (Clink)

The complete link method is similar to the single link method except that it uses the least similar pair between two clusters to determine the inter-cluster similarity (so that every cluster member is more like the furthest member of its own cluster than the furthest item in any other cluster). This method is characterized by small, tightly bound clusters.

C. Average Linkage Method

Cluster objects based on the average distance between all pairs of objects. Here we use the average distance from samples in one cluster to samples in other clusters.

D. Ward’s Procedure

This method is distinct from all other methods because it uses an analysis of variance approach to evaluate the distances between clusters. In short, this method attempts to minimize the Sum of Squares (SS) of any two clusters that can be formed at each step. Typical of properties of variance for statistical decision-making, this tends to create two many clusters or clusters of small sizes because the more the observations scattered, the sum of squares makes the distance bigger.

E. Centroid Methods

Clusters are generated that maximize the distance between the centers of clusters (a centroid is the mean value for all the objects in the cluster.

► Difficulties With Hierarchical Clustering

Can never undo the process. Here No object swapping is allowed and Merge or split decisions, if not well chosen may lead to poor quality clusters. Time complexity of at least *O* (*n2*), where *n* is the number of total objects.

► Non-Hierarchical Clustering

Also called k-means clustering determine a cluster center, then group all objects that are within a certain distance. Threshold is the lowest possible input value of similarity required to join two objects in one cluster.

1. Types Of Non-Hierarchical Clustering

A Sequential Threshold Method

First determines a cluster center, then group all objects that are within a predetermined threshold from the center - one cluster is created at a time.

B. Parallel Threshold Method

SIMULTANEOUSLY several cluster centers are determined, then objects that are within a predetermined threshold from the centers are grouped

C. Optimizing Partitioning Method

First a non-hierarchical procedure is run, then objects are reassigned so as to optimize an overall criterion.

D. Partitioning Method

Construct a partition of a database D of n objects into a set of k clusters. Given a k, find a partition of k clusters that optimizes the chosen partitioning criterion. Two Heuristic methods: k-means and k-medoids algorithms

K-MEANS: Each cluster is represented by the center of the cluster. Works when we know k, the number of clusters we want to find. The basic Idea behind this is Randomly pick k points as the “centroids” of the k clusters and then For each point, put the point in the cluster to whose centroid it is closest. Recompute the cluster centroids. Repeat loop (until there is no change in clusters between two consecutive iterations.)

2. Pros & Cons Of *K*-Means

Relatively efficient, Applicable only when mean is defined, What about categorical data?, Need to specify the number of clusters, Unable to handle noisy data and outliers.

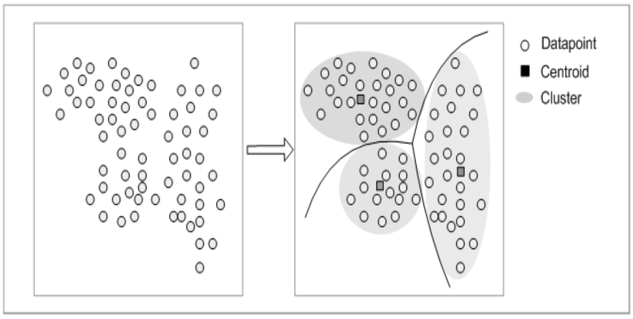
3. Clustering For A Large Databases

Most clustering algorithms assume a large data structure which is memory resident. Clustering may be performed first on a sample of the database then applied to the entire database. Some Algorithms that have been proposed like Birch, Dbscan, Cure.

Improvements: Integration of hierarchical method with other clustering methods for multi phase clustering.

A. BRICH (Balanced Iterative Reducing and Clustering Using Hierarchies)- uses CF-tree and incrementally adjusts the quality of sub-clusters.

B. CURE (Clustering Using Representatives)-selects well-scattered points from the cluster and then shrinks them towards the center of the cluster by a specified fraction.



BRICH (Balanced Iterative Reducing and Clustering Using Hierarchies)

Phases of BIRCH Algorithm:

Phase 1 is to scan all data and build an initial in memory CF Tree using the given amount of memory and recycling disk space. Phase 2 is to condense into desirable range by building a smaller CF tree, for applying global or semi global clustering method. Phase 3 apply global or semi global algorithm to cluster all leaf entries. Phase 4 is optional and entails additional passes over data to correct inaccuracies and refines the cluster further.

Effectiveness of this method is that finds a good clustering with a single scan and improves the quality with a few additional scans. It is a one scan process: trees can be rebuild easily and have Complexity O (n).

Weakness of method is that handles only numeric data, and sensitive to the order of the data record.

CURE (Clustering Using Representatives)

Firstly, it obtains a sample of the database then partition the sample into p partition. After that, partially cluster the points in each partition and remove outliers based on size of cluster. Cluster entire database on disk using c points to represent each cluster .an item in the database is placed in the cluster, which has closest representative point in it. *Effectiveness* is that it produces high quality clusters in presence of outliers, allowing complex shapes and different sizes. It is a One-scan method and has Complexity O (n).Sensitive to user-specified parameters (sample size, desired clusters, shrinking factor etc).*Weakness* is that does not handle categorical attributes (similarity of two clusters).

4. OTHER APPROACHES TO CLUSTERING

A. Density-Based Methods

This method is based on connectivity and density functions have a capability of Filter out noise, find clusters of arbitrary shape. Major features are Discover clusters of arbitrary shape, Handle noise, one scan, Need density parameters as termination condition.

B. Grid-Based Methods

Major features of the Grid-based methods In this Quantize the object space into a grid structure, Uses multi-resolution grid data structure, Quantizes the space into a finite number of cells, Independent of number of data objects, Fast processing time.

C. Neural Network Approaches

Represent each cluster as an exemplar, acting as a “prototype” of the cluster and new objects are distributed to the cluster whose exemplar is the most similar according to some distance measure

D. Competitive Learning

Involves a hierarchical architecture of several units (neurons) and Neurons compete in a “winner-takes-all” fashion for the object currently being presented

E. The Group Average Method

The group average method relies on the average value of the pair wise within a cluster, rather than the maximum or minimum similarity as with the single link or the complete link methods. Since all objects in a cluster contribute to the inter –cluster similarity, each object is , on average more like every other member of its own cluster then the objects in any other cluster.

F. Text Based Documents

In the text based documents, the clusters may be made by considering the similarity as some of the key words that are found for a minimum number of times in a document. Now when a query comes regarding a typical word then instead of checking the entire database, only that cluster is scanned which has that word in the list of its key words and the result is given.

The order of the documents received in the result is dependent on the number of times that key word appears in the document.

5. COMPARISON OF CLUSTERING TECHNIQUES

Algorithm	Type	Space	Time	Notes
Single Link	Hierarchical	$O(n^2)$	$O(kn^2)$	Not incremental
Average Link	Hierarchical	$O(n^2)$	$O(kn^2)$	Not incremental
Complete Link	Hierarchical	$O(n^2)$	$O(kn^2)$	Not incremental
MST	Hierarchical /Partitional	$O(n^2)$	$O(n^2)$	Not incremental
Squared Error	Partitional	O(n)	O(tkn)	Iterative
K-Means	Partitional	O(n)	O(tkn)	Iterative, Not categorical
Nearest Neighbor	Partitional	$O(n^2)$	$O(n^2)$	Incremental
PAM	Partitional	$O(tn^3)$ or $O(tkn^2)$	$O(n^2)$	Iterative
BIRCH	Partitional	O(n)	O(n)	CF-Tree; Incremental; Outliers
CURE	Mixed	$O(n^2 lgn)$	O(n)	Heap; k-D tree; Incremental; Outliers
ROCK	Agglomerati ve	$O(n^2 lgn)$	$O(n^2)$	Sampling; Categorical; Links
DBSCAN	Mixed	$O(n^2)$	$O(n^2)$	Sampling; Outliers

6. CLUSTERING APPLICATIONS

Data clustering has immense number of applications in every field of life. One has to cluster a lot of thing on the basis of similarity either consciously or unconsciously. So the history of data clustering is old as the history of mankind. In computer field also, use of data clustering has its own value. Especially in the field of information retrieval data clustering plays an important role. Some of the applications are listed below.

a. Similarity Searching In Medical Image Database

This is a major application of the clustering technique. In order to detect many diseases like Tumor etc, the scanned pictures or the x-rays are compared with the existing ones and the dissimilarities are recognized.

b. Image Segmentation

Clustering can be used to divide a digital image into distinct regions for border detection or object recognition.

A. ADVANTAGES OF CLUSTER ANALYSIS

Cluster analysis is a good way for quick review of data, especially if the objects are classified into many groups. In the above example, ‘Schools Like Mine’, 23 clusters of school with different properties were clearly clustered. Cluster Analysis is easy for user to assign or nominate themselves in to a cluster they would most like to compare with in exist school cluster database because each cluster is clearly named with understandable terms.

Cluster Analysis provides a simple profile of individuals. Given a number of analysis units, for example school size, student ethnicity, region, size of civil jurisdiction and social economic status in this example, each of which is described by a set of characteristics and attributes. Cluster Analysis also suggests how groups of units are determined such that units within groups are similar in some respect and unlike those from other groups

B. DISADVANTAGES OF CLUSTER ANALYSIS

Object can be assigned in one cluster only. For example in 'Schools Like Mine', schools are automatically assigned into the first twenty-two clusters. However, if schools want to compare themselves with integrated schools, they will have to manually assign themselves into cluster twenty-three. Data-driven clustering may not represent the reality because once a school is assignted to a cluster, it cannot be assigned to another one. Some schools may have more than one significant property or fall on the edge of two clusters.

Clustering may have detrimental effects to teachers who work in low-decile schools, students who are educated in them, and parents who support them, by telling them the schools are classified as ineffective, when in fact many are doing well in some unique aspects that are not sufficiently illustrated by the clusters formed In k-means clustering methods, it is often requires several analysis before the number of clusters can be determined .It can be very sensitive to the choice of initial cluster centres.

C. Classification

The conventional statistical approaches for image classification use only the gray values. Different advanced techniques in image classification like Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy measures and Genetic Algorithms (GA) are developed for image classification. The use of textural features in ANN helps to resolve misclassification. SVM was found competitive with the best available machine learning algorithms in classifying high-dimensional data sets. Fuzzy measures show the detection of textures by analyzing the image by stochastic properties [27]. The genetic algorithm searches a space of image processing operations that produce suitable feature planes, and a conventional classifier uses those feature planes to output a final classification. A comparative study of some of these techniques for image classification is made to identify relative merits.

1. Neural Networks

There are a number of standard classification methods in use. Probably neural network methods are most widely known. The biggest advantage of neural network methods is that they are general: they can handle problems with very many parameters, and they are able to classify objects well even when the distribution of objects in the N-dimensional parameter space is very complex. The disadvantage of neural networks is that they are notoriously slow, especially in the training phase but also in the application phase. Another significant disadvantage of neural networks is that it is very difficult to determine how the net is making its decision. Consequently, it is hard to determine which of the image features being used are important and useful for classification and which are worthless.

2. Nearest-Neighbor Classifiers

A very simple classifier can be based on a nearest-neighbor approach. In this method, one simply finds in the N-dimensional feature space the closest object from the training set to an object being classified. Since the neighbor is nearby, it is likely to be similar to the object being classified and so is likely to be the same class as that object. Nearest neighbor methods have the advantage that they are easy to implement. They can also give quite good results if the features are chosen carefully (and if they are weighted carefully in the computation of the distance.) There are several serious disadvantages of the nearest-neighbor methods. First, they (like the neural networks) do not simplify the distribution of objects in parameter space to a comprehensible set of parameters.

Instead, the training set is retained in its entirety as a description of the object distribution. (There are some thinning methods that can be used on the training set, but the result still does not usually constitute a compact description of the object distribution.) The method is also rather slow if the training set has many examples. The most serious shortcoming of nearest neighbor methods is that they are very sensitive to the presence of irrelevant parameters. Adding a single parameter that has a random value for all objects (so that it does not separate the classes) can cause these methods to fail.

3. Decision Trees

Decision tree methods have also been used for star-galaxy classification problems. In axis-parallel decision tree methods, a binary tree is constructed in which at each node a single parameter is compared to some constant. If the feature value is greater than the threshold, the right branch of the tree is taken; if the value is smaller, the left branch is followed. After a series of these tests, one reaches a leaf node of the tree where all the objects are labeled as belonging to a particular class. These are called axis-parallel trees because they correspond to partitioning the parameter space with a set of hyper planes that are parallel to all of the feature axes except for the one being tested.

4. Support Vector Machines

The support vector machine (SVM) is superior of all machine learning algorithms. SVM employs optimization algorithms to locate the optimal boundaries between classes [28]. The support vector machine (SVM) is a machine learning algorithm based on statistical learning theory. The principle of SVM is structural risk minimization (SRM). The risk of a learning machine (R) is bounded by the sum of the empirical risk estimated from training samples(Remp) and a confidence interval (ø): R = Remp+ ø . Currently, one SVM classifier is able to separate only two classes. Integration strategies are needed to extend this method to classifying multiple classes.

5. Fuzzy Measures

In Fuzzy measures, different stochastic relationships are identified to describe properties of an image. If the fuzzy property is more related to a region, then a fuzzy measure is used. Fuzzy function is used if a stochastic property is to be described by a particular distribution of gray values. The fusion of these two stochastic properties is represented as a fuzzy measure and fuzzy function defines on an area which is achieved by a fuzzy integral.

6. The Genetic Programming System

The genetic programming system based on a linear chromosome manipulates image processing programs that take the raw pixel data planes and transform them into a set of feature planes [29]. This set of feature planes have a multi-spectral image derivedrom the original image through a certain sequence of image processing operations.

The system then applies a conventional supervised classification algorithm to the feature planes to produce a final output image plane. The pixel in the output image plane specifies whether that feature is there or not.

7. Benefits and Limitation Of The Methods

8. Comparisons of The Classification Methods

Parameter	Type of Approach	Non-linear decision boundaries	Training Speed	Accuracy	Good Perfor m-ance
Artificial Neural Networks	Non Para-metric	Efficient when the data have only few input variables	Network structure, momentum rate, learning rate, converging criteria	Depends on number of input classes	Networ k structur e
Support vector Machines	Non-parametric with binary classifier	Efficient when the data have more input variables	Training data size, kernel parameter, class separability	Depends on selection of optimal hyper plane	Kernel parame ter
Fuzzy Logic	Stochastic	Depends on the priori knowledge of decision boundaries	Iterative application of the fuzzy integral	Selection of cutting threshold	Fuzed fuzzy integral
Genetic Algorithm	Large time series data	Depends on the direction of decision	Refining irrelevant and noise genes	Fused fuzzy integral	Feature selectio n

VII. CHARACTERISTICS OF IMAGE QUERIES

What kinds of query are users likely to put to an image database? To answer this question in depth requires a detailed knowledge of user needs – why users seek images, what use they make of them, and how they judge the utility of the images they retrieve. Potentially, images have many types of attribute which could be used for retrieval, including:

1) The presence of a particular combination of color, texture or shape features (e.g. green stars).
2) The presence or arrangement of specific types of object (e.g. chairs around a table).
3) The depiction of a particular type of event (e.g. a football match).
4) The presence of named individuals, locations, or events (e.g. the Queen greeting a crowd).
5) Subjective emotions one might associate with the image (e.g. happiness).
6) Metadata such as who created the image, where and when.

Level 1 comprises retrieval by primitive features such as color, texture, shape or the spatial location of image elements. Examples of such queries might include “find pictures with long thin dark objects in the top left-hand corner”, “find images containing yellow stars arranged in a ring” – or most commonly “find me more pictures that look like this”. This level of retrieval uses features (such

Machine Learning Algorithm	Benefits	Limitations
Neural Network	• Can be used classification or regression • Represent Boolean functions (AND, OR, NOT) • Tolerant of noisy inputs • Instances can be classified by more than one output	• Difficult to understand structure of algorithm • Too many attributes can result in over fitting • Optimal network structure can only be determined by experimentation
Support Vector Machine	• Models nonlinear class boundaries • Over fitting is unlikely to occur • Computational complexity reduced to quadratic optimization problem • Easy to control complexity of decision rule and frequency of error	• Training is slow compared to Bayes and Decision tree • Difficult to determine optimal parameters when training data is not linearly separable • Difficult to understand structure of algorithm
Fuzzy Logic	• Different stochastic relationships can be identified to describe	• Precise solution are not obtained if the direction of decision is not clear
Genetic Algorithm	• Can be used in feature classification and feature selection • Efficient search method for a complex problem space • Good at refining irrelevant and noisy features selected for classification	• Computation or development of scoring function is nontrivial • Complications involved in the representation of output data

as a given shade of yellow) which are both objective, and directly derivable from the images themselves, without the need to refer to any external knowledge base. Its use is largely limited to specialist applications such as trademark registration, identification of drawings in a design archive, or color matching of fashion accessories.

Level 2 comprises retrieval by derived (sometimes known as logical) features, involving some degree of logical inference about the identity of the objects depicted in the image. It can usefully be divided further into:

a) Retrieval of objects of a given type
b) Retrieval of individual objects or persons
Level 3 comprises retrieval by abstract attributes, involving a significant amount of high-level reasoning about the meaning and purpose of the objects or scenes depicted. Again, this level of retrieval can usefully be subdivided into:

a) Retrieval of named events or types of activity
b) Retrieval of pictures with emotional or religious significance
Success in answering queries at this level can require some sophistication on the part of the searcher. Complex reasoning, and often-subjective judgment, can be required to make the link between image content and the abstract concepts it is required to illustrate. Queries at this level, though perhaps less common than level 2, are often encountered in both newspaper and art libraries.

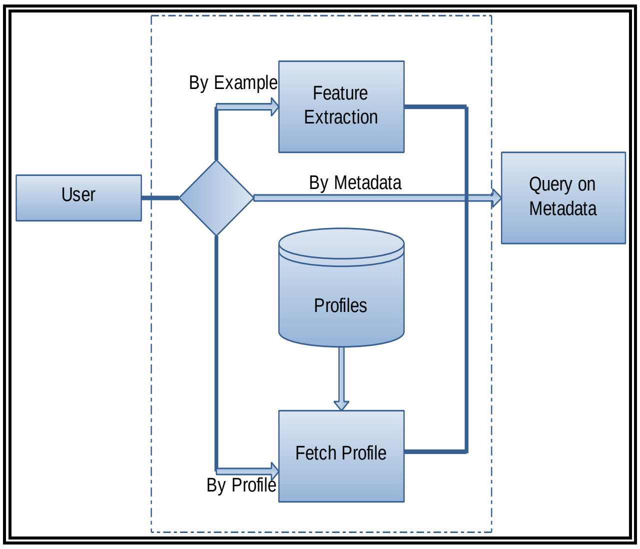
The most significant gap at present lies between levels 1 and 2. Many authors refer to levels 2 and 3 together as semantic image retrieval, and hence the gap between levels 1 and 2 as the semantic gap. Note that this classification ignores a further type of image query – retrieval by associated metadata such as who created the image, where and when. This is not because such retrieval is unimportant. It is because (at least at present) such metadata is exclusively textual, and its management is primarily a text retrieval issue.

A. Query By Visual Example

Querying by visual example [30, 31, 32] is a paradigm, particularly suited to express perceptual aspects of low/intermediate features of visual content. Visual content refer to color, shape and texture features of images.

B. Query By Texts

User mainly used keywords to indicate what they wanted [33, 34]. Textual queries usually provide more accurate description of users' information needs as it allow users to express their information needs at the se-mantic level and high level abstractions instead of limited to the level of preliminary image features.



IX. TOWARD INTELLIGENT IMAGE RETRIEVAL

Bridging the semantic gap for image retrieval is a very challenging problem yet to be solved. Even though there are a lot of significant efforts and works on image retrieval research, there are still some spaces which need to be improved besides the challenges that is associated with mapping low level to high level concepts. Researchers are moving towards to intelligent image retrieval that are also support more abstract in concept by understanding the image content in terms of high level concepts, which is closely related to the problem of computer vision and object recognition besides more intelligent system. In developing a complete intelligent image database system, at least the following four important issues must be addressed:

a) Feature Space Selection: determine what image feature, or combination of image features, is to be used for image matching and retrieval purposes.
b) Feature Capturing: selects algorithms to capture the image feature or the image feature set identified by the feature space selection.
c) Indexing and Search Scheme: Creates effect indices and data structure based on the selected feature space to speed up image retrieval on the databases.
d) Database Query Scheme: provide methods that enable users to effectively form database queries, and to refine the queries based on retrieved images.

X. CONCLUSION

This paper provides a detail review of recent image retrieval current research work. Recent works are mostly lack of semantic features extraction and user behavior consideration. Therefore, there is a need of image retrieval system that is capable to interpret the user query and automatically extract the semantic feature that can make the retrieval more efficient and accurate.

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