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A new approach for image databases design

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Abstract This paper focuses on the methodologies to organize and structure image databases. Conventional relational database techniques are optimized to deal with textual and numeric data; however, they are not effective to handle image data. Some progresses have been made in developing new approaches to establish and use image databases, but the applications of these approaches are very labor-intensive, error-prone, and impractical to large-scale databases. In this paper, we propose a new approach to develop the structure of a large-scale image automatically. It is an integrated approach from existing technologies for the new application where the management of image data is focused. In addition, we present a solution to data indexing for the image database with different image types.

Keywords Visual data · Data indexing · Hash function · Image databases · Content-based image retrieval (CBIR) · Industrial information integration engineering (IIIE)

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1 Introduction

Visual information such as photographs, medical images, surveillance images, industrial images, and aerial and satellite images, is playing more and more important role in our modern society [27, 57]. One example is online web pages with visual information; even in very early stage of the Internet, researchers had identified the critical technical challenges in storing and searching unstructured and complex multimedia data [6]. Another example is in industrial applications [1] or called industrial information integration [47–49]; the majority of data exchanges and communication are based on visual data, available three dimensional (3D) scanners and computer aided design (CAD) and computer aided manufacturing (CAM) tools have accelerated the growth rate of image data greatly [2–4, 10, 43, 48, 50, 51, 53, 54]. The explosive growth of image data from digital devices is making database management extremely tedious and clumsy tasks [5, 20, 34, 52]. Correspondingly, the techniques for organizing, storing, processing, and retrieving multimedia data are becoming more and more important. Note that traditional relational database approaches are ineffective to deal with multimedia data; since it usually includes a large amount of unstructured and visual information. In this section, a brief summary of existing database technologies for multimedia databases and their limitations is provided.

1.1 Existing techniques for image databases

The newer generations of database products, such as Not only SQL (*NoSQL*), EXtensible Markup Language (*XML*), and *columnar databases*, are designed to support unstructured and semi-structured data. These products are functioned primarily on the information in the textual format. In their applications, numerical values of individual pixels are evaluated; while high-level abstractions of image are ignored. The whole of a part of an image is merely treated an assembly of pixels without the consideration of physical meaning or contexts associated with the image. As the matter of fact, the nature of visual data needs a completely different structure due to its richness of physical meaning. In contrast to textual data in conventional databases, visual data does not fits well to SQL, nor the techniques applicable to relational or object-relational databases.

With the rapid growth of image data, it becomes essential to store and retrieve images in large-scale databases effectively [32]. The most noticeable approach used in image databases is based on image indexing [8]. Images are processed based on the indexes or descriptors associated with images. Once indexes are created, traditional database approaches can be used. The indexes or annotations serve as the bridges between textual data and visual information. This method has been applied widely; however, a number of disadvantages can be observed: *firstly*, defining annotations for an image is often manually; it is too labor-intensive. *Second*ly, the procedure to create annotations for images is too slow; it is inapplicable to the cases of streaming new information into database. Typically, such streaming could be very fast, and very voluminous. *Thirdly*, the procedure can be very error-prone due to manual interventions; the preponderance of errors would diminish actual value of data.

One of good example of all these problems was given in [28]. Manually constructed annotations required the substantial amount of highly professional staff to perform tasks on the highest level. In regards astronomical images databases, Wang [44] suggested to use NoSQL type database for annotations (also be called as headers), and use file systems for data storage; his approach is obviously limited to astronomical applications since the problems of using file systems to store large amount of information are well known. Ponomarenko et al. [40] introduced another example of the image database, where images were collected to evaluate the distortion of test images. That database was very specific; the applications of the developed tools to other types of databases are questionable. Lai et al. [24] established a semi-manual indexing process; but the publication lacked of the technical details for an improvement of fully automated indexing.

Another type of approaches for an image database is *content based image retrieval* (CBIR) approaches [15, 17, 25, 26, 39, 45], Navathe et al. [36], Obeid et al. [13, 35, 37, 38], Joshi et al. [7, 21]. A CBIR approach obtains visual information directly from images themselves rather than using metadata. The most common variations of CBIR are those using image features such as intensity histograms, colors histograms, and shapes. The desired numerical characteristics of these features can be combined into vectors and these vectors can be used as a distance measure between different images. However, the major issues occurring to CBIR are how to choose features, and how the corresponding metrics are used to determine numerical values. Lebrun et al. [26] discussed the design of images databases. They suggested using a graph technique to store and retrieve the elements of shapes such as edge. This technique was applicable only to a database with a small number of objects in each image. However, it showed some lights of developing annotations automatically. In the method developed by Gisolf et al. [17], imaging database of forensic data served as a collection of images; the essence of processing visual data was to determine the camera where a picture was taken by; however, little attention was paid to the structure of database. The focus was the identification of image sources, and its applications to other areas were confined. Chaturvedi et al. [7] used the fuzzy logic clustering algorithm to build retrieving algorithm; it was proven with the high efficiency in comparing images with completely different palettes. No evidence was given if this algorithm can be applied in images with close colored histograms. In addition, different classes of images required different feature types and metrics; which possessed the difficulties in automation.

Chen et al. [9] introduced a pipeline to segment human image database to reduce manual intervention; the human images were organized into the catalogues of action semantic, cloths attributes, the shapes and poses. To facilitate the verification and validation of algorithms, Forsyth [16] established the benchmarks of storage and retrieval for multimedia databases. Horster et al. [19] represented images by latent Dirichlet allocation (LDA) models in CBIR; each image was treated as the mixture of topics and objects shown in the image, which made it possible for reasoning at a high level of abstraction. Xie et al. [46] adopted common visual patterns (CVPs) for image retrieval; similarities of two images were determined based on CVPs. Zhao and Grosky [56] proposed image retrieval schemes to extract features based on color histograms and color angiograms. Numerous techniques were developed and applicable only to sophisticated medical databases. For example, Zare et al. [55] suggested using three annotation techniques to construct the classification frameworks of X-ray image databases. Lu et al. [29] integrated the image-guided surgery toolkit and the medical imaging interaction toolkits for the development of an image-guided surgery navigation system. Ko et al. [22] developed an automatic approach to create annotations for medical images; correspondingly, images were retrieved using keywords. Dubey et al. [14] presented a descriptor of image features based on the local diagonal external pattern; it was mainly applied in CT image retrieval.

1.2 Limitations of existing technologies

Enriched image collections offer the opportunities in developing practical techniques for data storages, processing, and classifications [23]. Immense amounts of image data are continuously produced in medical research, clinical practice. Therefore, CBIR techniques must be advanced to process large-scale data efficiently. When the textual information is used to describe semantic content, image retrieval brings an additional overhead of manually annotating every image in databases [42]. Rui et al. [41] conducted on a comprehensive literature survey on the image feature representation and extraction, data indexing, and database design to clarify research directions in the development of image databases.

Mogharrebi et al. [33] reviewed existing research works and identified the challenges in patent image retrieval domain; current techniques for pattern search do not support image retrieval; in other words, patent images are unsearchable. They suggested to used Affine-Sift technique to retrieval image.

Traditional indexing for image retrieval is text-based; where a text descriptor is used to represent high-lever abstract information. Inadequate text description is problematic [56]. Many visual information systems used low-level features such as color, texture, shapes for image queries. There are semantic gaps between low-level abstractions and high-level abstractions (Obeid et al. [37]. Existing annotation methods on image data are often noisy and redundant; it required that feature selection be more precise and compact representation of images [31]. Innovative approaches to automatically generate annotations and utilize them for data management of image databases are very demanding.

2 Overview of the proposed approach

In this paper, we propose a new approach used for image storage and retrieval in image databases. It is capable of identifying objects based on their visual contents in images. Therefore, each image can be represented by a set of identified objects; these objects can be real or perceived. Since an image might consist of different types and number of objects; we propose to classify and store images not only based on photographic quality but also the objects they portray. Exemplified objects in a scene image are *persons*, *landscapes*, *buildings*, *animals*, and *vehicles*. It seems that the proposed new approach is similar to image indexing, i.e., its implementation requires creating annotations of images. However, the proposed approach is innovative in the sense that: (1) the process to generating annotations is fully or almost fully automated, (2) the generated annotations are well structured, and (3) it provides a richer, more robust, and more meaningful annotations than other existing methods. From another perspective, images can be processed using modern image analysis tools; technical photographic features of images are analyzed in data processing. Therefore, the proposed approach has its similarities to CBIR; it can be called as a hybrid method of CBIR and indexing methods. In addition, we also discuss and analyze different indexing approaches. Indexing is a very important component of structured databases. Different types of data require different types of indexing methods.

In the rest of the paper, we will provide the details of the proposed approach. In Sect. 3, the procedure of image storage and retrieval is discussed, and the main steps and activities are introduced. In Sect. 4, the algorithm for data retrieval is proposed; an example is introduced to verify its performance. In Sect. 5, the potential areas of applications are explored. In Sect. 6, the presented works are summarized and the directions for future research in this field are briefed.

3 Proposed procedure for data storage

Storage and retrieval are two most fundamental functions of data management for databases. Generally, the structure of a database can be hierarchical; we seek the solutions to identify and classify images, and a hierarchical data structure can be very helpful for searching and retrieving operations. On the other hand, human classification by its very nature is hierarchical in general.

In the following, the procedure for analyzing the images is described. The outcome from executing this procedure is meaningful annotations which can be used for both storage and retrieval of image data. Moreover, the annotations can be generated automatically. The proposed procedure consists of the following steps:

(1). Image classification
(2). Image segmentation
(3). Object classification
(4). Annotation generation

The details of the activities and results at each step are explained as follows.

3.1 Image classification

Images are classified according to image types; images are classified at the first step. In this paper, am image is classified into one of the following seven types:

- Photographic images,
- Medical images,

- Satellite images,
- Aerial images,
- Industrial images,
- Surveillance images, and
- Unstructured and semi structured documents.

Images can be easily classified and automated by identifying the sources where these images are acquired.

3.2 Image segmentation

The second step is *image segmentation*. Image segmentation is to decompose an image into sub-images at the next level; each of sub-images is still an image. Image segmentation benefits to data compression as well. If a considerable portion of an image is empty, the representation of using identified objects for original image can condense the size of data significantly. Note that the techniques for data segmentation are very mature now. Interested readers might find the details of different techniques in the literature [15, 39]. We plan to use well known methods to segment images. The result of image segment will be a plurality of sub images derived from an original image.

3.3 Object classification

Once an image is segmented into a number of sub-images with object individuals, the third step is to classify objects. The task at this step is called as *object classification*, *object identification*, or *object recognition*. It is the most critical task in the proposed approach. Taking into account the fact that any image is the representation of physical objects, object identification is not only feasible but also essential. The classification relates to types of image, and it is performed by comparing an object of interest with the images of reference objects stored in the database. The features of an object in the database are represented in a vector form. For example, a building should be positioned with at least three parameters, i.e. X, Y, and Z.

The database with reference objects is also equipped with the mechanisms to construct an image from a set of given attributes. The rules for the classification are based on the image recognition procedures to map image types into objects. These image classification procedures can be automated completely.

3.4 Generating annotations

The last step is to assign standard individual characteristics to images. The set of individual characteristics and the total number depend on the types of image. Two images have the same individual characteristics. Most of the characteristics relate to geometries, e.g. the dimensions and proportions of an object. What these characteristics are, and the algorithms for computing their values are the subjects of image recognition. Two most popular methods for image recognitions are the correlation and Lucas-Kanade approaches [30].

Finally, the integration of image classification, image segmentation, object classification, and assignments of individual characteristics to images allows to produce the annotation for sub-image individuals of original image. The flowchart of the whole procedure of analyzing images for the storage and retrieval purpose is illustrated in Fig. 1.

The tangible result from the aforementioned procedure is the annotations of image suitable for storage and retrieval. Certain annotation represents the corresponding physical meaning; the annotation itself is generated automatically. The annotations associated with images are important in the sense that an original image is assigned with a unique numerical identifier. Even though multiple images share equivalent annotations, they are uniquely identifiable. This annotation also has a reference to its constitutive elements from the *objects DB*.

The structure of each element from an image database is shown in Fig. 2.

3.5 An illustrative example

The goal of our paper is to establish new architecture of the image database. We experimented with the objects in the database and the functions to construct images of objects in different positions and taken from different points of view. The database will be completely implemented in near future. In this section, we present an image example to illustrate how it is processed and how the annotation is constructed in using the proposed approach.

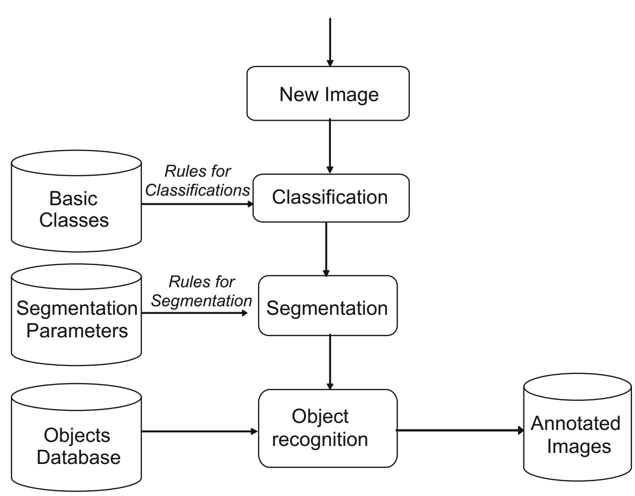


Fig. 1 The flowchart of image analysis

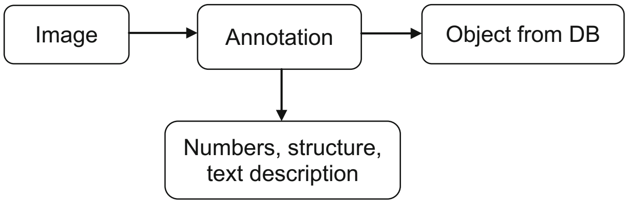


Fig. 2 Structure of elements in image database

This example serves for illustration purpose only. Let's start with the query image [18] in Fig. 3.

Step 1. Image classification
It was determined that according to the source of the image, this is regular photo picture.
Step 2. Image segmentation
Segmentation is performed by a MATLAB program, which was an implementation of the Watershed method. It found two segments with different objects as results (Fig. 4).
Step 3. Object classification
Objects were classified by using of the image recognition procedure in MATLAB. This procedure accepted inputs parameters of abstract objects. Four DB objects were used as example: 'human', 'animal', 'building', and 'car'. This procedure found that the object in the left segment was 'human', and the object in the right segment was 'animal' (Fig. 5).

The further analysis of the identified object gave us more detailed information about objects. For example, that a human object was a male and the image was taken from the back. The image with the second object was taken from the side and so on. The levels of classification can be determined based on the required quality of classification.

Step 4. Generating annotations
The algorithm of generating annotations for images is beyond the scope of the presented work. We will

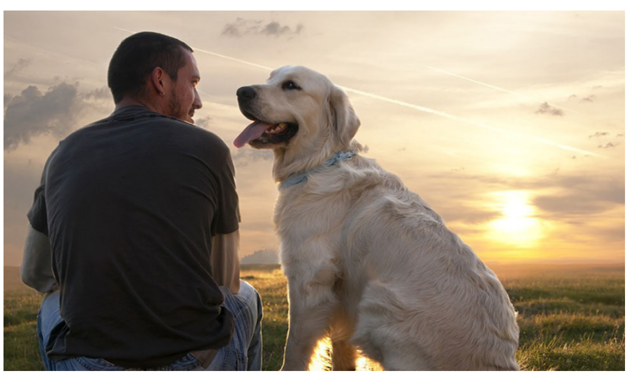


Fig. 3 Query image example

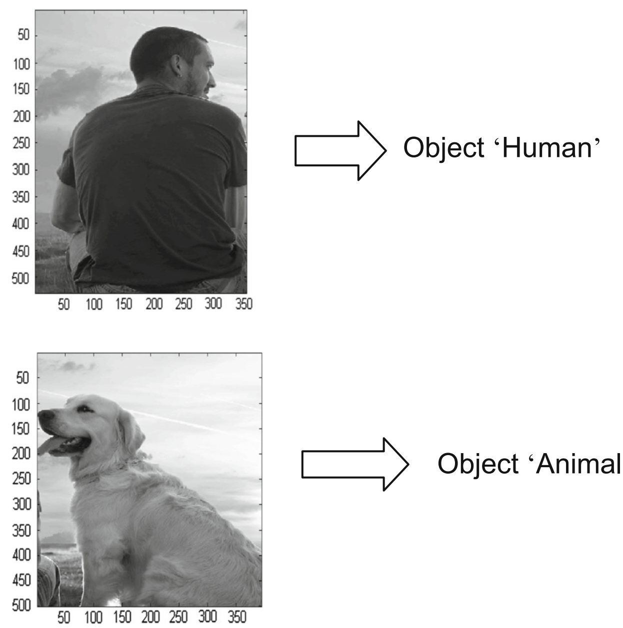
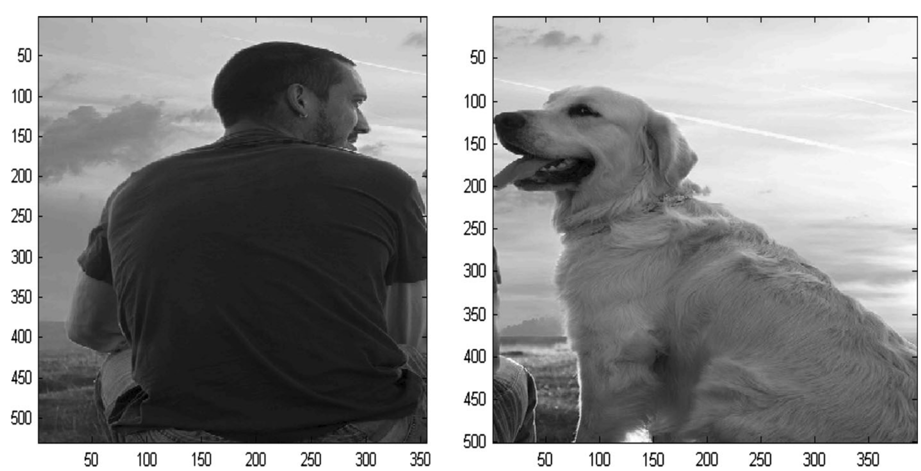


Fig. 5 Classified objects of sub-images

Fig. 4 Results of image segmentation



develop it in the future. However, the obtained information showed a clear path of how the annotations can be constructed in this particular case.

For example, the annotation can be constructed as follow:

"*Query image contains two segments. Segment 1 depicts a human object, male; the picture is taken from the back. Segment 2 depicts an animal, which is a dog; image is taken from the side*".

3.6 Indexing procedures

It is well known that the usage of indexes could improve the efficiency of database. Therefore, we have developed several indexing algorithms: different types of indexing methods should be applied to different types of images.

For example, medical images are unique in sense of identifications. It is possible to use a combination of a person ID, date/time the imaging was performed, type of the image, and image number as an image unique identifier.

Theoretically, the Hash table method [26] is the fastest and most widely used. It makes sense to explore its application in medical databases. We will consider the speed and popularity of hash tables and apply it in the storage of medical images. For example, suppose that the PID (Patient Identification Number) is the only data to uniquely identify medical images, we can use this PID as the database index. However, using the PID as the index in a database that employs a hash table would lead to many collisions or to insufficient usage of storage. For example, one person can have more than one entry (image) in the database over a period of time, or even in the same day. To reduce collisions down to an acceptable level, one has to use additional attributes to build a unique identifier. These attributes can be a time stamp (date/time of a procedure), type of image, and number of images in one session. As the result, the suggested schematic of the index structure is shown in Table 1.

The hash function in this case can be presented as an assignment of the PID value. Generally, it is the most time consuming portion of the index calculations. As it requires to execute a hash function itself and to move through the linked list. In case of collision avoidance, the movement through a linked list has a limited complexity (performing only a limited number of the comparison and assignment operations). Therefore, the cost in computational time for the composite index that we propose is only marginally greater than that of the more simplistic approach of using the PID only.

Concerning other portions of the composite index, the *date/time* can be organized as a stack, in descending chronological order with the latest dates on the top. That is, *date/time* is the second component of the composite key. For the same PID, there may be multiple images from different dates. The most recent date will be on top; the next most recent date will be the next on the stack.

Some additional fields that could be included in annotation are the type of the image and the number of images in the set of similar images. The type of the image is just a number. For example, such a numbering scheme could assign the following values: MRI is 1, CT is 2, Ultrasound is 3, and X-Ray is 4, etc. It is quite possible that there might be multiple images belonging to a set of images of a specific type of image on a specific day. For instance, a CT will most likely consist of many images. The number assigned to a specific image in a set of images is just an ordered number. Therefore, the last field in Table 1 is the ordered number of the object.

It could cause some concern that the hash table for such a large key would use too much memory for both of main memory and secondary storage. However, it is our argument that this is not an issue, and that this becomes increasingly less important as the cost of memory and secondary storage continue to decline. As an example, suppose the PID is 9 digits, and that it is the "the primary key". An integer representation of this field could contain 1 billion possible values (10^9). Assuming an integer size of 4 bytes ($2^4 = 32$ bits), it leads to 4 GB required memory. It is highly doubtful that an organization would have anywhere near 1 billion unique patients. Even so, assuming the maximum number of patients that this PID could represent, the space required for all these keys would be approximately 4 GB. In an age of multi-terabyte storage, this is not a high price to pay. The extra space required for the rest of the composite key would similarly not be too demanding: there are a finitely small number of dates for all the procedures per patient; there are only a handful of possible types of images; a capacity of just under 100,000 images per set could accommodate 55 min of motion video (far greater than the time required for the typical procedure); and the length of a pointer is a small number of bytes.

Regarding *satellite images,* the image identification can be performed precisely, and is based upon the nature of an image. The hash function in this case can be presented as the satellite ID multiplied by 1000, plus the sequence number of the image. To define the database indexes,

Table 1 Suggested indexing structure

PID	Date	Time	Ordered number of the object(image)
111111111	01012014	235007	0000001

aerial images can be treated in the same way as satellite images are. A hash table would be the preferred indexing approach here. *Surveillance images* can also be indexed using a simple hash function. If it is for a single surveillance camera, the image number can serve as the index. If there is no image number, the time that the image is captured could serve as the image number. If there are multiple surveillance cameras, the index can be calculated as the product of the camera ID (a unique sequence number identifying the camera) times the maximum number of images taken by that camera, plus the number of the image. In the case of *regular photographic pictures,* using a hash table as the indexing method is not realistic. This is due to the absence of a precise identification of the camera, and a precise identification of which sequential image this is from that camera. Given the hierarchical nature of our suggested annotation, a B+ tree approach [11, 36] would be the preferred method. Based on the annotation method we have described, the image description can be presented as a set of attributes such as the type of image, the type of landscape, the type of crowd, rural landscape features, urban landscape features, and human figure features, human face features, and so on.

4 Proposed procedure for data retrieval

The other most fundamental function of a database is retrieval. A query for a database of images is fundamentally different from a query for a general purpose relational database [44]. Due to the nature of visual information, the standard SQL-based approach is inapplicable to information retrieval.

In this section, we will briefly discuss the processing of queries in our approach. The goal of a query in an image database is to find the image(s) that most closely satisfy the requirements of the query. The goal could also be to find attributes of images, or to find objects from images. There are two basic types of queries in an image database:

(1). To find an image that most closely matches the input reference image. This would entail finding similar images, such as similar faces, similar objects, similar scenes, and similar places.

(2). To find object(s) which provides the best match image to the input image based on the annotation. This entails finding the attributes of images, and finding the objects from images.

These two types of queries are closely related, but they are different. The retrieval process for these types of queries consists of the following steps. These steps correspond heavily to the same steps used to annotate and store images discussed earlier.

1. *Image classification* The image query needs to be classified, according to the expected source of the image that will satisfy this query. Normally, this classification can be easily and automatically done by identifying how the desired image would have been obtained. In rare cases, the image query may need to be classified manually.
2. *Image segmentation* The image query is decomposed into its constituent parts.
3. *Object classification*. The objects in the constituent parts of the image query are classified according to the objects database. (This is the same objects database used for this same step in the storage procedure.) The purpose of this step is correspondingly the same (as in the storage procedure): to find the objects that most closely match the requirements of our query. This narrows the search area.
4. *Assignment of individual characteristics* The image query is assigned appropriate characteristics, as is common in the field of image recognition. The choice of the individual metrics used should coincide with set of metrics which would be used in the construction of the class. This step also results in the annotation for the image query.
5. *Annotation comparison* Using standard DB tools (such as SQL) and the annotation for the image query, find the set of objects that most closely meets the requirements. The annotation and the set of images from the DB should coincide (in whole or in part) with the image query. The result will be the set of objects and images, along with appropriate relevancy scores, that show the degree of similarity between returned results and the image query.
6. *Image comparison* Correlation analysis or Lucas-Kanade type algorithms [12] can be used to compare the image query with the DB images that have been returned in the previous step. The set of images returned in answer to our query will have a limited number of elements. Therefore, it will be feasible to use the computationally extensive methods mentioned above.

5 Potential areas of applications

Approaches similar to our approach are being used in such specialized applications as automated fingerprint analysis, and to a lesser extent, in facial recognition. However, our approach can be used in a more general sense than these. Therefore, our approach has a broader range of applicability. Potential fields of applications include any kind of web based databases that makes heavy use of:

- Photographic images collections
- Medical images of different modalities (such as CT, MRI, Ultrasound, and EIT or Electric Impedance Tomography)
- Satellite images
- Aerial images
- Surveillance images
- Industrial scenes
- Unstructured and semi structured document images
- Art collections
- Advertising images (such as a virtual show room)
- World Wide Web itself (when viewed as a sort of database)
- Multidimensional Programming Languages and so on.

6 Conclusion and future research

We have proposed a hybrid method to store and retrieve information in/from a database that consists primarily of visual information. We have defined the potential applications, formulated logical structure of visual database, and formulated the indexing methods. The general approaches for the data indexing are also underlined.

The main strategy for information storage and retrieval of this type of database is to classify the image according to its source, to decompose the image into its constituent objects, to classify each of those objects by identifying the type of object according to a database of objects, and to assign individual characteristics to the image. Object oriented approach is the key element of the proposed visual database.

Our approach is new as it is completely or almost completely automated, and it attempts to use techniques in ways they have not been used before. This approach is using elements from image indexing method (but as automated annotations) and the Content Based Image Retrieval method (CBIR). In addition, it also uses the object oriented storage/retrieval approach.

As for the future research, we are going to finish the formulation of system requirements, design the library of generic objects, build definition of attributes, investigate usage hash functions in case of medical imaging, develop the methods for automatic annotation generations, develop the methods of data storage on physical level, and construct a prototype of the system. Currently, we are in the process of development and implementation of methods for automatic annotation generation.

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