Content-Based Image Retrieval Systems in Medical Applications - Clinical Benefits and Future Directions

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Summary
This article gives an overview of the currently available literature on content-based image retrieval in the medical domain. It evaluates after a few years of developments the need for image retrieval and presents concrete scenarios for promising future research directions. This need is mainly due to the large amount of visual data produced and the unused information that these data contain, which could be used for diagnostics, teaching and research. The necessity for additional, alternative access methods to the currently-used, text-based methods in medical information retrieval is detailed. A short overview of nonmedical image retrieval is given as well. The lack of evaluations of the retrieval quality of systems becomes apparent along with the unavailability of large image databases free of charge with defined query topics and gold standards. However, some databases are available, from the NIH (National Institutes of Health), for example. Ideas for creating such image databases and evaluation methods are proposed.

Key words:
Medical image retrieval, content-based search, visual information retrieval, PACS

Abstract

In the medical field, images, and especially digital images, are produced in ever-increasing quantities and used for diagnostics and therapy. The Radiology Department of the University Hospital of Geneva alone produced more than 12,000 images a day in 2002. The cardiology is currently the second largest producer of digital images, especially with videos of cardiac catheterization (1800 exams per year containing 1800 images each). The total amount of cardiologic image data produced in the Geneva University Hospital was around 1 TB in 2002. Endoscopic videos can equally produce enormous amounts of data.

Content-based visual information retrieval (CBVIR) or Content-Based Image Retrieval (CBIR) has been one on the most vivid research areas in the field of computer vision over the last 10 years. The availability of large and steadily growing amounts of visual and multimedia data, and the development of the Internet underline the need to create thematic access methods that other more than simple text-based queries or requests based on matching exact database fields. Many programs and tools have been developed to formulate and execute queries based on the visual or audio content and to help browsing large multimedia repositories. Still, no general breakthrough has been achieved with respect to large varied databases with documents of differing sorts and with varying characteristics. Answers to many questions with respect to speed, semantic descriptors or objective image interpretations are still unanswered.

This article also identifies explanations to some of the outlined problems in the field as it looks like many propositions for systems are made from the medical domain and research prototypes are developed in computer science departments using medical datasets. Still, there are very few systems that seem to be used in clinical practice. It needs to be stated as well that the goal is not, in general, to replace text-based retrieval methods as they exist at the moment but to complement them with visual search tools.

1. Introduction to image retrieval

This section gives an introduction to content-based image retrieval systems (CBIRSs) and the technologies used in them. Image retrieval has been an extremely active research area over the last 10 years, but first review articles on access methods in image databases appeared already in the early 80s [1]. The following review articles from various years explain the state-of-the-art of the corresponding years and contain references to a large number of systems and descriptions of the technologies implemented. Insert [2] gives an extensive description of image archives, various indexing methods and common searching tasks, using mostly text{based searches on annotated images. In [3], an overview of the research domain in 1997 is given and in [4], the past, present and future of image retrieval is highlighted. In [5] an almost exhaustive overview of published systems is given and an evaluation of a subset of the systems is attempted in [6]. Unfortunately, the evaluation is very limited and only for very few systems.

This article describes common problems such as the semantic gap or the sensory gap and gives links to a large number of articles describing the various techniques used in the domain. For an even deeper introduction into the domain, several theses and books are available [8{11].

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The only article reviewing several medical retrieval systems so far, is to our knowledge [12].It explains using one paragraph per topic a number of medical image retrieval systems. No systematic comparison of the techniques employed and the data/evaluation used has been attempted. This review paper in contrast is the first review that concentrates on image retrieval in the medical domain and that does a systematic overview of techniques used, visual features employed, images indexed and medical departments involved. It also offers future perspectives for image retrieval in the medical domain and will be a good starting point for research projects on medical image retrieval as useful techniques for certain sorts of images can be isolated and past errors can be avoided.

1.1 Content-based image retrieval systems

Most of these systems have a very similar architecture for browsing and archiving/indexing images comprising tools for the extraction of visual features, for the storage and efficient retrieval of these features, for distance measurements or similarity calculation and a type of Graphical User Interface (GUI).
Although early systems existed already in the beginning of the 1980s [13], the majority would recall systems such as IBM's QBIC1 (Query by Image Content) as the start of content-based image retrieval [14, 15]. The commercial QBIC system is definitely the most well-known system. Another commercial system for image [16] and video [17] retrieval is Virage2 that has well known commercial customers such as CNN.
Most of the available systems are, however from academia. It would be hard to name or compare them all but some well{known examples include Candid [18], Photobook3 [19] and Netra [20] that all use simple color and texture characteristics to describe the image content. Using higher level information, such as segmented parts of the image for queries, was introduced by the Blobworld4 system [21, 22]. Pic Hunter [23] on the other hand is an image browser that helps the user to find an exact image in the database by showing to the user images on screen that maximize the information gain in each feedback step. A system that is available free of charge is the GNU Image Finding Tool (GIFT5) [24, 25]. Some systems are available as demonstration versions on the web such as Viper6, WIPE7 or Compass.
This general system setup is shown in Figure1. All shown components are described in more detail further on.
(Figure 1)

1.2 Visual features used

Visual features were classified in [5] into primitive features such as color or shape, logical features such as identity of objects shown and abstract features such as significance of scenes depicted. Still, all currently available systems only use primitive features unless manual annotation is coupled with the visual features as in [26]. Even systems using segments and local features such as Blob world [21, 22] are still far away from identifying objects reliably.

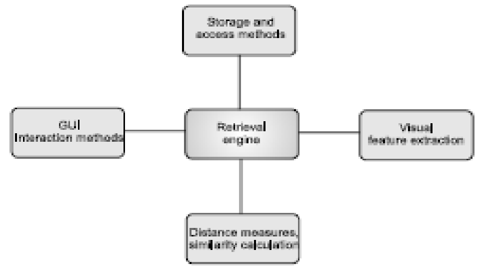

Figure 1: The principal components of all content–based image retrieval systems.

No system offers interpretation of images or even medium level concepts as they can easily be captured with text. This loss of information from an image to a representation by features is called the semantic gap [7]. The more a retrieval application is specialized for a certain, limited domain, the smaller the gap can be made by using domain knowledge.

1.2.1 Color

In specialized fields, namely in the medical domain, absolute color or grey level features are often of very limited expressive power unless exact reference points exist as it is the case for computed tomography images.
In stock photography (large, varied databases for being used by artists, advertisers and journalists), color has been the most effective feature and almost all systems employ colors. Although most of the images are in the RGB (Red, Green, and blue) color space, this space is only rarely used for indexing and querying as it does not correspond well to the human color perception.
This means that differences in the color space are similar to the differences between colors that humans perceive.

1.2.2 Texture

Partly due to the imprecise understanding and definition of what exactly visual texture actually is, texture measures have an even larger variety than color measures. Some of the most common measures for capturing the texture of images are wavelets [32, 33] and Gabor filters [24, 34, 35] where the Gabor filters do seem to perform better and correspond well to the properties of the human visual cortex for edge detection [36, 37]. These texture measures try to capture the characteristics of the image or image parts with respect to changes in certain directions and the scale of the changes.

1.2.3 Local and global features

Both, color and texture features can be used on a global image level or on a local level on parts of the image. The easiest way to use regional features is to use blocks of fixed size and location, so called partitioning of the image.

1.2.4 Segmentation and shape features

Fully automated segmentation of images into objects itself is an unsolved problem. Even in fairly specialized domains, fully automated segmentation causes many problems and is often not easy to realize.
In image retrieval, several systems attempt to perform an automatic segmentation of the images in the collection for feature extraction [21, 46]. To have an effective segmentation of images using varied image databases the segmentation process has to be done based on the color and texture properties of the image regions.

1.3 Comparison techniques used

Basically all systems use the assumption of equivalence of an image and its representation in feature space. These systems often use measurement systems such as the easily understandable Euclidean vector space model [15, 58] for measuring distances between a query image (represented by its features) and possible results representing all images as feature vectors in an n{dimensional vector space. This is done, although metrics have been shown to not correspond well to human visual perception[59]. several other distance measures do exist for the vector space model such as the city-block distance, the Mahalanobis distance [15] or a simple histogram intersection [60]. Still, the use of high{dimensional feature spaces has shown to cause problems and great care needs to be taken with the choice of distance measurement to be chosen in order to retrieve meaningful results [61, 62].
Various systems use methods that are well known from the text retrieval field and apply them to visual features where the visual features have to correspond roughly to words in text [24, 67, and 68].
This is based on the two principles:

- A feature frequent in an image describes this image well;
- A feature frequent in the collection is a weak indicator to distinguish images from each other.

Several weighting schemes for text retrieval that have also been used in image retrieval are described in [69]. A formal definition of vector-space, probabilistic and Boolean models for information retrieval is attempted in [70].

1.4 Storage and access methods

These methods often need to use dimension reduction techniques or pruning methods [72] to allow
for an efficient and quick access to the data. Some indexing techniques such as the KD-trees are described in [73]. Principal Component Analysis (PCA) for feature space reduction is used in [74]. This technique is also called Karhunen - Loeve Transform (KLT) [75]. Another feature space reduction technique is the Independent Component Analysis (ICA) described in [76] also explains a variety of other techniques such as for feature selection.

2. Use of image retrieval in medical applications

The management and the access to these large image repositories become increasingly complex. Most access to these systems are based on the patient identification or study characteristics (modality, study description) [85] as it is also defined in the DICOM standard [86]. Imaging systems and image archives have often been described as an important economic and clinical factor in the hospital environment [87{89]. Several methods from the computer vision and image processing fields already have been proposed for the use in medicine more than ten years ago [90, 91]. Several radiological teaching _les exist [92, 93] and radiology reports have also been proposed in a multimedia form in [94].
Web-interfaces to medical image databases are described in [95].Content-based retrieval has also been proposed several times from the medical community for the inclusion into various applications [101{103], often without any implementation. Still, for a real medical application of content-based retrieval methods and the integration of these tools into medical practice a very close cooperation between the two fields is necessary for a longer period of time and not simply an exchange of data or a list of the necessary functionality.
An interface of a typical content-based retrieval system is shown in Figure 2.

2.1 The need for content-based medical image retrieval

The goals of medical information systems have often been defined to deliver the needed information at the right time, the right place to the right persons in order to improve the quality and efficiency of care processes [104]. Such a goal will most likely need more than a query by patient name, series ID or study ID for images. For the clinical decision-making process it can be beneficial or even important to find other images of the same modality, the same anatomic region of the same disease. Although part of this information is normally contained in the DICOM headers and many imaging devices are DICOM-compliant at this time, there are still some problems. DICOM headers have proven to contain a fairly high rate of errors, for example for the field anatomical region, error rates of 16% have been reported [105]. This can hinder the correct retrieval of all wanted images.

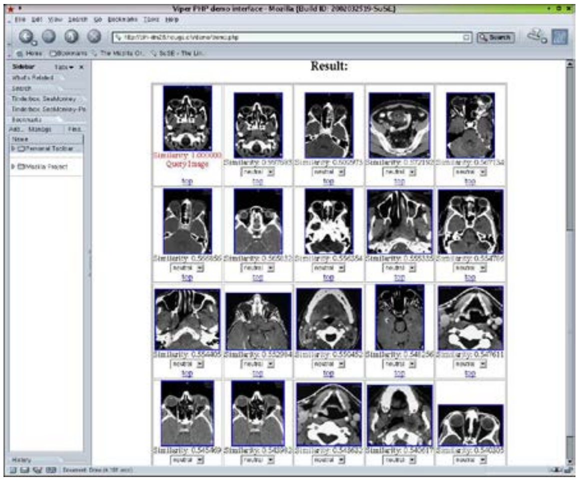

Figure 2: A screenshot of a typical image retrieval system showing retrieved images similar to an example in a web browser interface.

2.2 The use in PACS and other medical databases

There is a large number of propositions for the use of content-based image retrieval methods in the medical domain in general [101{103]. Other articles describe the use of image retrieval with an image management framework [114{119], sometimes without stating what has actually been implemented and what is still in the status of ideas. Also the integration into PACS systems [85, 120{123] or other medical image databases [92, 124{126] has been proposed often, but implementation details are generally rare.

The use of content{based techniques has been proposed several times in a PACS environment. PACS are the main software components to store and access the large amount of visual data used in medical departments. Often, several layer architectures exist for quick short-term access and slow long-term storage. More information on PACS can be found in [130]. A web-based PACS architecture is proposed in [131]. The general schema of a PACS system within the hospital is shown in Figure 3.

The IHE (Integrating the Healthcare Enterprise) 13 standard is aiming at data integration in healthcare including all the systems described in Figure 3.

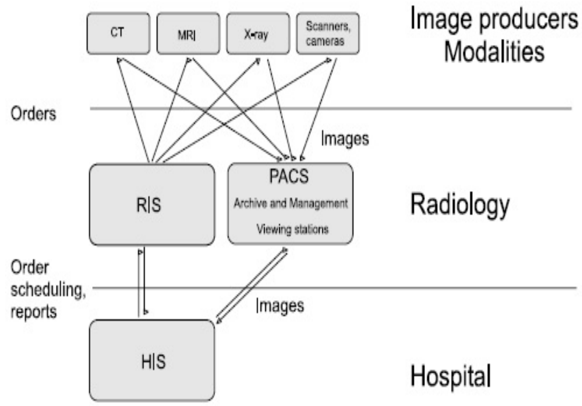

Figure 3: The basic position of a PACS within the information system environment in a hospital.

2.3 The use in various medical departments

A categorization of images from various departments has been described in [54, 100]. A classification of dermatologic images is explained in [75, 136, 137]. Cytological specimens have already been described very early (in 1986, [138]) and also later on [139] whereas the search for 3D cellular structures followed later on [96].

Many other articles use medical images to demonstrate their algorithms but a clinical evaluation of their use has rarely been done. In [53, 54, 155], MRIs (Magnetic Resonance Images) of the brain are used to demonstrate the image search algorithms but the articles do not talk about any medical integration. [115, 156] also use MRIs of the head for testing their algorithms. CT brain scans to classify lesions are used in [157]. The searches for medical tumors by their shape properties (after segmentation) have been described in [147]. Functional PET (Photon Emission Tomography) images for retrieval are used in [158]. Spine x-rays are used in [113, 159].

Table 1 shows an overview of several image types and the systems that are used to retrieve these images.

Images used	Names of the systems
HRCTs of the lung	*ASSERT*
Functional PET	*FICBDS*
Spine X–rays	*CBIR2, MIRS*
Pathologic images	*IDEM, I-Browse, PathFinder, PathMaster*
CTs of the head	*MIMS*
Mammographies	*APKS*
Images from biology	*BioImage, BIRN*
Dermatology	*MELDOQ, MEDS*
Breast cancer biopsies	*BASS*
Varied images	*I^2C, IRMA, KMed, COBRA, MedGIFT, ImageEngine*

Table 1: Various image types and the systems that are using these images.

2.4 The use in fields close to medicine

There is a number of fields close to the medical domain where the use of content{based access methods to visual data have been proposed as well or are already implemented. In the USA, a biomedical research network is about to be set up, and the sharing of visual data and their management include the use of similarity queries [160]. Multidimensional biological images from various devices are handled in the Bio-Image project [161].
In [162] drug tablets are retrieved by their visual similarity which is mainly for the identification of ecstasy tablets. Another pharmaceutical use is described in [163] where powders are retrieved based on visual properties.

3. Techniques used in medical image retrieval

This section describes the various techniques that are currently used or that have been proposed for the use in medical image retrieval applications.
Many of the techniques are similar to those used for general content-based retrieval but also techniques that have not yet been used in medical applications are identified. A special focus is put on the data sets that are used to evaluate the image retrieval systems and on the measurements used for evaluation. Unfortunately, the performance evaluation of systems is currently strongly neglected.

3.1 Features used

This sections describes the (visual) features that are used in the various applications. The section text is added to discuss whether this should be named content-based retrieval or rather not.

3.1.1 Query formulation

The query formulation with using exclusively visual features can be a big problem. Most systems in CBIR use the Query by Example (QBE) paradigm which needs an appropriate starting image for querying. This problem of a sometimes missing starting image is known as the page zero problems. If text is attached to the images, which is normally the case in medical applications, then the text can be used as a starting point and once visually relevant images have been found, further queries can be entirely visual [115] to find visually similar cases not able to be found by text or to sort the found cases by their visual similarity.

3.1.2 Text

Many systems propose to use text from the patient record [120] or studies [121] to search by content. Others define a context{free grammar [97], a standardized vocabulary for image description [142] or an image definition language [126] for the querying of images in image repositories. [167, 168] uses text from radiology reports to transform it into concepts in the UMLS met thesaurus to then retrieve the images. The use of text for queries is undeniable efficient but the question is whether this can really be called content{based queries as the text does not necessarily define the image content.

3.2 Comparison methods and feature space reductions

Most systems do not give many details on the distance measurements or comparison methods used which most likely implies an Euclidian vector space model using either a simple Euclidean distance (L2) or something close such as city block distance or L1. To efficiently work with these distances even in large databases, the dimensionality is often reduced.
This can be done with methods such as Principal Component Analysis (PCA) [74, 124] or Minimum Description Length (MDL) [151] that try to reduce the dimensionality while staying as discriminative as possible. In principle, redundant information is removed but this can also remove small but important changes from the feature space. Techniques such as KD{trees [145] and R{trees [173] are also used in medicine for efficient access to such a large feature spaces.

3.3 Image databases used for evaluation

The data used for demonstrating the capabilities of the visual access methods are extremely varied in size and quality. From 15 PET studies in [158] to more than 25,000 images in [92] is the spectrum of the articles analyzed for this review.
Those systems that do perform evaluation often only use screenshots of example results to queries [121,124, 145, 149, 169]. A single example result does not reveal a great deal about the real performance of the system and is not objective as the best possible query result can be chosen arbitrarily by the authors. This problematic in retrieval system evaluation is described in detail in [179]. Most other system evaluations show measures with a limited power for comparison. In [151], the precision of the four highest ranked images is used which does not reveal much about the number of actually relevant items and gives very limited information about the system. [74] Measures the number of times a differently scaled or rotated image retrieves the original which is also not very close to medical image retrieval reality.
In medical statistics commonly used measurements are sensitivity and specificity defined as follows:

1. sensitivity = (pos. items classified as pos. / all positive items)

2. specificity = (neg. items classified as neg. / all negative items)

3. accuracy = (items classified correctly / all items classified)
4. precision = (no. relevant items retrieved / no. items retrieved)
5. recall = (no. relevant items retrieved / no. relevant items)

Studies on clinical effects of image retrieval technologies might still be a distance away but there are several necessities that can be done at the moment such as the definition of standard databases that are freely available, the definition of query topics for these databases including the creation of a gold standard" or ground truth for these topics. This can, in the long run, make way for real clinical studies once the general retrieval performance is proven.

3.5 Techniques not yet used in the medical field

The preceding subsections already showed the large variability in techniques that are used for the retrieval of images. Still, several very successful techniques from the image retrieval domain have not been used for medical images as of yet. The entire discussion on relevance feedback that first improved the performance of text retrieval systems and then, 30 years later, of image retrieval systems has not at all been discussed for the medical domain. A few articles mention it but without any details on use and performance.

4. Potential clinical benefits

and future research. This section gives an overview of the potential application areas of medical image retrieval systems by the image content and the potential clinical benefits of it. Some propositions for future research are made that can influence the research outcome of content-based retrieval methods in the medical domain.

4.1 Application fields in medicine and clinical benefits

Three large domains can instantly be stated for the use of content-based access methods: Teaching, research and diagnostics. Other very important fields are the automatic annotation/codification of images and the classification of medical images. First to benefit will most likely be the domain of teaching. Here, lecturers can use large image repositories to search for interesting cases to present to the students. These cases can be chosen not only based on diagnosis or anatomical region but also visually similar cases with different diagnoses can be presented which can augment the educational quality. Indeed, in multiplying the routes to access the right data, cross-correlation approaches between media and various data can be eased. On the other hand, anonym zed image archives can be made available for medical students for educational purposes. Content-based techniques allow browsing databases and then comparisons of diagnoses of visually similar cases. Especially for Internet-based teaching, this can offer new possibilities. As most of the systems are based on Internet technologies this does not cause any implementation problems.

4.2 Future research

When thinking about future research directions it becomes apparent that the goal needs to be a real clinical integration of the systems. This implies a number of changes in the ways that research is done at the moment. It will become more important to design applications in a way that they can be integrated easier into existing systems through open communication interfaces, for example based on XML (extensible Markup Language) as a description language of the data or HTTP (Hyper-Text Transport Protocol) as a transport protocol for the data [184]. Such a use of standard Internet technologies can help for the integration of retrieval methods into other applications. Such access methods are necessary to make the systems accessible to a larger group of people and applications and to gain experience that goes far beyond a validation of retrieval results.

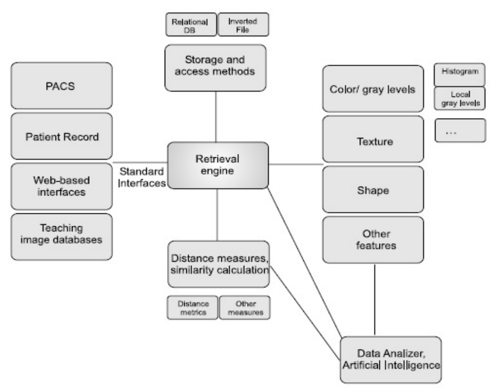

Figure 4: A modular schema for retrieval system development.

This can not only be seen as engineering but as research as the practical use of the integrated methods needs to be researched. Although first applications will most likely be on large image archives for teaching and research, a specialization of the retrieval systems for promising domains such as dermatology or pathology will be necessary to include as much domain knowledge as possible into the retrieval. This will be necessary for decision-support systems such as systems for case-based reasoning. Such a specialization can be done in the easiest way with a modular retrieval system based on components where feature sets can be exchanged easily and modules for new retrieval techniques or efficient storage methods can be integrated easily. Figure 4 shows such a component-based architecture where system parts can be changed and optimized easily. Easy plug-in mechanisms for the different components need to be defined.

5. Conclusion

The large number of research publications in the field of content{based medical image retrieval especially in recent years shows that it is very active and that it is starting to get more attention. This will hopefully advance the field as new tools and technologies will be developed and performance will increase. Content-based visual information retrieval definitely has a large potential in the medical domain. The amount of visual data produced in medical departments shows the importance of developing new and alternative access methods to complement text. Content-based methods can be used on a large variety of images and in a wide area of applications. Still, much work needs to be done to produce running applications and not only research prototypes. When looking at most current systems, it becomes clear that few to none of them are actually in routine use.

An important factor is to build prototypes that are integrated with a hospital-wide communication structure and that use open standards, so data can be exchanged with other applications. It needs to become easy to integrate these new functionalities into other existing applications such as HIS (Hospital Information System)/RIS (Radiology Information System)/PACS or other medical image management or viewing software. In this way, it will become much easier to have prototypes running for a sample of users and to get feedback on the clinical use of systems. To get acceptance, it is important to be integrated into the current applications and with interfaces that the users are familiar with. To win acceptance from the users it is also important to show the performance of the systems and to optimize the performance of systems for certain specialized tasks or people. The development of open toolboxes is another important factor for successful applications. Not only do interfaces for the communication with other applications need to be developed, also within the application it is important to stay modular, so parts and pieces can be exchanged easily. This will help to reduce the number of applications developed and will make it possible to spend more time on the important tasks of integration and development of new methods and system optimizations.

It is clear that new tools and methods are needed to manage the increasing amount of visual information that is produced in medical institutions. Content-based access methods have an enormous potential when used in the correct way. It is now the time to create medical applications and use this potential for clinical decision-making, research and teaching.

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