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A Study of Gaps in CBMIR using Different Methods and Prospective

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***Abstract*—**In recent years, rapid advances in software and hardware in the field of information technology along with a digital imaging revolution in the medical domain facilitate the generation and storage of large collections of images by hospitals and clinics. To search these large image collections effectively and efficiently poses significant technical challenges, and it raises the necessity of constructing intelligent retrieval systems. Content-based Image Retrieval (CBIR) consists of retrieving the most visually similar images to a given query image from a database of images[5]. Medical CBIR (content-based image retrieval) applications pose unique challenges but at the same time offer many new opportunities. On one hand, while one can easily understand news or sports videos, a medical image is often completely incomprehensible to untrained eyes.

***Keywords*—**Classification, clustering, content-based image retrieval (CBIR), relevance feedback (RF), statistical similarity matching, support vector machine (SVM).

I. Introduction

CONTENT-Based Medical Image Retrieval (CBMIR) is the application of CBIR technology in medical field[6-7]. When CBMIR technology describes the image's content, it is always extract image's characteristics such as color, texture, shape and spatial relation [1-3] to form image's low-level feature vector as the basis of making index and matching. Since there are certain gaps between the description of these low-level features to medical image and the description of doctor's, it is always cannot get satisfied results directly use these low-level features as retrieval basis. Therefore, it is necessary to find some kind of mapping relation between image's low-level features and high-level semantic information are called Semantic gaps.

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II. Challenges

Although the semantic gap [4] & another gap is the sensory gap [8] that describes the loss between the actual structure and the representation in a (digital) image; might seem more tangible to bridge in the medical domain, there are many other gaps to fill and limitations to overcome:

A. Color Gaps

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.

B. Texture Gaps

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 and Gabor filters where the Gabor filters [9-10] do seem to perform better and correspond well to the properties of the human visual cortex for edge detection.

C. Local and Global Features Gaps

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 for local feature extraction [11].

D. Segmentation and Shape Features Gaps

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. 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.

III. Bridging the Gap

The difficulty faced by CBIR methods in making inroads into medical applications can be attributed to a combination of several factors. Some of the leading causes can be categorized according to the "gaps" model presented above.

A. The Content Gap

It is important to consider image content in light of the context of the medical application for which a CBIR system has been optimized. Too often, we find a generic image retrieval model where the goal is to find medical images that are similar in overall appearance. The critical factor in medical images, however, is the pathology – the primary reason for which the image was taken. This pathology may be expressed in details within the image (e.g., shape of a vertebra or texture and color of a lesion) rather than the entire image (e.g. spine x-ray or cervicographic image) [12].

B. The Feature Gap

Extracted features are used to define the image content. As such, decisions on the types of features, scale(s) at which the features are extracted, and their use individually or in combination determines the extent to which the system "knows" the image and, to a large extent the system capability. It is necessary for the system to support as many types of features as possible and also capture them at several scales.

C. The Performance Gap

Benefits of medical imaging to science and healthcare have led to an explosive growth in the volume (and rate) of acquired medical images [13]. Additionally, clinical protocols determine the acquisition of these images. There is a need for the system response to be meaningful, timely and sensitive to the image acquisition process. These requirements make linear searches of image feature data, very often presented in the literature, impractical and a significant hurdle in the inclusion of CBIR into medical applications.

D. The Usability Gap

This gap is rarely addressed during the design and development of CBIR systems [14]. However, it is the one of most concern to the end user of the system and therefore has the greatest potential for affecting the acceptance of a new technology. An idealized system can be designed to overcome all the above gaps, but still fall short of being accepted into the medical community for lack of (i) useful and clear querying capability; (ii) meaningful and easily understandable responses; and (iii) provision to adapt to user feedback.

IV. Gaps which are not Addressed while CBMIR Retrieval

A. The Interdisciplinary Gap

While one can easily understand a photo and news or sports videos, a medical image is often completely incomprehensible to untrained eyes. Unfortunately, the "CB" part of the "CBIR" is conducted and provided by medical image analysis computer scientists, while the "IR" part is performed by the medical professionals. Albeit critical, it is often a challenge for the computer scientists to understand the medical domain and its semantics. On the other hand, it is certainly helpful, but also a challenge, for the medical professionals to know the ins and outs of the "CB" parts, i.e., its potentials and limitations [16].

B. The Regulatory Gap

The clinical world is unique in yet another aspect that it is heavily guarded by government regulations. This is more true in some countries such as the United States than others. Regulatory wise, a CBIR system may deserve less scrutiny than an end to end computer aided diagnosis system [5]. But as it gets more semantic, the line may be blurred.

C. The Vertical Information Gap

Doctors always use all available data about the patient to make informed decisions. The CBIR system needs to incorporate the same information in order to support the doctors' decisions at the semantic level. However, this is not a trivial task because not all data are in electronic form; and even with future prevalence of EMR/EHR (Electronic Medical/Health Record), some data may not be in structured forms for machine consumption; and finally, emerging data sources, such as genomic or proteomic data, pose new challenges in terms of sheer data volume and ambiguity or uncertainty in relevance.

D. The Data Gap

Due to security, privacy, and legal considerations surrounding the health data in general, medical images and associated data cannot be obtained easily without careful anonymization and in many cases, prior consent of the patient [17]. This is one of the main reasons, in addition to the limited quantity in the first place, that medical images seem to be always in short supply. Furthermore, one cannot assume data uniformity or completeness in general, especially not across institutions. Missing data or variabilities (e.g., due to differences in, or evolution of, imaging equipments) is common in medical imaging.

V. Problems not Addressed so far in Medical based CBMIR

- Most of the general articles such as [26] state that the medical domain is very specialized so that general systems cannot be used. This is true but it is the case for all specialized domains such as trademark retrieval or face recognition, and specialized solutions need to be found. The more specialized the features of a system are the smaller the range of application and compromises for each specific application area needs to be found.
- Implementations of image retrieval systems are a step-by-step process and first systems will definitely not meet all the high requirements that are asked for. Image retrieval based on visual features is often proposed but unfortunately nothing is said about the visual features used or the performance obtained [19].
- For medical image retrieval systems, the evaluation issue is almost non-existent in most of the papers

[1,4,7,11,16,22,24,26,27] Still, there are several articles on the evaluation of imaging systems in medicine or on general evaluation of clinical systems and the problems with it.
- Another rarely mentioned evaluation parameter is the speed of the system which is very important for an interactive system.
- Measurement parameters need to show the usefulness of an application and the possible impact that an application of the method can have.
- Finally, it will be interesting to evaluate the clinical impact of the application when it is used in real clinical practice.

VI. Prospective of CBIR

When thinking about future research directions it becomes apparent that the goal needs to be a real clinical integration of the systems[20]. 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 extensible markup language (XML) as a description language of the data or Hyper-Text Transport Protocol (HTTP) as a transport protocol for the data [31]. 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 [23]. This can not only be seen as engineering but as research as the practical use of the integrated methods needs to be researched. The integration into PACS is an essential step for the clinical use of retrieval systems [24]. PACS solutions currently allow search by patient and study characteristics and are mainly a storage place for images. A project to allow further search methods in medical image databases based on a standard communication interface is the Medical Image Resource Center (MIRC). Here, search by several characteristics, including free-text, is allowed based on a standard platform. The future of PACS or medical image storage systems might be in a separate architecture with a storage component just as PACS systems currently are and an automatic indexing system where important characteristics from the images and the linked case information are stored to allow for retrieval methods based on structured information, free text and the visual image content[25]. Of course, evaluation of the retrieval quality is an extremely important topic as well. Research will need to focus on the development of open test databases and query topics plus defined gold standards for the images to be retrieved. Retrieval systems need to be compared to identify good techniques. This can advance the field much more than any single technique developed so far. But evaluation also needs to go one step further and prepare field studies on the use and the influence of retrieval techniques on the diagnostic process. So far, only one study on the impact of image retrieval system on the diagnostics of HRCT images of the lung has been published and shows a significant improvement in diagnostic quality even for senior radiologists [26]. Practitioners need to give their opinion on the usability and applicability of the technologies and acceptance needs to be gained before they can be used in daily practice. Such communication with the system users can also improve the interface and retrieval quality significantly when good feedback is delivered. User interaction and relevance feedback are two other techniques that need to be integrated more into retrieval systems as this can help to lead to much better results. Image retrieval needs to be interactive and all the interaction needs to be exploited for delivering the best possible results [27]. Multimedia data mining [28] will also be made possible once features of good quality are available to describe the images. This will help to find new relationships among images and certain diseases or it will simply improve the retrieval quality of medical image search engines. 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 [29]. 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. Following diagram 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.

VII. Conclusion

Our goal is to bring disparate data sources, such as images, the output of image analysis algorithms, general patient information and clinical data, and external ontologies, into one global, unified picture. The usage of descriptive information, i.e. metadata, is the first step toward an adaptable and flexible search system [30]. The metadata establishes the required abstraction for integrating the disparate sources into a coherent picture, ensuring consistency across modalities and compatibility across patients. The second step is the integration of ontologies, linking semantic knowledge to metadata. More precisely, the specification of semantics is achieved by linking at least one concept originating from an external ontology to each metadata object. Feature extraction will be done by using following concept Feature selection then Feature weighing and after that Parameter-zing the function [31]. When a query image is inputted, its low-level visual features are extracted. Then, all images in the database are sorted based on a similarity metric, e.g., Euclidean distance. If the user is satisfied with the result, the retrieval process is ended. If, however, the user is not satisfied, expert physicians can label some top query relevant images as positive feedbacks and/or some query irrelevant images as negative feedbacks [32]. Using these feedbacks, the system is trained based on a learning machine (an embedded RF algorithm). Then, all the images are re-sorted based on the new similarity metric. If the user is still not content with the result, expert physicians repeat the process. Specially, we explore the latest techniques like SVM, RF given in [24,25] and categorization methods and prefiltering of images to reduce the search space. Consequently, new concepts are gaining popularity to narrow down the semantic gap and improve image understanding and retrieval based on the degree of user involvement in the retrieval process [33, 34].

Recently, SVM has been widely applied in RF, which plays an essential role in improving the performance of CBIR [35]. The main advantage of SVM is that it can generalize better than many other classifiers. To improve the conventional SVM based RF and designing an image retrieval system using the perceptual categories of the domain experts. But, such a system is more likely to be accepted by the end users. A physician is more likely to identify with and accept a system such as the one described here because the decision processes involved bear some resemblance to those of the physician. If an expert physician disagreed with the disease labels assigned by our system to a new image, the physician could question the system about the perceptual categories detected in the image and ascertain the appropriateness of those categories. In that sense, the system described here possesses superior explanatory powers for a richer interaction with the physician.

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