Bridging the Gap: Enabling CBIR in Medical Applications

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Abstract

Content-based Image Retrieval (CBIR) for medical images has received a significant research interest over the past decade as a promising approach to address the data management challenges posed by the rapidly increasing volume of medical image data in use. Articles published in the literature detail the benefits and present impressive results to substantiate potential impact of the technology. However, the benefits have yet to make it to mainstream clinical, biomedical research, or educational use. No major commercial software tools are available for use in medical imaging products, although several are available for commercial stock photo collections. CBIR has had some success in isolated instances in applications on limited data sets addressing specialized medical problems and at biomedical research laboratories and hospitals that are tightly coupled with software developers. This article explores some possible causes of this "gap" in the lack of translation of research into widespread biomedical use and provides some directions to alleviate the problem.

1. Introduction

Content-Based Image Retrieval (CBIR) technology has seen proposed to benefit not only the management of increasingly large image collections, but also to aid clinical medicine, research, and education relying on visual content in the data [1]. CBIR can be briefly defined as a set of methods that attempts to index an image based on the characteristics of its visual content, and to retrieve the images by similarity to queries that express some combination of these characteristics. These characteristics may include intensity, color, texture, shape, size, or location, or their combination. Sketching a cartoon, selecting an example image, or some combination of these methods is typically used to form the query. The retrieved results are typically ordered by some criteria; however, other methods have been employed such as clustering of similar images.

Practical application of CBIR depends on many different techniques applied at several stages in the indexing and retrieval workflow. These techniques include image segmentation and feature extraction; feature indexing and database methods; image similarity computation methods; pattern recognition and machine learning methods; image compression and networking for image storage and transmission; Internet technologies such as Javascript, PHP, AJAX, Applet/Servlet; and human factors and usability. More recently, natural language processing has also been included into this list, in light of the possibility for exploiting text descriptions of image content and the availability of standardized vocabularies [2]. It is through careful selection of appropriate methods from these fields that a successful CBIR application can be developed.

CBIR has been a research area for nearly two decades, but its focus on biomedical images has been relatively recent, and within the past decade [1]. With an increasing use of imaging techniques in biomedicine, the potential benefit of CBIR as an image management tool and its additional value in research and education has appealed to many. In spite of this interest and promised benefits, the technology is yet to be adopted into widespread use, either commercially or within research and education institutions. This is in contrast to the quality of results presented in the literature, availability of commercial products, and, even some services for non-medical use. It is also noteworthy that a survey of search results on the term "CBIR" on Google Scholar (http://scholar.google.com) reveals, for example, a steep increase in the number of articles discussing CBIR systems or components in leading journals and conference publications over the last eight years. However, there are fewer articles discussing advances in feature indexing, machine learning, relevance feedback, transmission, networking, database development, and usability issues: topics that are important to mainstream implementation of this technology. In contrast, there is a much higher number of articles on statistical similarity methods and reports of evaluations on relatively small image collections that test a very specific range of queries.

This article explores some of the shortcomings that may have adversely affected the acceptance of the technology into mainstream clinical use, biomedical research, or education. Some ideas presented here were introduced at a technical workshop organized by the authors and conducted during the 2008 SPIE Medical Imaging conference held in San Diego, California.

2. Gaps in CBIR

One approach to making a fair assessment of the state of the field is by comparing CBIR applications presented in the literature. However, given the large number of research domains that are included in this technology and its sensitivity to the nature and content of the data, it is necessary to develop comparison methods that analyze more than the selection of particular techniques and the experimental results presented in the literature. Rather, it may be better to formally describe an idealized CBIR system and identify the shortcomings in the candidate system. These shortcomings have been labeled as "gaps" and extensively discussed in [3]. The concept of the gap is a generalization of the well-known "semantic gap" that refers to the difficulty of capturing high-level imaged content semantics from extracted low-level image features. These gaps have been broadly categorized into four types and defined below:

1. **The Content Gap** addresses a system's ability to foster human understanding of concepts from extracted features. In medical applications, it also refers to the extent to which the system adapts to varying modalities, context, and diagnostic protocols.

2. **The Feature Gap** addresses the extent to which the image features are extracted. This is measured along several dimensions: degree of automation, degree of detail captured along the content axis (object structure), use of multi-scalar techniques, the use of space and (if available) time dimension in image data, and use of all channels on each dimension.

3. **The Performance Gap** addresses practicalities of system implementation and acceptance. It evaluates system availability, extent of integration into the medical infrastructure, use of feature indexing techniques, and the extent to which the system was evaluated.

4. **The Usability Gap** measures the richness of available query features and the extent to which they can be combined, available support for comprehending the results returned by the system, and available support for query refinement.

Addressing these aspects makes a CBIR system more usable, and may increase its acceptance into the medical (clinical, research, or education) workflow.

3. Bridging the Divide

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.

1. **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). In addition, there may be multiple image modalities that provide the critical information, e.g., histology slides, photographs, etc. In addition to expanding the scope of the CBIR system it is important to also consider analyzing patient histories or physician's notes for valuable information.

2. **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 determine 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. Medical CBIR applications are very sensitive to medical image content. So, developing toolboxes to permit user selection of features may also be very helpful in generalizing the applications and improving acceptance.

3. **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. 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.

4. **The Usability Gap:** This gap is rarely addressed during the design and development of CBIR systems. 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. The opposite is also true to some extent. A technically mediocre, but promising, system may obtain valuable end user feedback, and by technical improvement may increase user acceptance with the application of usability design principles. Other than item (iii), which still needs significant research effort, the usability gap can only be bridged by keeping the end user in mind from early system development, as well as by conducting well-designed usability studies with targeted users. In general, a high involvement of the user community in system design and development can significantly improve adoption and acceptance.

4. Conclusions

Success of a technology is often due to the confluence of available technology at the time of critical need. Content-Based Image Retrieval of medical images has achieved a degree of maturity at a research level at a time of significant need. However, the field has yet to make noticeable inroads into mainstream clinical, medical research, or training. In this article we have tried to explore the field through the concept of gaps or shortcomings in comparison with an idealized system. In addressing or minimizing these gaps, a system may be better positioned for use in medical settings described above. To make CBIR systems more compatible with the requirements of mainstream medical applications, developers should consider: the use of large reference (or gold-standard) data sets and development of reusable code libraries, toolkits or toolboxes; incorporating a large feature set and indexed (rapid) feature retrieval; early adoption of system usability features; and, above all greater collaboration with the medical community.

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