Augmented Medical Image Management for Integrated Healthcare Solutions

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***Abstract*— In today's medicine, several diagnostic tasks are particularly difficult and are plagued by high inter- and intra-observer variability. For instance, reading mammographs in modern Western medicine or tongue images (photographs or videos of the stuck-out tongue) in traditional Chinese medicine require particular skills and long experience. For these tasks, image-based access to an archive with cases of known pathology would be a beneficial aid for both diagnosis and medical education. Thus, retrieving information stored in electronic healthcare records (EHR) based also on image patterns rather than only on alphanumerical indexing is required. Even modern EHR archives do not yet offer such augmented functionality.**

In this paper, we present a novel concept for an augmented medical information management (AMIM). Key functionalities of the concept are content-based medical image retrieval based on similarity of both the global image and local regions, capturing human expert knowledge with visual similarity metrics, retrieval from EHR archives and the Internet based on both visual and textual patterns, and a cheap and effective paradigm for home-based telemedicine. The latter functionality is based on a smart self-calibrating hand-held imaging device for standardized self-acquisition of tongue images. This idea is directly extendable to other diagnosis scenarios for wide-spread diseases, for example, screening for skin tumors. It will help significantly reduce the costs of healthcare systems and in particular improve the quality of life of (senior) citizens.

***Index Terms*—Information System, Information Retrieval, Image Processing, Image Retrieval, Telemedicine, Electronic Healthcare Record**

I. Introduction

Medical imaging plays vital roles for many health-related applications such as medical diagnostics, drug evaluation, medical research, training and teaching. Due to the rapid progress in the technologies for obtaining and storing digital images for diagnostic purposes in medicine (from photography over digital radiography to functional MRI and PET) and the rapid expansion of computer networks and the Internet, medical image databases for training and supporting diagnostics have become technologically feasible. However, the rapid expansion in these technologies has not been accompanied yet by a similar development in the technologies for image management. If the Digital Imaging and Communication in Medicine (DICOM) protocol is used, any retrieval is based solely on textual information hosted in the (sometimes erroneous [1]) DICOM-headers. Thus, the information that is contained in such databases remains unexploited to a large extent [2].

Content-based image retrieval (CBIR) by itself has been one on the most active research areas in the field of computer vision, image processing and data mining over the last 10 years [2,3]. Many algorithms, architectures and systems have been studied and developed to help search and browse through large multimedia databases based on content. Because of the importance of medical imaging, recently there is increasing interest by informatics researchers and physicians to develop CBIR algorithms, as well as architectures for medical image applications. In addition to efficient and convenient repositories of medical images, these CBIR systems can be also used as aids for medical diagnostics and training of physicians [3,4,5].

However, there are scientific and technological shortcomings of existing approaches that have to be resolved before a CBIR methodology can be implemented successfully into medical applications. In particular:

- A general framework for CBIR is required which can also support retrieval based on similarity of local features. This is a novel functionality because the CBIR systems to date use only global features. Thus, they cannot support the retrieval of similar images based on, for example, a specific organ or an anatomical detail which is contained in a segment of an image.
- Similarity measures between images are required that capture the subjective perception of a trained specialist. This will close the so called semantic gap [2,3] between the meaning of medical images and their computational representation based on pixels. Until now, similarity in

CBIR systems is based on objective distance metrics between basic numerical features of the images.

- Tools for mining medical information from the image archive as well as the Internet are required that combine both textual and visual features. This is also a technologically novel idea since at the present time most information mining tools use only textual information.

In this paper, we propose a solution to the abovementioned problems and show how these methods can be combined to a prototype for an efficient homecare telemedicine-based system.

II. Methods

A. Local Features

One of the most difficult problems in content-based image retrieval (CBIR) for medical applications and in general is to find relevant images based on the objects contained in an image. In other words, instead of finding images that are globally similar one wants to find images that contain similar segments. The difficulty of this task stems from the fact that segmenting an image in regions that have some physical meaning is one of the most difficult problems in image processing since it contains a strong element of subjectivity. Indeed to this date, most medical CBIR systems are based only on global features or fixed portioning of the image into regions [3,6].

Nevertheless, the ability to retrieve based on objects contained in an image is a very important and extremely useful capability for medical CBIR systems [7,8]. In almost all cases, diagnostics is based on local regions of the image, and the physicians are particularly interested in certain conditions of the body part such as an abnormal size or texture. For this purpose, we have developed a new flexible hierarchical image representation that is based on a multi-scale image segmentation algorithm [9]. This segmentation approach provides a hierarchical data structure in which differently sized segments of the image containing different parts of the human anatomy can be found at different scales (Fig. 1). Searching this data structure using appropriate distance metrics [10] provides the capability to find images that contain similar parts of the human anatomy. Thus, it solves in an elegant and reliable manner the very important problem for medical CBIR of retrieving images that are not only globally similar but also contain similar regions.

B. A Similarity Metric Capturing Human Perception

There are diagnostic tasks using medical images such as mammography in modern western medicine (MWM) and diagnosis from tongue images (Fig. 2) in traditional Chinese medicine (TCM) that require great expertise and skill [11,12,13,14]. For such tasks, the availability of a database with already diagnosed cases along with a retrieval system that captures the perception of a human expert would be enormously beneficial as an aid both for diagnostics and training. One could retrieve "similar" cases and thus gain

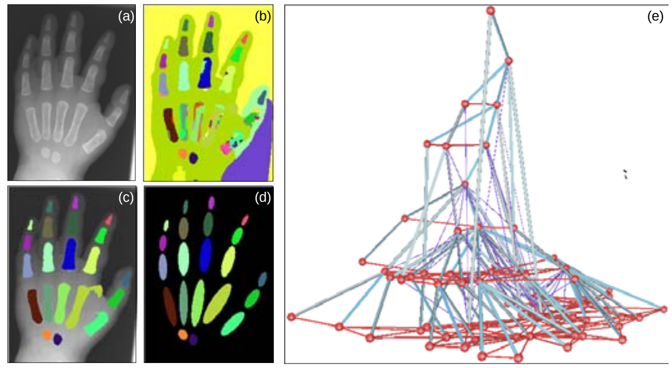

Fig. 1. Hierarchical image analysis of a hand-wrist radiograph: (a) hand radiograph; (b) regions from various layers of the representation are color-coded separately (and may overlap); (c) for each bone (localized region), an optimal representation is determined; (d) corresponding blob representation; and (e) hierarchical tree structure for the various layers of representation.

valuable insight and experience about the pathology of the unknown case at hand [15] or the outcome of treatment.

Machine learning methods are used to capture the notion of similarity as perceived by experts. For this purpose, regression algorithms are developed that will learn by presenting examples for the similarity between pairs of images as perceived by specialists. Fig. 3 depicts the architecture of such a retrieval system. The similarity distance is represented as f(**u**,**v**), where **u** and **v** denote the features of the query and the database image, respectively. Regression methodologies based on (i) neural networks, (ii) relevance vector machines, and (iii) support vector machines can be used to determine f(.,.) that best captures the experts perception.

Relevance feedback is a post-query process to refine the search by using positive and/or negative indications from the user learning the relevance of retrieved images. For medical applications, two approaches for relevance feedback must be considered. In the first approach, the impact of the feedback image in the similarity between the query image and a database entry is explicitly weighted. An alternative method is based on incremental learning strategies in order to adjust the learning machine using the feedback information.

C. Web Mining for Medical Information

In addition to the image repository of a hospital or clinic, the World Wide Web contains a wealth of information that can be valuable to many medical applications in diagnostics, research, and education. However, currently all indexing and searching of web resources are solely based on the textual data that is often available with images. With respect to medical images, only a small fraction of the databases is available and directly searchable via browser-based interfaces. For example, Google delivers only 130 image results for the term "lung CT" whereas collections such as CasImage (http://www.casimage.com/) and the Health Education Assets Library (HEAL, http://www.healcentral.org/) already contain at least 1,000 lung CTs. No retrieval based on visual features is currently possible and so the wealth of medical image information so far is inaccessible for medical practitioners or limited to one or two databases that can be searched by hand

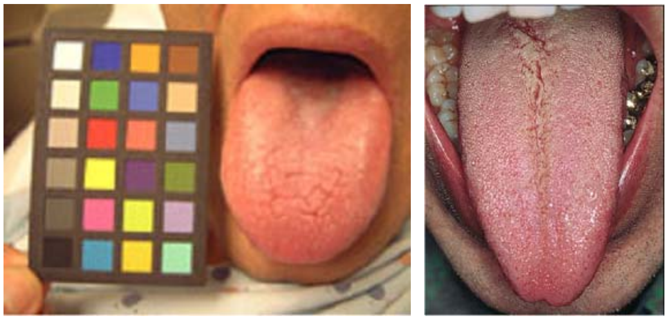

Fig. 2. Tongue images acquired with color plate for calibration (left [17]) and without (right [14]).

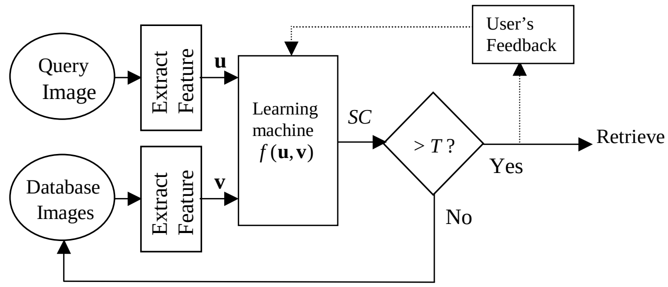

Fig. 3. AMIM image retrieval framework with relevance feedback. The similarity metric captures the perception of a human expert.

and with key words. The Health On the Net Foundation (HON, http://www.hon.ch/) tries to create a reliable source for medical information search on the web but the multimedia repository contains currently only 6,800 documents that can be searched only by text. The Radiological Society of North America (RSNA) created the MIRC standard (Medical Imaging Resource Center, http://mirc.rsna.org) to unify the interfaces to medical radiological teaching sources on the Internet. Still, no visual search is possible in this standard.

According to our approach for augmented medical image management (AMIM), available medical web sources for images are indexed in textual and visual form in collaboration with HON, to make the wealth of knowledge available to practitioners for teaching, research and also diagnostic aid. Analyzing visual and textual features will allow us to mine the large amount of information accessible to find co-occurrences of visual features and textual keywords. This can be used for semi-automatic or even automatic annotation of non-annotated images. We think that many semantic connections will be found and new ways of browsing will be established through the exploitations of visual features for retrieval. For teaching purposes, even images with a different diagnosis but similar visual appearance are of great importance.

For the combined retrieval methodology, visual features that are similar in spirit to those used in text retrieval (frequency-based feature weights, inverted files) are examined. A suitable visual feature space is created for this, relying on global but also local features. Taking into account the way people interact with the system through user log files allows to optimize performance and discover the user's information needs in terms of the combinations of the various groups of features [16].

D. An Efficient Home-based Telemedicine Paradigm

Integrating the three AMIM components for content-based access methods to medical image archives will improve health care and medicine. Further improvement is expected, if the image acquisition is performed by the patient at home (Fig. 4). While home-based mammography will not be available in near future, the technology already exists to develop home-based photography and video imaging. By means of a smart self-calibrating hand-held imaging device for standardized self-acquisition of tongue images, one tongue image per day or week can be captured manually and transferred automatically to the TCM center, where it is analyzed and used to remind the patient for possible check-up. This idea is directly extendable to other diagnostic scenarios for widespread diseases, for example, risk patients for skin tumors.

Accordingly, the objective is to develop a new generic, integrated, modular and hierarchical vision system that can be configured for executing high performance image and video acquisition tasks. Inspection stripe units, made of illumination laser, camera, and pre-processing elements can be composed for parallel operation, offering great flexibility by means of a rapid application development tool. Such heterogeneous components, that traditionally require time-consuming calibration and adaptation tasks, are integrated into a unified system and software environment. The offered quality control capability will enhance the handling of defects and the associated operations.

However, it is still a technical challenge to design an innovative high-resolution image processing system achieving the quality standards required for such applications. This objective requires innovations, advances and breakthroughs to the state of the art in this field. Nevertheless, in near future such devices might easily be integrated in small cell phones.

III. Discussion

Our concept of augmented medical image management will have a high impact in a number of healthcare-related areas such as diagnostics, teaching, research, and remote healthcare provision.

A. Diagnostics

Firstly and most importantly, the diagnostic ability of physicians that will have access to the proposed system stands to improve. In the domain of evidence-based medicine, case-based reasoning, and computer-aided diagnosis it is essential for a system to supply relevant/similar cases for comparison. In such a constellation, the AMIM system would play the role of a second opinion. It can accommodate this task in a number of scenarios. In one of them, a physician could use a textual search on the annotated images in order to retrieve images with the same diagnosis gaining experience on the visual appearance of specific diseases with different imaging modalities. In another scenario, for the special case of mammography (MWM) and diagnosis based on tongue images (TCM), one could use the image under observation as a query and retrieve “similar” looking (according to a specialist’s opinion) annotated images and thus use the available system as “a second opinion” for the specific case. In yet another scenario, the physician could define regions of the image which in his opinion contain the visual features that best capture the suspected pathology and find annotated images that contain similarly looking regions.

However, another idea is the comparison of the distance of a new case with the existing cases. In such a case, the dissimilarity as opposed to the similarity of an image with known cases can be used to gain knowledge. This is more natural compared to the normal workflow in medicine where the first requirement is to find out whether the case is pathologic or not. Dissimilarity could be used by highlighting regions in the image with the strongest dissimilarity. Such a technique can help to find abnormal regions that might otherwise be missed. A combination of the two approaches is also possible where the first request is whether the image contains abnormalities. If it does, a second query to find similar cases is performed on another image database containing the pathologic cases. This directly supports computer-aided diagnoses, e.g. for tumor stating.

B. Research

Furthermore, research will essentially benefit from the proposed system. AMIM technology will provide researchers with more options for the choice of cases to include into research and studies. More specifically, it will allow researchers

- to find relevant images based on both local and global visual features,
- to use both text-based and visual features, and
- to include similar images based on the perception of trained experts that are not physically present.

While the latter item has been demonstrated for the special cases of mammography and tongue images, we conjecture that by including visual features directly into medical studies, new correlations between the visual appearance of a case and its diagnosis or textual description will be found. Visual data can also be mined to find changes or interesting patterns which can lead to the discovery of new knowledge by combining the various knowledge sources.

C. Teaching

The field of medical teaching will also benefit a lot from our AMIM approach. Here, instructors can use medical image repositories to search for interesting cases to present to their students. These cases can be chosen not only based on diagnosis or anatomical region but also on visual similarity. Cases with different diagnoses can also be presented to augment the educational experience of the students. Indeed, AMIM increases the routes to accessing the “right data” and thus facilitate students retrieving the relevant cases. The field of Internet-based teaching stands to also benefit remarkably since most of the technologies can be integrated in self-guided eLearning tasks that can be used without a teacher.

D. Remote Healthcare

In remote healthcare we envision that by the year 2015 broadband Internet connection has become a norm for most families around the world. Mrs. Jane, a 70 year old lady, is staying alone at home being constantly connected with her children a few hundred miles away. She is also regularly monitored by remote doctors on her tongue images captured weekly in a small device located in her bed-room or even a hand-phone. The tongue images are sent to remote medical centers, automatically pre-checked by computers if everything looks fine, and manually monitored by physicians in any case of suspicion. If required, Mrs. Jane will be advised to go to the closest clinic for further check-up.

With the new wireless transmission technologies the need and the market for high-resolution portable imaging systems is steadily increasing. Although very high-resolution linear CCD cameras exist on the market, the very large bandwidth required between camera and processing memory and the amount of pixels generated put high constraints on the communication bandwidth, on the frame memory hardware and of the processing power required to analyze the received images. A classical state of the art approach results in a very costly and bulky system, probably composed of several units in parallel to achieve the required data bandwidth and processing speed. Such systems would easily result complex and costly to be attractive for the customers. A different approach needs to be envisaged. The AMIM system, which is based on CMOS random access imaging, is a step in the direction of improving portable imaging systems in the context of a healthcare application.

We envision that in the near future this type of non-traditional medical imaging can play a significant role in regularly monitoring the health status of patients by computers. Furthermore, home-based healthcare solutions will be integrated for specific applications such as skin tumors and many more.

E. Non-Medical Applications

During the last few years there has been a tremendous progress in technologies of medical imaging. New imaging modalities have been developed and new techniques for storing and transmitting images. However, the progress in technologies for managing this information especially based on content has not been as rapid. As a result, the wealth of information that is contained in image repositories is not completely exploited. Thus, the problem of retrieval based on content is considered as the “holy grail” for researchers in this area. This problem is not specific to medical images only. In the area of CBIR in general this is a well-known problem. Most CBIR systems today are based on low-level features, while the desire is to retrieve images based more on “semantics”. Our work addresses exactly this problem with an application in medical imaging. The methodologies we propose allow for better utilization and access of the stored

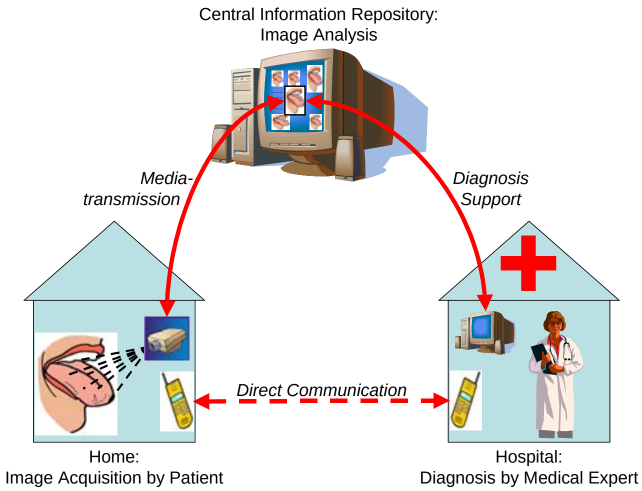

Fig. 4. A new paradigm for efficient and cheap home-based telemedicine applied to tongue image diagnosis. Combining content-based access methods to medical image archives with a self-calibrating hand-held imaging device, medical image acquisition is performed at home. This will reduce costs of the healthcare system and increase the quality of life, in particular for elderly citizens and in remote areas.

information in repositories of images (medical) and in this context contribute to close the "semantic gap".

IV. Conclusion

In conclusion, a medical image database system was proposed in which advanced features are integrated such as: semantics from visual similarity based on experts' opinions, textual and visual retrieval, and on harvesting relevant information from the web. Based on these methodologies, a low cost, pervasive image-based diagnosis systems can be developed for senior citizens in home care.

More specifically, AMIM stands to benefit socially and economically both poor and less developed but also rich and well-developed societies. Socially, the field of medicine and healthcare provision benefits mostly. Capturing similarity as perceived by a medical specialist is the "holy grail" of the field of artificial intelligence as applied to medicine since it endows a machine with the specialist's knowledge. Thus, it both greatly increases the availability and simultaneously reduces the cost of the services that are provided by the specialist. Information that is inherently stored in medical images and the attached metadata is extracted and made available integrating it into the routine of radiologists.

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