IDEA GROUP PUBLISHING
701 E. Chocolate Avenue, Suite 200, Hershey PA 17033-1240, USA
Tel: 717/533-8845; Fax 717/533-8661; URL-http://www.idea-group.com
ITB12776

This paper appears in the book, *Emerging Trends and Challenges in Information Technology Management, Volume 1 and Volume 2* edited by Mehdi Khosrow-Pour © 2006, Idea Group Inc.

A Content-Based Approach to Image Retrieval in Medical Applications

Thomas Lehmann, Thomas Deselaers, Henning Schubert, Mark Oliver Güld, Christian Thies, Benedikt Fischer, & Klaus Spitzer
Aachen University of Technology

INTRODUCTION

Digital imaging has become the most prominent modality in medicine. Beside computed tomography (CT) or nuclear medicine, which have been always digital, plain radiography, endoscopy, and microscopy are nowadays captured directly digital, too. Picture archiving and communication systems (PACS) have been established in the hospitals all over the world to manage these information resources. PACS are used to store and handle the images, which are transferred based on the digital imaging and communications in medicine (DICOM) protocol. DICOM supports interconnections of PACS modules from different vendors, e.g. for post-processing of the images and their annotation with alphanumerical attributes such as patient and study information, image descriptions, and diagnostic reports. This textual information, which is stored within the DICOM header, is currently the only means to access and retrieve medical images from the PACS archive. Since an image tells more than a thousand words, recall and precision of this type of medical image information retrieval is limited in general [1,2].

This paper presents intermediate results of the IRMA project (http://irma-project.org) for content-based image retrieval in medical applications. The IRMA project aims at describing medical images by means of their visual properties in an adaptive multi-resolution approach [3].

METHODS

In a first step of processing, the images are categorized according to a terminology consisting of four orthogonal axis covering the anatomy (A) and bio-system (B) shown in the image as well as the creation (C) and direction (D) of imaging [4]. This is done based on global image features, i.e. a feature vector is assigned to the entire image. For each category, a global prototype is defined and used for both geometry and contrast registration of the images. Relying on a reference database of more than 15,000 radiographs that have been ABCD-classified by trained radiologists, an unseen image is categorized automatically. Currently, this categorization can be performed with an error rate of about 15%, 9%, or less than 5%, if the best match or a set of the five or ten best matches is considered, respectively [5].

The next part in the chain of processing extracts local image features. In contrast to the previous stage, a feature vector is now assigned to every pixel within an image. Based on an initial watershed segmentation, a region merging scheme is applied until the entire image is represented by a single region [6]. This final stage is considered as the root node of a hierarchical attributed region adjacency graph (HARAG), which is obtained directly from logging the merging steps. Node attributes such as size, position, shape, or texture are used to describe the regions, which represent single objects [7]. From the automatically computed regions, objects are extracted by classification of the attribute vectors [7,8]. By separating these two steps, the user's knowledge of the image content becomes a classifier. On a low-level, manually generated interval queries can be performed. On a high level, supervised learning by the support vector machine, the nearest neighbor, and the Bayes classifier are available. Edge attributes such as the normalized distance, the angle between two regions' main axis, or the relative gray scale are used to represent spatial and/or temporal relations between individual objects (scene description [9]).

In order to incorporate medical a-priori knowledge on a higher level of semantics, structural prototypes are trained from manual reference segmentations in each of the categories. As a result, a pruned HARAG is obtained where node and edge attributes are represented by Gaussian mixture models (GMM). Accordingly, image similarity is expressed by means of graph to sub-graph matching techniques. In particular, a neural network based on the approach of Schädler and Wysotzki [10] is used to efficiently compute the graph-based image similarity [9].

RESULTS

Content-based image retrieval in medical applications that is based on global similarity has been established successfully and is available as online demonstration at http://irma-project.org/onlinedemos_en.php. Query images can be selected from the local hard disc and transferred into the system (Fig. 1a). The query response is calculated immediately within only a few seconds (Fig. 1b). All user interaction is protocolled to allow to step back to any past state of the system, as well as boolean combinations of those (Fig. 1c). This principle is called extended query refinement [11].

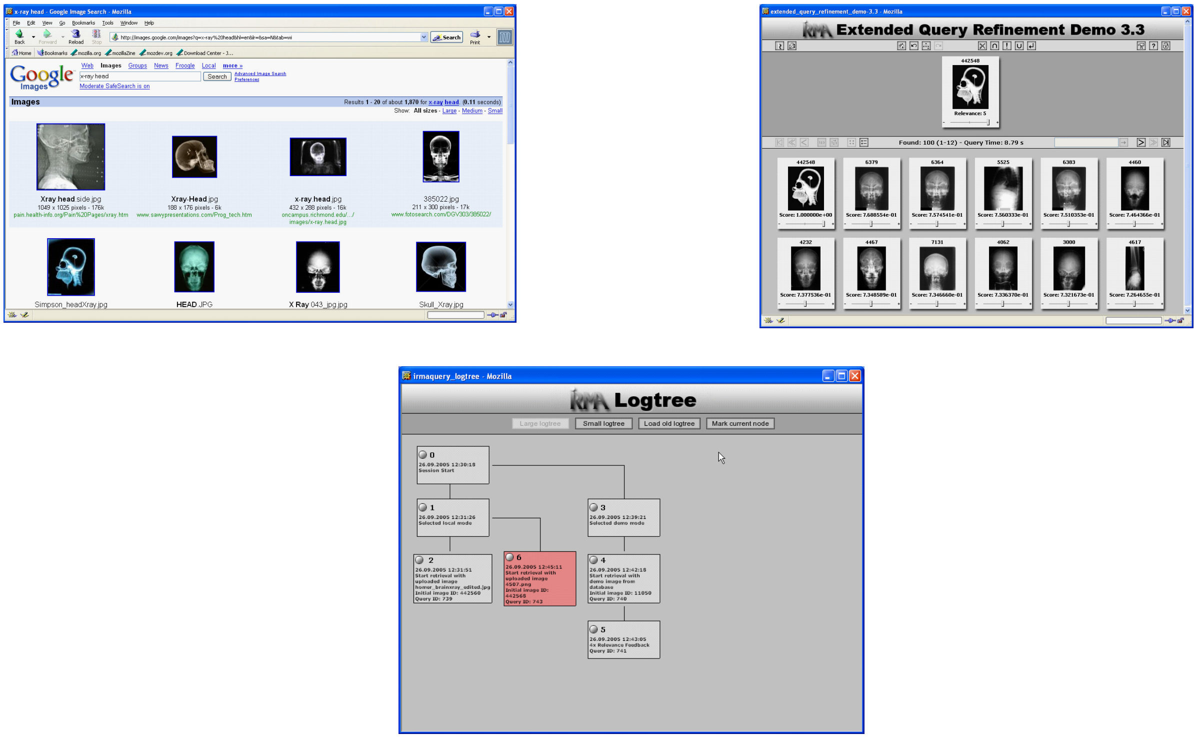
Content-based image retrieval based on local features is used for quantitative and qualitative analysis of contained objects. On a set of 105 radiographs of human hands, which were extracted arbitrarily from the categorized IRMA database, a manually generated query for the metacarpal bones, based on 25 sample regions, results in a recall of 0.6 and a precision 0.53 [7]. The best result for automated training was obtained by the support vector machine with a recall of 0.58 and a precision of 0.67 based on 50 training regions [8]. By separating image partitioning and classification the training of the classifiers is focused on the attribute vectors and no low-level knowledge on image processing is required. Moreover supervised training is efficiently performed by point & click training of sample regions.

Content-based image retrieval based on structural information is still in development. First results are obtained from standardized plain radiographs of human left hands, which are acquired routinely to determine the bone maturity of infants. Based on manual reference segmentations of 96 hand radiographs, in total 1,289 individual bones have been identified and labeled. The structural category prototype is computed and used to extract relevant regions from HARAGs of unseen query by example (QBE) images. It is shown that this kind of scene analysis on a high level of semantics outperforms content-based image retrieval (CBIR) that is only based on descriptions of relevant objects. Also, it can be adopted to any local pattern that may be of interest in the QBE image.

CONCLUSIONS

In conclusion, a novel concept of automatic image content modeling is proposed. A reliable proof-of-concept is given for bone maturity assessment and comprehensively evaluated using on a large set of ground truth radiographs. However, the IRMA concept of attributed graph-based modeling of image content is rather general. For instance, it can be used directly to empower physicians for interactively marking a region of interest (ROI) within the QBE image to be diagnosed, and

Figure 1. An x-ray image of the skull is searched via Google (a), transferred to the IRMA content-based image retrieval system, and similar images are retrieved from the system (b). The sliders below each responded image allow for interactive query refinement. All interaction is protocolled and allows to restore any system stage of the session (c).



retrieving images from the PACS archive containing similar local patterns. Allowing access to the corresponding medical records, this will impact diagnostics, research, and medical education. Furthermore, the management of multimedia information resources is augmented.

ACKNOWLEDGEMENTS

Since 2001, the IRMA project has been funded by the German Research Foundation (DFG) under grant number Le 1108/4.

REFERENCES

1. Tagare HD, Jaffe CC, Duncan J: Medical image databases – A content-based retrieval approach. Journal of the American Medical Informatics Association. - JAMIA 1997; 4(3): 184-98
2. Müller H, Michoux N, Bandon D, Geissbuhler A: A review of content-based image retrieval systems in medical applications – Clinical benefits and future directions. International Journal of Medical Informatics 2004; 73(1): 1-23
3. Lehmann TM, Güld MO, Thies C, Fischer B, Spitzer K, Keysers D, Ney H, Kohnen M, Schubert H, Wein BB: Content-based image retrieval in medical applications. Methods of Information in Medicine 2004; 43(4): 354-361
4. Lehmann TM, Schubert H, Keysers D, Kohnen M, Wein BB: The IRMA code for unique classification of medical images. Proceedings SPIE 2003; 5033: 109-117
5. Lehmann TM, Güld MO, Deselaers T, Keysers D, Schubert H, Spitzer K, Ney H, Wein BB: Automatic categorization of medical images for content-based retrieval and data mining. Computerized Medical Imaging and Graphics 2005; 29(2): 143-155
6. Lehmann TM, Beier D, Thies C, Seidl T: Segmentation of medical images combining local, regional, global, and hierarchical distances into a bottom-up region merging scheme. Proceedings SPIE 2005; 5747:546-555
7. Thies C, Ostwald T, Fischer B, Lehmann TM: Object-based modeling, identification and labeling of medical images for content-based retrieval by querying on intervals of attribute values. Proceedings SPIE 2005; 5748:382-391
8. Thies C, Schmidt-Borreda M, Lehmann TM, Seidl T: A classification framework for content-based extraction of biomedical objects from hierarchically decomposed images. Proceedings SPIE 2006; 6144: in press
9. Fischer B, Winkler B, Thies C, Güld MO, Lehmann TM: Strukturprototypen zur Modellierung medizinischer Bildinhalte. Proceedings BVM 2006; in press [German Language]
10. Schädler K, Wysotzki F: Comparing structures using hopfield style neural network. Applied Intelligence 1999; 11(1): 15-30
11. Lehmann TM, Plodowski B, Spitzer K, Wein BB, Ney H, Seidl T: Extended query refinement for content-based access to large medical image databases. Proceedings SPIE 2004; 5371: 90-98

Related Content