Intelligent Medical Image Search

Intelligente Bildsuche in der Medizin

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Summary Due to vast progress of medical image devices, clinicians today rely deeply on images for screening, diagnosis, treatment planning and follow up. However, these medical images are still indexed by keywords and can not be searched and retrieved for their content. In this article we present the project MEDICO that strives to implement intelligent medical image search by means of machine learning algorithms and semantic technologies. ►►► **Zusammenfassung** Mit dem technologischen Forschritt in der medizinischen Bildgebung gewinnen medizinische Bilder in der Früherkennung, Diagnose, Behandlungsplanung und bei Nachfolgeuntersuchungen zunehmend an Bedeutung. Demgegenüber werden medizinische Bilder derzeit nur mit einfachen Stichwörtern indiziert und eine inhaltsbasierte Suche ist nicht möglich. Im Fokus dieses Artikels steht das Projekt MEDICO, das die Realisierung einer intelligenten Suchmaschine für medizinische Bilder auf Basis von maschinellen Lernalgorithmen und semantischen Technologien anstrebt.

Keywords J.3 [Computer Applications: Life and Medical Sciences] Medical information systems; H.3.3 [Information Systems: Information Storage and Retrieval: Information Search and Retrieval] ►►► **Schlagwörter** Semantische Technologien, medizinische Ontologien, medizinische Bildgebung, maschinelles Lernen

1 Introduction

Today, medical images from various modalities such as computed tomography, magnetic resonance imaging or ultrasonography provide information about morphology, function and metabolism of the human body and have become indispensable for detecting and differentiating pathologies, planning interventions and monitoring treatments. At the same time, medical image modalities have matured both with regards to image quality and ease of use, and various new post processing applications became available. For instance, computer aided detection tools are used in oncology to support radiologists as second reader in finding and evaluating breast lesions, lung nodules or colon polyps [1; 4; 8; 18]. As a result the number of image studies is growing rapidly and even small to medium sized hospitals produce and store millions of medical images every year resulting in storage needs beyond 1 TB [14].

While medical images provide a wealth of information to clinicians, current medical image databases, called PACS (Picture Archiving and Communications System), as well as associated Radiology Information Systems (RIS) are still indexed by keywords assigned by humans or meta data originating from the image acquisition and not by the image contents. This limitation is severely hampering clinical workflows. In order to retrieve a certain image, displaying, e. g., large multifocal spleen lesions, a clinician typically successively has to

- query the system for the patient name,
- use demographic information like age and gender to resolve homonymies,
- select an imaging study based on the acquisition date or imaging modality,
- select the most likely series[1],
- (possibly transfer and) load the series into some 2D/3D viewer,

[1] In DICOM (Digital Imaging and Communications in Medicine) the leading standard for medical images, a set of related images is called a (DICOM) series. For instance, a series would encompass the individual 2D images ("slices") acquired with Computed Tomography that together form a 3D volume of some body region. Typically one imaging examination, referred to as study in DICOM, consists of multiple series that are acquired using different machine settings, before or after administration of some contrast media, or that result from a variety of post-processing options (e. g., to enhance soft tissue contrast).

- locate the spleen by browsing the images contained in the series, and
- validate that he indeed found the case with the large multifocal lesions he had in mind.

The most common reason for retrieving archived images in clinical routine is in order to compare a patient's current study with a previous one to evaluate the progression of disease and treatment. To ease the pain for the clinicians at least in this common scenario, modern systems often offer support by automatically prefetching old studies of current patients from the archive and by allowing side-by-side viewing, in some cases supported by automated alignment of the two imaging series. In other scenarios many radiologists tend to avoid this search process altogether. For instance, they may simply keep interesting teaching or research cases on their local work station. Or, instead of searching for and comparing the original images they restrict themselves to search and retrieve corresponding radiology reports.

The limitations of such indirect text-based image retrieval motivated the development of Content-Based Image Retrieval (CBIR) systems, where image retrieval typically is based on low-level features such as color, shape and texture that are automatically extracted from the images themselves. Usually, CBIR systems are queried by example images and classifiers such as nearest neighbor are used to compare the feature vector of the query image with those stored in the database. However, such CBIR systems face the semantic gap, defined in [17] as "the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation". Various attempts to improve the performance of CBIR systems and bridge the semantic gap have been suggested, such as image segmentation into blobs or the use of relevance feedback [7; 17]. Nonetheless it is commonly agreed that CBIR systems are most successful if applied to specific constrained domains such as pathological images, head MRIs, lung CTs, or mammographies. A comprehensive review of applications of CBIR in the medical domain can be found in [12].

While not abandoning the strengths of classical CBIR based on comparing low level features for retrieval of, e. g., similar liver lesions, the primary goal of the MEDICO[2] project is retrieval based on *semantic image annotations*.

In Sect. 2, we describe the MEDICO project – a scenario for future medical image search – by detailing the clinical as well as the technical perspective, its requirements and the role of semantics. Section 3 presents the technological ingredients of a semantic image search infrastructure such as query pattern, ontologies, image annotation, and semantic reasoning and retrieval. Section 4 concludes with an outlook on future activities.

2 Future Medical Image Search

2.1 A Future Scenario: MEDICO

The vision of MEDICO is to automatically extract the meaning from the medical images and to seamlessly integrate the extracted knowledge into medical processes, such as clinical decision making. In other words, the computer shall learn to interpret images, to catalogue them, shall find them in databases and detect similarities.

Clinician's Perspective

For highlighting the practical impact of such a system, let us face a patient who is suffering from night sweats and exhaustion. Moreover, the lymph nodes in the neck area of the patient have enlarged over an extended period of time. Based on computer tomography images, the responsible radiologist creates a first report of the findings.

In a subsequent step, the MEDICO system will perform a semantic image analysis that integrates all results and findings, i. e., the automatically identified anatomical and pathological structures, the manual descriptions by the radiologist, and the information from any previous findings are placed into a common context. This becomes technically possible by storing all semantic descriptions in a database and by efficiently linking them to

- previous examinations of the same patient,
- patient records with similar diagnosis or treatments, and
- external knowledge resources, such as publications that are relevant in the context of the particular symptoms of the first diagnosis.

By analyzing the images from previous examinations of the patient, the radiologist can observe whether the MRI scans from three months earlier also have shown enlarged lymph nodes. By investigating similar cases, he can learn about the disease progress and effectiveness of treatments, and by studying relevant literature, he can review statistical reports and recommended treatments.

Based on the comprehensive information about the patient history, about selected similar cases, and the state-of-art in medicine, the radiologist arrives at a diagnosis of Hodgkin's lymphoma.

By linking medical knowledge with new image processing methods, knowledge-based data processing, and machine learning, MEDICO envisions to improve the quality and efficiency of medical care.

Technical Perspective

To implement such a scenario, low level features, segmentations and quantitative measurements derived from image processing are associated with concepts from medical ontologies. For instance, an automatic detector of the spleen will associate a 3D mesh with the anatomical con-

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cept "spleen" with Id 7196 in the Foundational Model of Anatomy ontology (FMA), and – if enlarged – in addition with code R16.1 ("splenomegaly, not elsewhere classified") of the International Statistical Classification of Diseases and Related Health Problems (ICD 10). A second CAD application specialized on detecting lesions in solid organs could further analyze the detected volume and label found spleen lesions as "hypodense" and "multifocal", two imaging observation characteristics defined in RadLex, the Lexicon for Uniform Indexing and Retrieval of Radiology Information Resources.

Given the sheer number of anatomical structures and their pathological changes, MEDICO won't be able to fully capture the often very subtle content of arbitrary medical images. Instead it strives to provide a platform with

- basic tools to a) manually annotate images with formal concepts and b) formulate mixed queries based on DICOM metadata, semantic annotations and example images,
- interfaces to allow a) automated image processing tools to store semantic annotations and b) more advanced applications for both point-of-care and translational research (e. g., clinical decision support, clinical trials, patient recruiting, epidemiological studies) to query for them.

At the same time the project will build both image parsing tools and exemplary concrete applications in the context of selected disease domains.

2.2 Semantic Requirements

For connecting and linking all the different knowledge resources, a common understanding is required. That is, clear definitions of the medical technical terms are necessary as well as handling ambiguities and capturing relationships between the different medical terms. This common understanding of a domain or application – the semantics of the objects and relationships in the world of interest – is formally, and thus machine-processable, captured by *ontologies*. An ontology is a formal representation of a set of concepts within a domain and the relationships between those concepts. It can be used for defining a domain formally and for reasoning about the properties of that domain.

For overcoming the limitation of conventional medical image retrieval systems and for enabling intelligent image search, we identified the following four semantic requirements.

Cross-Modal Data Integration

Clinical care and research deal with large volumes of complex information that originates from different sources, with different structure and different semantics. There exist a wide range of different imaging technologies and modalities as well as advanced techniques for analyzing imaging data generating additional quantitative parameters. But currently, large amounts of heterogeneous image data are stored in distributed and autonomous image databases being indexed by keywords without capturing any semantics. The well-founded formulation of diagnosis requires the combination, comparison and interrelation of findings of different modalities, e. g., to precisely diagnose cardiac diseases, a clinician may need to consider morphological findings from CT, functional findings from MR and echocardiography, and metabolic findings from SPECT (Single Photon Emission Computed Tomography). The missing link here is a flexible and generic image understanding.

Seamless Integration of External Knowledge Resources

In the process of diagnosis, clinicians often consult external knowledge resources, such as medical literature, expert publications, background information, coding systems, details to clinical trials, etc. For accessing those resources, clinicians need to switch between applications sometimes even workstations. In order not to interrupt the workflow in the research and diagnosis process clinicians require a seamless access to external relevant knowledge resources. Reflecting the clinician's last accomplished steps, as well as the medical context of the patient and diagnose progress, ad hoc access to recommendations of external, context-relevant knowledge resources within one system allow the clinician to arrive more efficiently at a diagnosis.

Discovering Hidden and Implicit Knowledge on the Basis of Inference

In the medical domain, detailed knowledge about the relationship between entities, such as the spatial or part-of relationships, provides the clinicians important details within the diagnosis progress. Clinicians, for instance, document spatial information, such as "on the left" or "near by" very precisely, as this information is required for locating identified abnormalities, such as lesions. By combining the knowledge documented within patient reports with external domain ontologies, additional valuable knowledge can be derived. The anatomy ontology (FMA), for instance, captures more detailed spatial information that can be made explicit by inference and, thus, be used for specifying search requests as well as for enhancing search results. By mapping keywords from text-based queries to semantic concepts of the underlying ontology, it is possible to infer implicit and hidden results.

Improved Quality and Relevance of Search Results

Conventional medical image retrieval systems inquire documents by processing the structural information of the query expression relying on a fixed data structure of the – usually only one – underlying knowledge base. Current search engines integrating multiple and distributed knowledge bases, such as the internet or intranet applications, process arbitrary keywords as queries and return lists of relevant documents in a ranked and prioritized

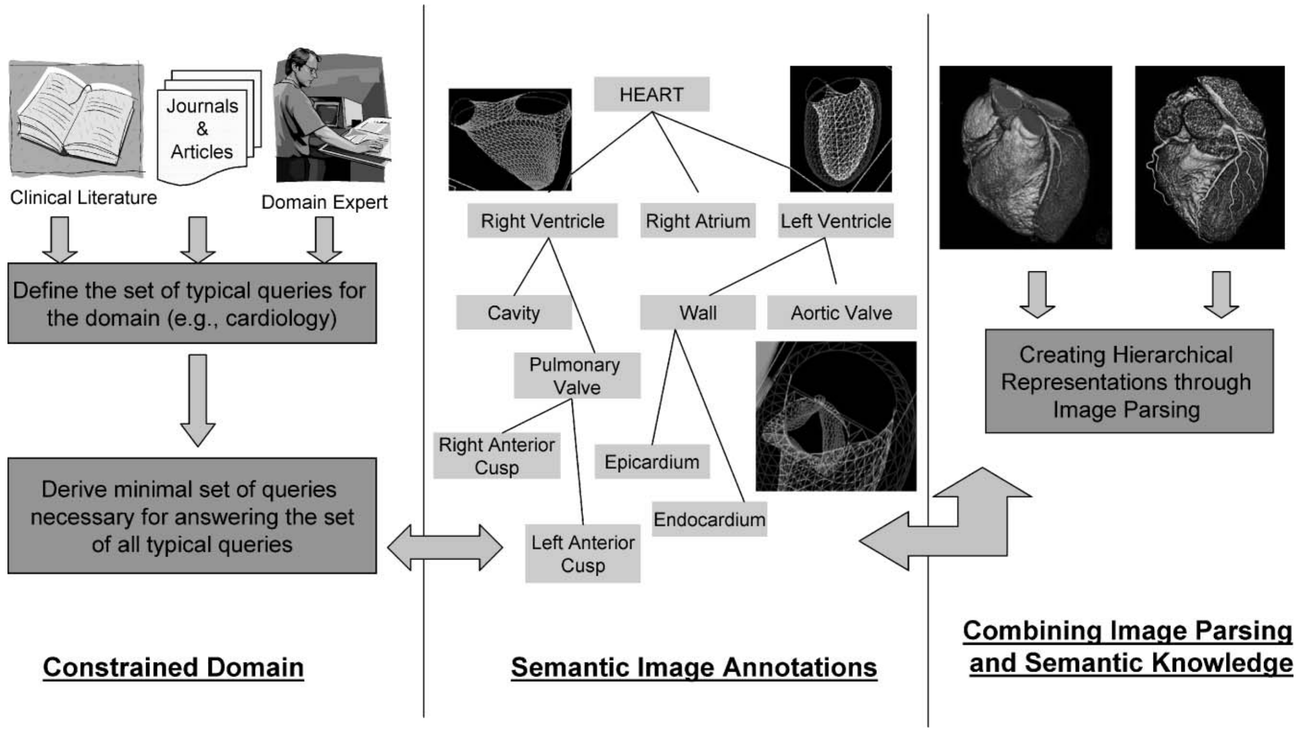

Figure 1 The combination and integration of multiple semantics pave the way for Intelligent Medical Image Search.

manner. The ranking is based on various methods and algorithms using statistical methods and reflecting the interconnectivity of documents.

The medical domain is dealing with huge and complex datasets within a constrained domain for which the ranking algorithms of current search approaches is not appropriate: The result list becomes too large and ranking by relevance is due to the precise meaning of the medical terms difficult to realize. But by providing the user semantic representation that even reflects the context and expertise of the user, far more precise queries can be provided. Using semantics allows replacing the simple keyword-based retrieval by context-sensitive matching mechanism reflecting the comprehensive, collective knowledge base, i. e., the patient history, the experience of similar patient cases, and external expertise know-how.

2.3 Integration of Semantics

Generic image understanding is still a long-term agenda due to the high-complexity of the problem. However, the *medical domain is constrained* and hence it is possible to define an almost complete set of queries for capturing its semantics. Thus, the scope and level of detail of the semantics of the domain, i. e., the relevant metadata for annotating medical images, can be determined by the set of derived query patterns. Moreover, the derived query patterns guide us in identifying the relevant (fragments of) ontologies.

Semantic image annotation can be realized by different approaches, for instance by automated image annotation, by (multi-modal) manual annotation of images, by automatic extraction from DICOM headers, DICOM structured reports, as well as by automatic extraction from radiology reports. Based on the comprehensive representation of the domain knowledge, hidden and implicit knowledge can be derived and enhance medical image search. But this requires the *combination* and integration of *image parsing knowledge with semantic knowledge* captured by external medical knowledge resources. By enriching the hierarchical knowledge representation with imaging attributes, establishing alignments between the multiple knowledge resources and by specifying semantic reasoning and retrieval services, intelligent medical image search services can be provided.

3 Technological Ingredients

3.1 Constrained Domain

For improved semantic medical applications, we need to identify the right scope and the level of granularity of information the clinicians are looking for. In other words, for incorporating the external medical knowledge in the ontologies and hence to semantically enhance clinical data, one has to *identify the query strategies* that the clinicians are interested in. As medical context is sensitive as it concerns the human health, *reusing* standardized thus reliable medical *ontologies* instead of developing them from scratch is an important requirement. Consequently, it becomes necessary to decide for the appropriate, application related *ontologies* and their fragments (or *modules*).

To address the particular requirement of the constrained domain in MEDICO, we identified the following steps as relevant.

Query Pattern Derivation
The goal is to predict meta-information relevant for annotating medical data. This type of information is typically summarized by the queries the clinicians send to a clinical search engine. Clinical literature, journals and articles, patient records, and interviews with clinical experts are important input for deriving context specific query patterns capturing the particularities of the domain. The query pattern derivation approach is based on a combination of various techniques from natural language processing and text mining as described in detail in [2; 19; 20]. Using domain corpora, e. g., a corpus on lymphomas, statistically most relevant ontology concepts and relations (i. e., query patterns) are identified. Query patterns are used for semantically annotating medical images and clinical data, as well as for identifying the parts of ontologies that are most relevant for the application scenario.

Ontology Selection
As human health is a sensitive matter, the quality and the quantity of the medical knowledge to be used in the target application have to be ensured. This implies reusing the work of acknowledged authors and standardization committees when choosing medical ontologies. Typically these ontologies are very comprehensive and cross-linked, so that they cannot be easily read, navigated or understood. Therefore, we require some automatic support for identifying the appropriate (fragments of) ontologies that fulfill the requirements of the application scenario.

Within the MEDICO context, the interviews with the clinicians and radiologists showed that medical imaging and patient data need to be considered along three different perspectives;

- the anatomical spatial perspective that addresses body parts and their locations,
- the radiology-specific perspective, which describes the relationships between various image modalities and anatomical regions as shown on medical images, and finally
- the disease perspective that concerns the distinction between the normal and the abnormal imaging features.

Ontology Modularization
For an effective reuse of the large medical ontologies we require (modular) ontology subsets that can be easily navigated by humans and reasoned by machines. Ontology modularization can be addressed automatically or user-driven, but in both cases the segmentation of the ontology is a difficult task. The question of how to establish an ontology fragment of the right size, covering the required concepts with limited amount of, human and computational, resources is addressed by several modularization approaches [5; 6; 23].

As the ontologies modules need to cover all concepts and relationships for describing the particular scenario, ontology modularization can be realized based on the query patterns, as these patterns reflect the user relevant level of detail and coverage that the ontology is expected to contain [21].

3.2 Semantic Image Annotation

As mentioned before, there are multiple ways of generating semantic image annotations.

Automated Image Parsing
In [15] our method is presented to hierarchically parse whole body CT images and efficiently segment multiple organs taking contextual information into account. The framework currently segments six organs and detects 19 body landmarks very fast and robust in about 20 seconds. The landmarks form an anatomical network that restricts the search space for the organ detection. New anatomy can be easily incorporated since the framework can be trained and handles the segmentation of organs and the detection of landmarks in a unified way. The detected landmarks and segmented organs facilitate the semantic navigation inside the body (see Fig. 3) and generate semantic annotations such as “spleen” or “splenomegaly”. The underlying machine learning techniques are presented in [22].

Manual Image Annotation
While automated image parsing remains incomplete, manual image annotation remains an important complement. Indeed, to integrate manual image annotation in the reporting workflow of radiologists is one of the objectives of the Annotation and Image Markup Project (AIM, [3; 13]) that is closely related to MEDICO in aiming at developing an ontology for medical image annotations. Currently, users of the MEDICO system can manually add semantic image annotations by selecting or defining anatomical landmarks or arbitrary regions / volumes of interest. Further research is directed towards dialogue based semantic image annotation, retrieval and navigation [16].

Extraction of Information from DICOM Headers and DICOM Structured Reports
Today basically all medical images are stored in a specific standardized format called DICOM (Digital Imaging and Communications in Medicine, see http://medical.nema.org/). Metadata such as patient demographics and acquisition parameters are stored in DICOM headers. This metadata is extracted and converted into a DICOM ontology based on OWL that is aligned with our medical image annotation ontology (see [10] for details). With further acceptance of DICOM structured reports, an additional source of semantic image annotations will become available. As described in part 16 of the DICOM standard, DICOM structured reports already are based on formal clinical healthcare terminology like, e. g., concepts from SNOMED®.

Automated Extraction from Radiology Reports

The goal is to semi-automatically identify terms and relations in radiology reports that are generated by clinicians in the process of analyzing the patient's disease pattern by investigating medical imaging data. Although radiology reports are stored as written documents, they do not follow the general way of grammar. For instance, the sentences lack verbs and punctuations, abbreviations are very common and temporal and spatial information for describing image content are used extensively. Thus, means for automatic extraction of knowledge from radiology reports have to address those textual particularities.

3.3 Combining Image Parsing and Semantic Knowledge

The overall MEDICO ontology hierarchy [11] details the relationship between thesauri and ontologies relevant or the MEDICO context. It encompasses different types of ontologies.

On the top of the hierarchy, upper ontologies describe the very abstract and general concepts that can be shared across many applications but being relevant for this context as well. Phenomena, such as time, space, processes, etc. are usually well thought out, extensively axiomatised, and less likely to be changed. The further one comes to the bottom of the hierarchy, the more domain specific the ontologies become. From the left to the right, the different aspects of the conceptualization of the medical domain are specialized. The *Information Element Ontologies* contains the information elements, such as images or text documents that will be annotated. The *Clinical Ontologies* capture the knowledge about the application, i. e., the knowledge required for describing the task enactment, i. e., for instance stating that the person in the role of 'Clinician' 'is responsible for' the task 'Clinical Examination'. The *Medical Ontologies* on the right side encompass the relevant domain ontologies covering the different aspects of semantic image retrieval: anatomy, disease, and visual aspects. The *Annotation Ontology* includes concepts, which are used to annotate information elements with concepts from Medical Ontologies that were detected during image parsing.

Ontology Alignment

Information integration is concerned with access to heterogeneous information sources, such as textual patient data, medical images, and relational databases. The heterogeneous information needs to be mediated in order to provide an integrated and coherent view of the data. In addition, the specific information needs of the clinicians and radiologists must be satisfied by these information sources. In medical imaging, a single ontology is not enough to support the required complementary knowledge from different perspectives, such as anatomy, radiology, or diseases. Ontology alignment is therefore an important requirement for the semantic information integration task in the MEDICO system: Each customized ontology module represents a piece of knowledge that is necessary to realize the entire application. These knowledge pieces are not arbitrary but they need to be interrelated within the context of the application. Therefore, the separate ontology modules will be integrated and aligned to deliver the whole picture.

Semantic Reasoning and Retrieval

The scenario of semantic image search is characterized by reuse and integration of distributed ontological knowledge that may introduce inconsistencies. Reasoning can be used to detect erroneous modeling and inconsistencies in an automated way and report it to the knowledge engineers.

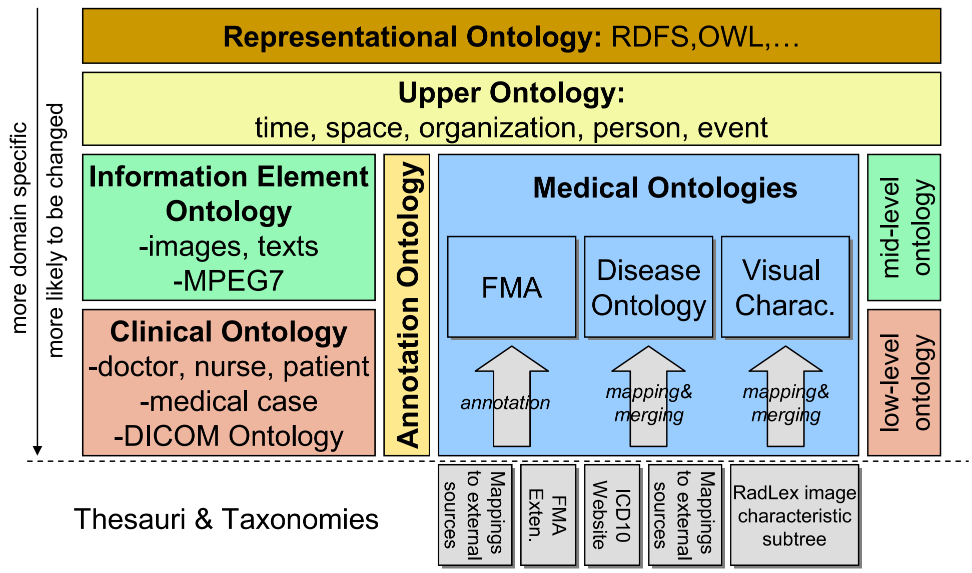

Figure 2 MEDICO Ontology Hierarchy (originally published in [11]).

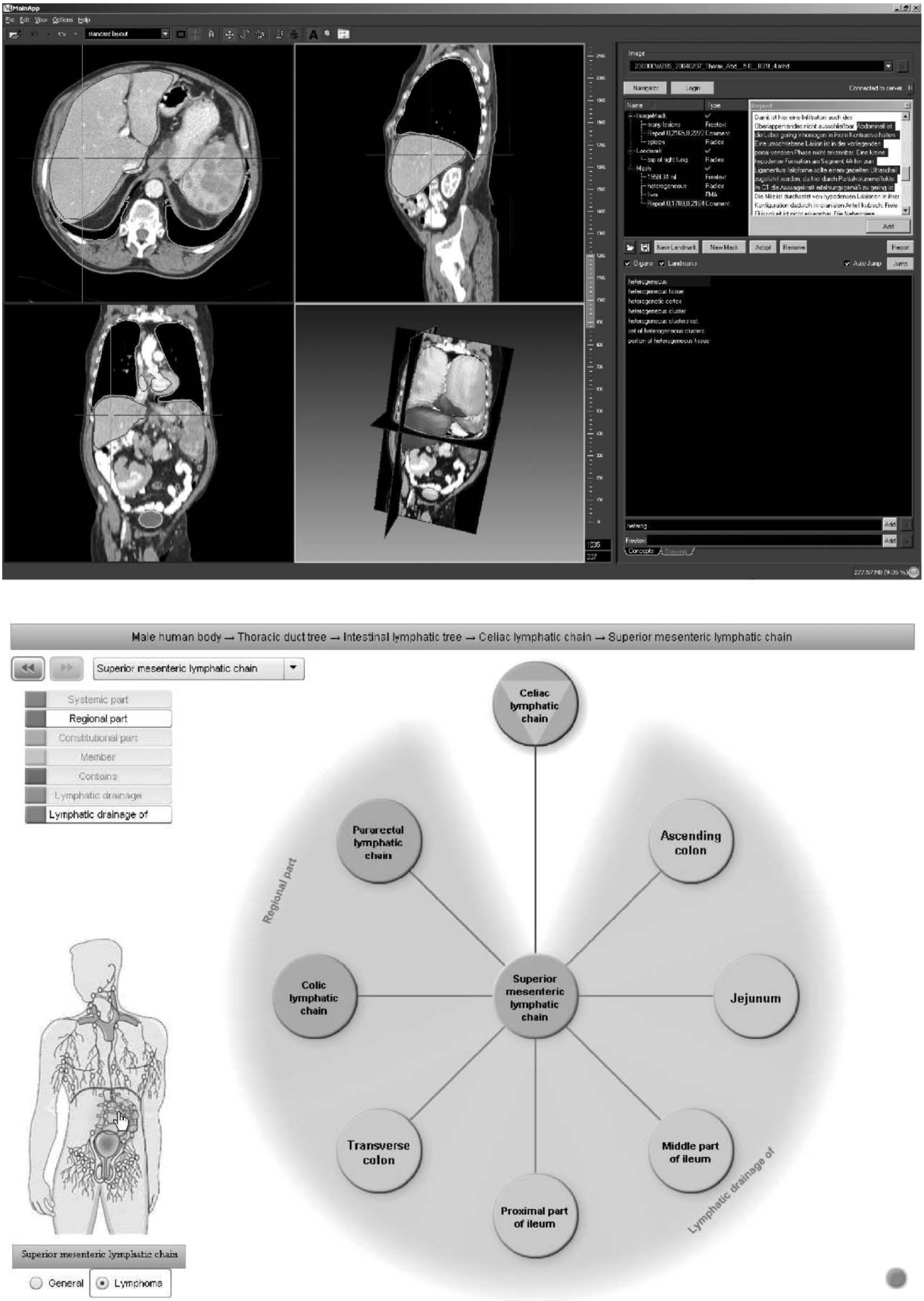

Figure 3 A MEDICO application integrating automated landmark and organ detection with manual image annotations and FMA based navigation in the image volume using the plug-in shown at the bottom.

For discovering new knowledge in form of relations and concepts, several specific reasoning services will need to be incorporated. Hidden and new knowledge can be inferred by integrating multiple information and knowledge sources. For example, in the lymphoma use case, we want to be able to infer the relevant image modalities (MR, CT, scan, etc.) given the symptoms of head and neck. Moreover, results of image analysis algorithm can be used to enrich ontological representation, such that additional valid relationships, spatial as well as pathological and physiological, between anatomical structures. Semantic reasoning services automatically facilitate semantic query disambiguation as well as semantic query expansion and filtering.

4 Conclusion and Future Directions

Medical image data bases will continue to grow in size and relevance. The advent of initiatives like DICOM structured reporting and RadLex are manifestation of the need to more formally capture the content of radiology reports and therefore medical images. MEDICO will leverage these forthcoming standards and provide an infrastructure and exemplary applications that access medical images by their content. A first integrated prototype uses the Semantic Web standards OWL and RDF to represent both domain knowledge and image annotations in the same formalism. The basic functionality of the current prototype allows for

- manual as well as automated image annotation,
- semantic navigation of 3D volumes by linking detected or manually masked anatomical structures with the corresponding concepts in RadLex and FMA,
- multilingual search of images based on their semantic image annotations, and
- retrieval of images which are annotated with semantically similar concepts using query expansion [10].

Current work in progress includes linking image volumes with radiology reports. One click on the concept "spleen" in a graphical representation of the anatomy will be sufficient to center the 3D volume on the spleen and highlight the corresponding passages in the radiology report (see Fig. 3).

In the second half of the project, focus will shift towards knowledge based applications on top of our basic semantic image infrastructure for both point-of-care and translational research such as clinical decision support by finding similar patients or data mining to measure quality, to identify patients for clinical trials, or to support pharmaceutical or epidemiological studies.

References

[1] L. Bogoni, P. Cathier, M. Dundar, A. Jerebko, S. Lakare, J. Liang, S. Periaswamy, M. Baker, and M. Macari. Computer-aided detection (CAD) for CT colonography: a tool to address a growing need. In: Br J Radiol. 78(Spec No 1):57–62, 2005.

[2] P. Buitelaar, P. Wennerberg, and S. Zillner. Statistical Term Profiling for Query Pattern Mining. In: Proc. of ACL 2008 BioNLP Workshop (ACL'2008), Columbus, Ohio, USA, June 2008.

[3] D. Channin, P. Mongkolwat, V. Kleper, K. Sepukar, and D. Rubin. The caBIG^{TM} Annotation and Image Markup Project. In: Journal of Digital Imaging, Springer 2009.

[4] K. Doi. Computer-aided Diagnosis in Medical Imaging: Historical Review, Current Status and Future Potential. In: Comput Med Imaging Graph 31(4–5):198–211, Jun–Jul 2007.

[5] B. C. Grau, I. Horrocks, Y. Kazakov, and U. Sattler. Just The Right Amount: Extracting Modules from Ontologies. In: Proc. of the 16th Int'l Conf. on World Wide Web (WWW'07), pp. 717–726, New York, NY, USA, 2007.

[6] E. Jimenez-Ruiz, R. Berlanga, V. Nebot, and I. Sanz. Ontopath: A Language for Retrieving Ontology Fragments. In: R. Meersman and Z. Tari, editors, OTM Conferences (1), LNCS 4803, pp. 897–914, Springer, 2007.

[7] T. M. Lehmann, B. Wein, J. Dahmen, J. Bredno, F. Vogelsang, and M. Kohnen. Content-based Image Retrieval in Medical Applications: A Novel Multistep Approach. In: Proc. SPIE Vol. 3972, p. 312–320, Storage and Retrieval for Media Databases 2000.

[8] K. Marten and C. Engelke: Computer-aided Detection and Automated CT Volumetry of Pulmonary nodules. In: Eur Radiol. 17(4):888–901, Apr 2007.

[9] M. Möller and S. Mukherjee. Context-Driven Ontological Annotations in DICOM Images: Towards Semantic PACS. In: Proc. of BIOSTEC 2009.

[10] M. Möller, S. Regel, and M. Sintek. RadSem: Semantic Annotation and Retrieval for Medical Images. In: Proc. of the 6th Annual European Semantic Web Conf. (ESWC), 2009.

[11] M. Möller and M. Sintek. A Generic Framework for Semantic Medical Image Retrieval. In: Proc. of the Knowledge Acquisition from Multimedia Content (KAMC) Workshop, held at the 2nd Int'l Conf. on Semantics and Digital Media Technologies (SAMT), Nov 2007.

[12] H. Müller, N. Michoux, D. Bandon, and A. Geissbuhler. A Review of Content-based Image Retrieval Systems in Medical Applications – Clinical Benefits and Future Directions. In: Int'l J Med Inform. 73(1):1–23, Feb 2004.

[13] D. L. Rubin, P. Mongkolwat, V. Kleper, K. S. Supekar, and D. S. Channin. Medical Imaging on the Semantic Web: Annotation and Image Markup. In: AAAI Spring Symp. Series, Semantic Scientific Knowledge Integration, Stanford, 2008.

[14] E. Samei, J. Seibert, K. Andriole, A. Badano, J. Crawford, B. Reiner, M. Flynn, and P. Chang. AAPM/RSNA Tutorial on Equipment Selection: PACS Equipment Overview: General Guidelines for Purchasing and Acceptance Testing of PACS equipment. In: Radiographics 24(1):313–34, Jan–Feb 2004.

[15] S. Seifert, A. Barbu, S. Zhou, D. Liu, J. Feulner, M. Huber, M. Suehling, A. Cavallaro, and D. Comaniciu. Hierarchical Parsing and Semantic Navigation of Full Body CT Data. SPIE Medical Imaging, 2009.

[16] D. Sonntag. Towards Dialogue-Based Interactive Semantic Mediation in the Medical Domain. In: Proc. of the Third Int'l Workshop on Ontology Matching (OM-2008) collocated with the 7th Int'l Semantic Web Conf. (ISWC), 2008.

[17] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain. Content-based image retrieval at the end of the early years. In: IEEE Trans. on Pattern Analysis andMachine Intelligence 22(12):1349–1380, 2000.

[18] P. Taylor, J. Champness, R. Given-Wilson, K. Johnston, and H. Potts. Impact of Computer-aided Detection Prompts on the Sensitivity and Specificity of Screening Mammography. In: Health Technol. Assess. 9(6):iii, 1–58. Feb 2005.

[19] P. Wennerberg, P. Buitelaar, and S. Zillner. Towards a Human Anatomy Data Set for Query Pattern Mining based on Wikipedia and Domain Semantic Resources. In: Proc. of a Workshop on

Building and Evaluating Resources for Biomedical Text Mining (LREC'2008). Marrakech, Marocco, May 2008.

[20] P. Wennerberg, S. Zillner, and P. Buitelaar. Interactive Clinical Query Derivation and Evaluation. In: Proc. of the AAAI Spring Symp. on Technosocial Predicitve Analytics, Stanford, USA, Mar 2009.

[21] P. Wennerberg and S. Zillner. Towards Context Driven Modularization of Large Biomedical Ontologies. In: Proc. of the Int'l Conf. of Biomedical Ontology (ICBO2009), Buffalo, New York, July 2009.

[22] Y. Zheng, A. Barbu, B. Georgescu, M. Scheuering, and D. Comaniciu. Four-Chamber Heart Modeling and Automatic Segmentation for 3-D Cardiac CT Volumes using Marginal Space Learning and Steerable Features. In: IEEE Trans. Med Imaging 27(11):1668–81, Nov 2008.

[23] S. Zillner, T. Hauer, D. Rogulin, A. Tsymbal, M. Huber, and T. Solomonides. Semantic Visualization of Patient Information. In: Proc. of the 21th IEEE Int'l Symp. on Computer-Based Medical Systems (CBMS 2008), Jyväskylä, Finland, 2008.

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