CONTEXT-DRIVEN ONTOLOGICAL ANNOTATIONS IN DICOM IMAGES
Towards Semantic PACS

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Abstract: The enormous volume of medical images and the complexity of clinical information systems make searching for relevant images a challenging task. We describe techniques for *annotating* and *searching* medical images using ontological semantic concepts. In contrast to extant multimedia semantic annotation work, our technique uses the *context* from mappings between multiple ontologies to constrain the semantic space and quickly identify relevant concepts. We have implemented a system using the FMA and RadLex anatomical ontologies, the ICD disease taxonomy, and have coupled the techniques with the DICOM standard for easy deployment in current PAC environments. Preliminary quantitative and qualitative experiments validate the effectiveness of the techniques.

1 INTRODUCTION

Advances in medical imaging have enormously increased the volume of images produced in clinical facilities. At the same time, modern hospital information systems have also become more complex. Today's clinical facilities typically contain *hospital information systems (HIS)* for storing patient billing and accounting information, *radiological information systems (RIS)* for storing radiological reports, and *picture archiving and control systems (PACS)* for archiving medical images. Standardized languages such as DICOM (Digital Imaging and Communication, http://medical.nema.org/) have been developed for digitally representing the acquired images from the various modalities. Apart from the image pixels, a DICOM image also contains a header, which is used to store certain patient information such as name, gender, demographics, etc.

It has become challenging for clinicians to query for and retrieve relevant historical data due to the volume of information as well as the complexity of information systems. In particular, historical patient images are useful for analyzing images of a current examination since they help in understanding any progression of pathologies or development of recent abnormalities. In current PACS, radiologists can query for historical images using only meta attributes stored in the DICOM headers of the images. However, these attributes do not contain any information about the anatomy or disease associated with the image. Hence, radiologists are often overwhelmed with irrelevant images not connected with the current examination. With current querying based only on patient attributes, it is difficult for the radiologist to easily search for images using semantic information such as anatomy and disease.

In this paper, we describe *semantic* techniques for *searching* medical images. Our approach relies on *annotating* images with formal concepts such that the images themselves become queriable. Recent advances in the Semantic Web community have made it possible for knowledge to be formalized in languages such as *Web Ontology Language* OWL (McGuinness and van Harmelen, 2004), data to be annotated in RDF *Resource Description Format* (Hayes, 2004). At the same time, work on formalizing clinical knowledge has resulted in vocabularies and ontologies such as Radiologist Lexicon (RadLex, http://www.radlex.org), ICD9 (http://www.cdc.gov/nchs/icd9.htm) and the Foundational Model of Anatomy (FMA) (Rosse and Mejino,

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2003). Our technique leverages on the work in Semantic Web and clinical terminologies to annotate and search medical images with semantic concepts from two dimensions – anatomy and disease. We have used RadLex and FMA as the knowledge sources for anatomy and the ICD9 classification system for disease knowledge. The focus of our work has been on using existing ontologies for defining the semantics rather than creating a custom ontology from scratch. Hence, recent works on extending RadLex to a radiological ontology either in the *RadiO* initiative[1] or in (Rubin, 2007) are complementary to our approach.

Existing techniques on multimedia semantic annotation often do not translate easily to medical images because clinicians have limited time to perform the annotation. This becomes even more challenging while annotating images with concepts from multiple dimensions. Automated image annotation, while having the ability to free up the clinician's time, are not yet scalable enough to be applied to arbitrary anatomical regions and diseases. In our work, we have created mappings between different ontologies such that given concepts in one dimension we can use the mapping *context* and quickly identify the relevant concepts in other dimensions. Specifically, we have devised automated techniques for mapping RadLex, FMA and ICD9 taxonomies such that this context can be automatically generated.

The work in (Rubin et al., 2008) is similar to our research in annotating medical images with ontology-based semantics and the use of context for faster annotation. However, their notion of context is not tied to *diseases* but rather more anatomical. Since the rich information in medical images is implicitly related to diseases, it is important to capture this dimension as part of the context.

Another limitation of easily using current multimedia semantic annotation techniques for querying medical images is that they are often not adapted to today's clinical standards and health information systems such as, in particular, PACS. In our approach, the semantic annotations are directly included in the headers of DICOM images and do not require any additional storage mechanisms. A fast index of concepts is looked up for results during query time and the headers of relevant DICOM images are parsed to retrieve the original annotations. Consequently, only minimal infrastructural changes are required to convert today's PACS to tomorrow's *semantic PACS* using our technique.

[1]The Ontology of the Radiographic Image: From RadLex to RadiO, IFOMIS, Saarland University, http://www.bioontology.org/wiki/images/a/a5/Radiology1.ppt

Note that the RIS contains additional information beyond the basic patient attributes in DICOM headers in today's PACS. While in principle it is possible to query the RIS for additional meta information, in practice however, this becomes challenging due to the unstructured text format of radiology reports as well as due to the loose coupling between RIS and PACS which makes seamless querying across both of them together difficult. In contrast, our technique outlines a different paradigm where images themselves can be semantically enriched and queried.

The main contributions of our work are:

- Our technique enables medical images to be annotated with semantic concepts from anatomy and disease ontologies, storing the annotations in the headers of DICOM images, and querying the annotations using semantic concepts.
- We have integrated semantics from two dimensions, anatomy and disease, using the Radlex, FMA and ICD9. The integration is based upon mapping between the anatomy and disease ontologies.
- We have used the integrated semantics to contextualize the space of concepts in one dimension, anatomy for instance, given concepts in the other dimension, disease in this example, for faster identification of relevant images.

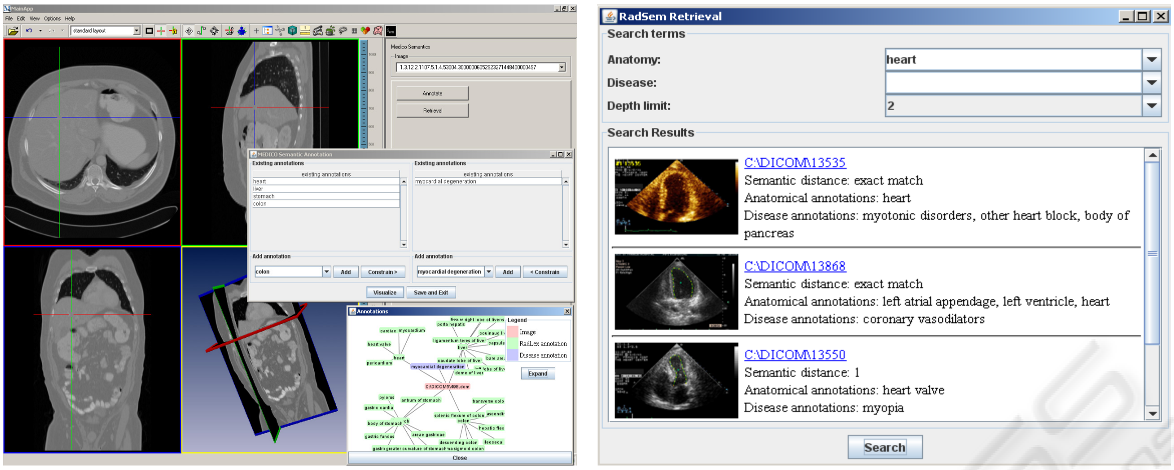
The research described in this paper on semantic annotation and retrieval is part of a broader effort in semantic understanding of medical images in the THESEUS MEDICO (Möller et al., 2008) project.

2 RELATED WORK

To the best of our knowledge, using formalized ontologies for enriching existing PACS has not been extensively researched in the community. The work in (Kahn et al., 2006) uses ontologies for integrating PACS with other clinical data sources, such as RIS and HIS, but does not address enriching medical images with additional semantics.

(Buitelaar et al., 2006) investigate methods for annotating multimedia data of all forms within one single retrieval framework and could be used for integrating heterogeneous clinical content from images to text to genomics data.

There has also been sizable research in retrieving images using ontology-based semantics as well as machine learning (Carneiro et al., 2007). The learning-based works, while being more scalable and automated, use *subjective* semantics that does not formalize notions of domain specific concepts and terms.



(a) (b)

Figure 1: Implementation of (a) Semantic Annotation, and (b) Semantic Retrieval within a 3D image browser.

A number of research publications in the area of ontology-based image retrieval emphasize the necessity to fuse sub-symbolic object recognition and abstract domain knowledge. (Su et al., 2002) present a system that aims at applying a knowledge-based approach to interpret X-ray images of bones and to identify the fractured regions.

3 SEMANTIC ANNOTATION AND RETRIEVAL

The essence of our technique lies in annotating images with concepts from anatomy and disease ontologies. Subsequently, these images can be queried using terms from these ontologies. We mapped the anatomical semantics to disease such that annotations can be performed efficiently and relevant images retrieved with minimal query terms and greater flexibility.

We use RadLex as the central terminology of anatomical concepts. RadLex contains a hierarchy of anatomical concepts corresponding to entities which can be identified in medical images. We also use the FMA, with around $70,000$ concepts, as a second source of formal human anatomical knowledge. We wanted to use the rich set of concepts in the FMA, but did not want to overload clinicians in using the FMA for image annotation since our goal is to identify anatomical landmarks. Furthermore, we use ICD9 as the ontology of diseases. By parsing the main table of ICD9 categories we constructed an OWL ontology which reflects the hierarchical structure of the original categorization within `subClassOf` relationships.

We have implemented simplistic heuristics for mapping RadLex to FMA as well as mapping RadLex to ICD9. This helps in constraining the space of concepts in one dimension (e.g., disease) knowing possible concepts in the other dimension (e.g. anatomy) and is an effective way to cope with $8,389$ RadLex and $8,686$ ICD9 concepts.

Our RadLex FMA mapping technique identifies correspondences between the pair of vocabularies by comparing terms at the lexical level and checking for perfect matches. This resulted in identifying $1,259$ identical concept names between the two data sets. The ICD9-RadLex mapping uses information in ICD9 which provides links between ICD9 identifiers and anatomical concepts. Our mapping technique was able to associate $3,694$ ICD9 terms to RadLex concepts covering 42.5% of the ICD9 vocabulary. While there are far more sophisticated ontology mapping techniques, we had to rely on rather simple methods based on string comparison of concept names due to scalability issues. For instance, PhaseLib (http://phaselibs.opendfki.de), an ontology-structure driven mapping technique was not able to cope with FMA and RadLex even with 2GB of memory. We plan to improve our string matching techniques for more complete mapping.

Fig. 2 gives an example of some of the relations between the ontologies described above. For this illustration we chose the anatomical concept “Heart”. The three big boxes in light gray denote the three ontologies used in the backend of RadSem. The smaller boxes in dark gray represent concepts from these ontologies, each with the identifier in the first line of the box. From the RadLex ontology in OWL we get only plain *subClassOf* relationships. These relationships provide information, that there is a connection, eg between “Heart” and “Pericardium”

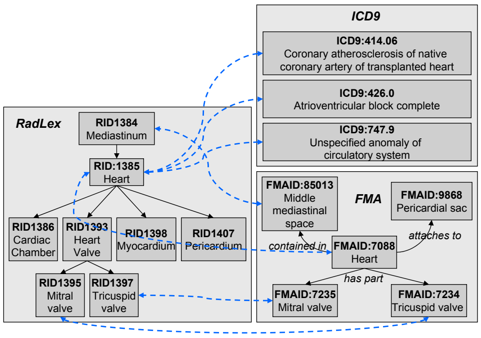


Figure 2: Example of some of the relations between the ontologies.

as well as between "Heart" and "Mitral Valve", but these connections are not further qualified. Qualified information can be obtained via the mapping to the FMA. Here we find the special connection `attaches_to` from "Heart" to "Pericardial sac". Meanwhile the relationship between "Heart" and "Mitral Valve" is of a different type: "Mitral Valve" is a part of the "Heart". The big box on the right side shows a subset of diseases in ICD9 which are related to the RadLex concept "Heart". Once an image is annotated with the *anatomical* concept "Heart", we can use these connections to constrain the set of concepts offered as *disease* annotations.

Semantic Search and Ranking. For the retrieval we implemented a simple yet efficient ranking algorithm. If a user searches for images annotated with, for instance, the concept *heart* then all images annotated with exactly this concept are returned as well as images annotated with concepts which have *heart* as an ancestor in the RadLex hierarchy. The depth of the hierarchy traversed can be set as an user parameter. The images are ranked in terms of the distance of the annotated concepts from the original query concept.

Constrain Annotation Dimensions. Initially, the number of possible annotations for an image is huge. We are using and 8,389 RadLex and 8,686 different ICD9 terms. To reduce these numbers, we leverage the fact, that certain diseases can only occur in certain organs or body parts. Myocarditis can only occur to the heart. Our mapping between RadLex and ICD9 provides us with such information.

4 SYSTEM AND EVALUATION

System. Fig. 3 shows the overall architecture of our system. The annotation workflow consists of fetching DICOM images from the database, using se-

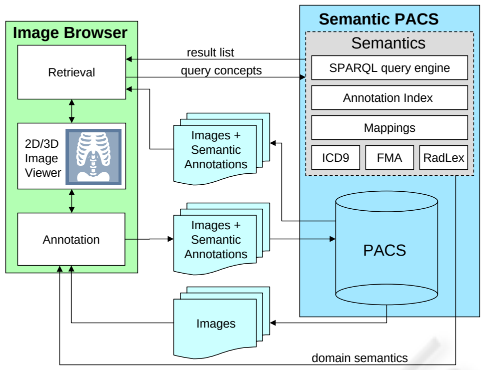


Figure 3: System Architecture.

mantics to annotate the images which are then saved into corresponding DICOM headers, and finally saving the semantically enriched DICOM images back into the database. The retrieval workflow consists of querying the semantic engine with concepts, which returns a list of pointers to images clicking any of which fetches the actual image. The DICOM headers of the images are parsed to recover the annotations. Our prototype is implemented in Java using Jena (http://jena.sourceforge.net) for managing ontologies and semantic metadata. All ontologies and mappings were either available in or converted to OWL format. For the FMA we used the OWL translation by (Noy and Rubin., 2007). Ontologies and mappings add up to more than 500 MB data in the triple store. Still, the combination of Jena and MySQL is providing us with reasonable response times below two seconds even for queries with constrains both on the anatomical as well as on the disease annotations.

To ease the task of finding appropriate annotations we use *auto-completing* combo-boxes. While typing in a search term, concept names with matching prefixes are shown in a drop down box and can be selected. Furthermore, we have also integrated the Prefuse visualization toolkit (http://prefuse.org) which displays the neighborhood of concepts and can be used to easily browse the ontology to identify the right concepts for annotation. Fig. 1(a) shows the annotation front end of the system. The list of disease terms available in the disease annotation panel can be constrained by the existing anatomy annotations. This is done using the mappings between ICD9 and RadLex.

Fig. 1(b) shows the retrieval front end. The user can search for anatomical and/or disease concepts terms. The anatomical terms are based on the RadLex and FMA vocabulary while the disease terms are based on ICD9. The user defined depth parameter limits the extent of the retrieval in the hierarchies of the ontologies starting from the concept with an

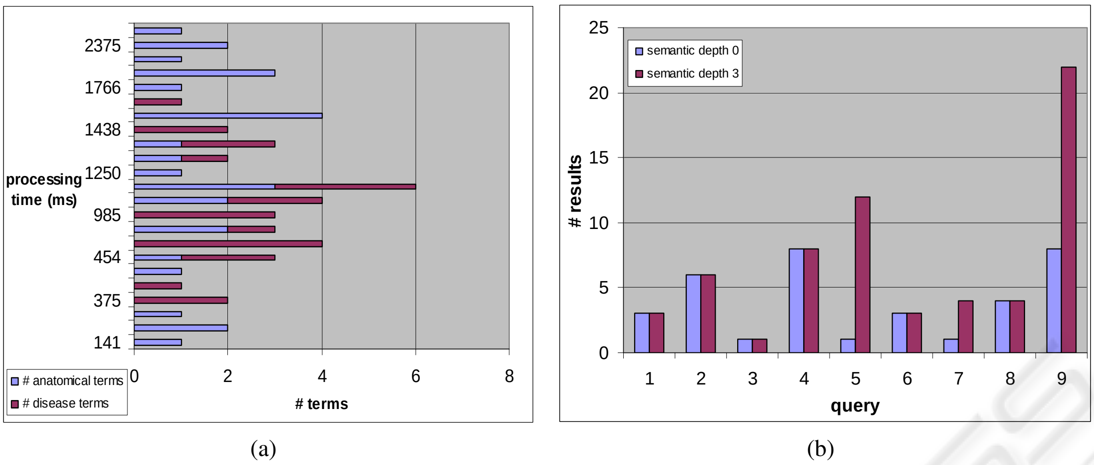


Figure 4: Evaluation: (a) query processing time vs. number of search terms; (b) search results with/without semantic search.

exact match. For instance, for the query anatomical concept "heart" and a depth of 3, the search examines all RadLex concepts which are at a distance up to 3 links away from "heart". The results are ranked in sorted order of the distance. Each result consists of the pointer to the image, the annotations, and the distance.

Evaluation. We performed preliminary experiments to evaluate the effectiveness of using semantic concepts in medical images during search. We manually annotated a set of 45 2D DICOM images with varying numbers of concepts from both RadLex and ICD9 and using up to 4 different concepts from each ontology. Furthermore, we created a set of 23 different queries each using a different combination of semantic concepts from RadLex and ICD9.

Fig. 4(a) shows the relation between the number of search terms and the query processing time. The time measured includes the time for semantic reasoning along the RadLex hierarchy, matching with annotated concepts, and ranking the results. It was measured on a 1.8GHz machine with 1GB RAM. Observe from Fig. 4(a) that certain queries with just anatomical concepts take longer time because of the overhead of semantic reasoning along the RadLex hierarchy. Here we perform *query expansion* which retrieves also all images which are annotated with a subclass of the query concept. The more children the query concept has, the higher is the effort for the query expansion. Overall the retrieval is always below 2.5 seconds.

Fig. 4(b) compares search results with and without semantic reasoning along the RadLex hierarchy. Clearly, semantic reasoning is useful for certain queries since it is able to consider a larger space of potentially relevant images.

We also did a preliminary evaluation on our constraining technique using the current RadLex-ICD9 mapping. Constraining was able to limit the space of possible ICD9 terms for certain RadLex concepts, for instance, limiting *heart* to 77, *myocardium* to 14, and *malleus* to 3 ICD9 concepts. Since the technique depends on the RadLex ICD9 mapping, future improvements in the mapping would significantly enrich it.

A demonstration of our prototype to radiologists at the University Hospital of Erlangen gave us valuable feedback. The radiologists liked the idea of splitting up the annotation into separate dimensions and using related context. They also suggested they would rather have the ability to specify complex queries, and would even be tolerant of retrieval delays, instead of being limited to simple queries which can be answered quickly. But in this case the search depth should be adjustable and the search progress should be made visible to allow the user to interactively influence the retrieval process. This is clearly a difference from typical Web search settings where users often do not accept retrieval times beyond a few seconds.

Our Prefuse visualization was welcomed as an interface for the exploration of formal domain knowledge in the system which is – if it exists at all – usually hidden by the application and hard to discover in its hierarchical structure by the users of existing clinical applications.

5 DISCUSSIONS

We described techniques for associating formal semantics to medical images and querying and retrieving relevant images using such semantics. Our techniques are based on manually annotating images using semantic concepts from RadLex, FMA and ICD9. We leverage on developments and standards in the Semantic Web In contrast to most image annotation work, we investigated serializing the RDF annotations to DICOM headers so that they can be directly archived with their respective images inside today's PAC systems. Another important contribution of our work is on making the annotation task simpler and quicker for physicians and radiologists who typically would be able to devote only minimal time for such activities. Towards this end, we have created mappings between anatomical and disease ontologies such that given annotations from one ontology we can automatically define the *context* in the other ontology and suggest focused and relevant concepts from it to the physician for further annotation. Our preliminary experimental evaluation validates the use of such context-driven ontological annotation.

The future directions of our work include more extensive evaluation of the current prototype as well as exploring possibilities for incorporating better and different kinds of semantics into the system.

Our current mappings between RadLex and ICD9 as well as between RadLex and FMA are not able to relate a sizable fraction of concepts between these ontologies. This is primarily because these concepts cannot be related by lexical term matching. We are working on improving the mapping by using fuzzy string matching techniques, the local graph structures of the terms in their respective ontologies.

While the system is able to store annotations directly within DICOM headers, it is still not integrated in an operational PACS environment. This integration would require modifications to the *DICOM Query/Retrieve* service which is the main module responsible for retrieving images from PACS. We are working on this integration so that the system can be easily deployed within current PACS.

Having rich semantic annotations on images opens up several new dimensions for better medical image queries. Adding Diagnosis Related Group codes (http://www.cms.hhs.gov/) will provide a more holistic semantic view of medical images, since they cover the classification of different kinds of treatments used by insurance companies. Images can be subsequently be queried, as an example, for disease progressions over time. Another application could be incorporating knowledge from other dimensions, such as geometric models of organs, for more sophisticated reasoning. We plan to investigate some of these promising directions as part of a next generation *Semantic PACS* platform.

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