



# Semantic Imaging and Scalable Intelligent Image Search

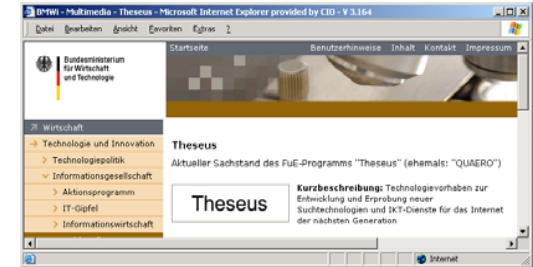


- August 2006: **industry-led consortium** (empolis, Siemens, SAP) submits **Theseus** proposal
- October 2007: BMWi grants 90 Mio EUR to Theseus over 5Y
- Medico is one of 6 use cases in THESEUS
- Vision:

**Provide Semantic Access to Medical Image Databases**

## Objectives:

- **Build the next generation of intelligent, scalable and robust search engines for the medical imaging domain:**
- Construct innovative, **hierarchical information representations** that will facilitate flexible image queries
- Formally address the intrinsic constraints of the medical imaging domain to define the **space of queries**
- Integrate higher level knowledge that will help explaining different semantic views in medical imaging: **structure, function, and disease**
- Create new synergies between **semantics** and **image understanding**



## Medico Partners:

- **Siemens AG**
- **Ludwig Maximilians University**
- **Erlangen University Hospital**
- **Fraunhofer Institute for Computer Graphics**
- **German Center for Artificial Intelligence DFKI**

- Medical images can only be searched using few parameters stored as meta data in so-called DICOM-headers (patient name, acquisition date, imaging modality etc) or indirectly by searching corresponding radiology reports
- ‘Content’ of the images can not be used for
  - quality control
  - data mining for clinical/epidemiological studies
  - decision making
  - workflow improvements

# Theseus-Medico: Next Generation of Intelligent Medical Image Search Engines



Clinical Literature

Journals & Articles

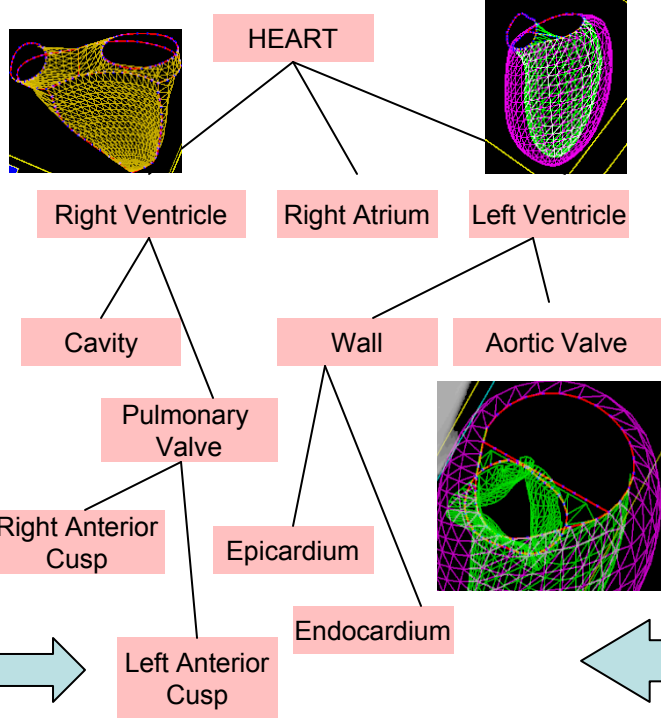
Domain Expert

Define the set of typical queries for the domain (e.g., cardiology)

Derive minimal set of queries necessary for answering the set of all typical queries

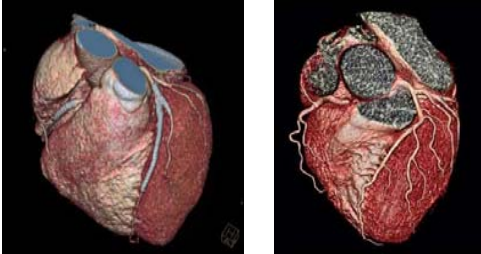
- Semantics of the domain defined by the set of minimal queries
- Queries can be mined from literature or defined by advisory clinicians

**Constrained Domain**



- Knowledge is represented in a hierarchical ontology, e.g., Foundational Model of Anatomy

**Semantic Image Annotations**



Creating Hierarchical Representations through Image Parsing

- Enrich hierarchical knowledge structure with imaging attributes

**Combining Image Parsing and Semantic Knowledge**

*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.*

# Semantic Image Annotations



Automated image parsing

(Multi-modal) manual  
annotation of images

Extraction from DICOM headers  
and DICOM structured reports

Byproduct of reporting

Automated extraction  
from radiology reports

Semantic  
Image  
Annotations  
(RDF triple store)

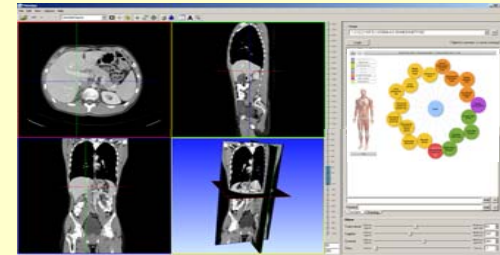
Medical thesauri and ontologies  
RadLex, FMA, ICD-10 etc

# Semantic Image Annotations



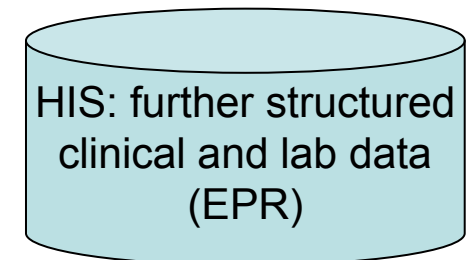
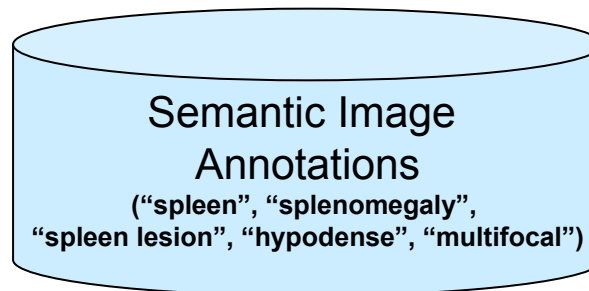
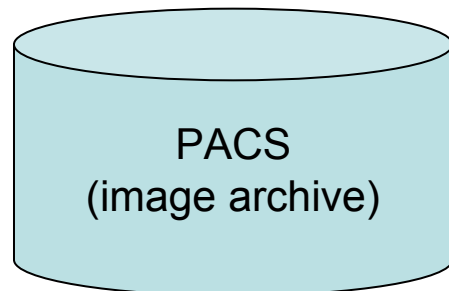
Semantic search (supporting e.g. synonyms (esp. multilingual) and hyperonyms)  
“Show me yesterdays patient with the large multifocal spleen lesions.”

Context based volume retrieval /  
“Semantic navigation” of 3D data sets



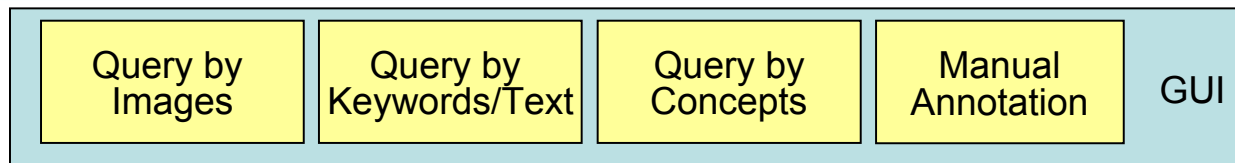
Clinical decision support, workflow improvements, quality control  
e.g. linking ICD codes or biopsy outcomes to medical images

Translational research (clinical trials, patient recruiting, epidemiological studies)

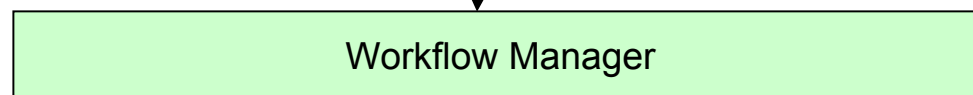


# System Overview

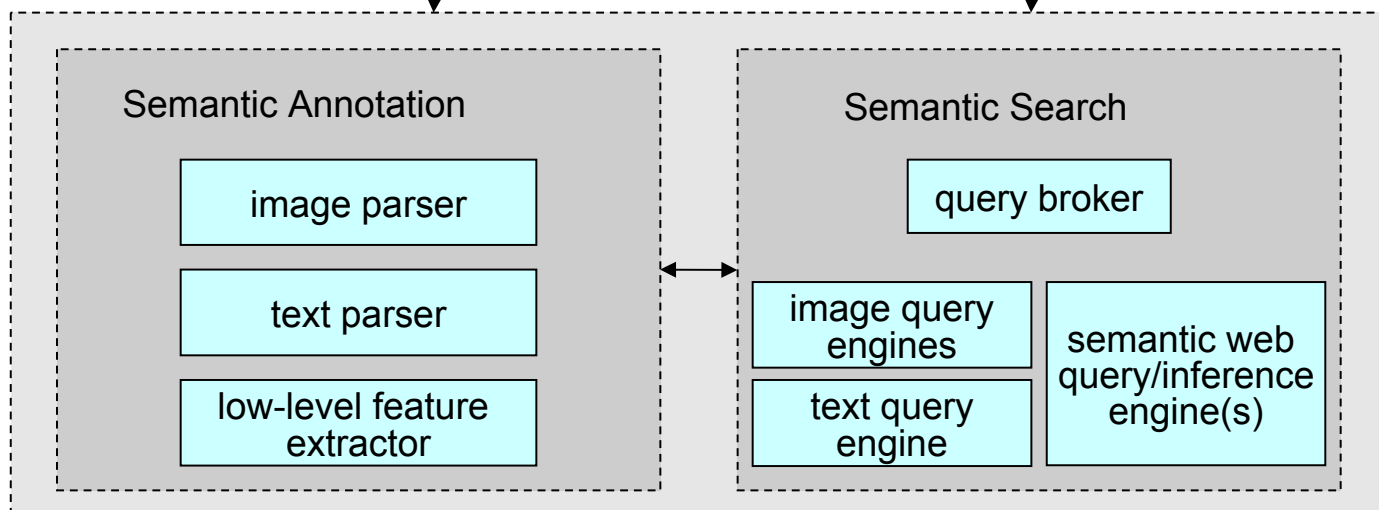
**Presentation Layer**



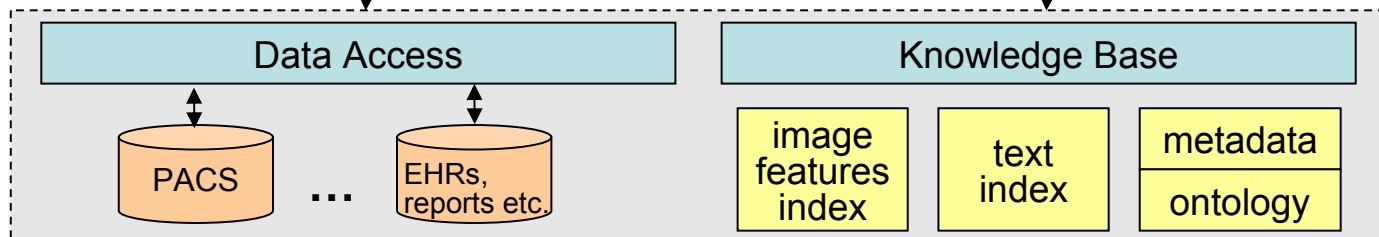
**Application Layer**



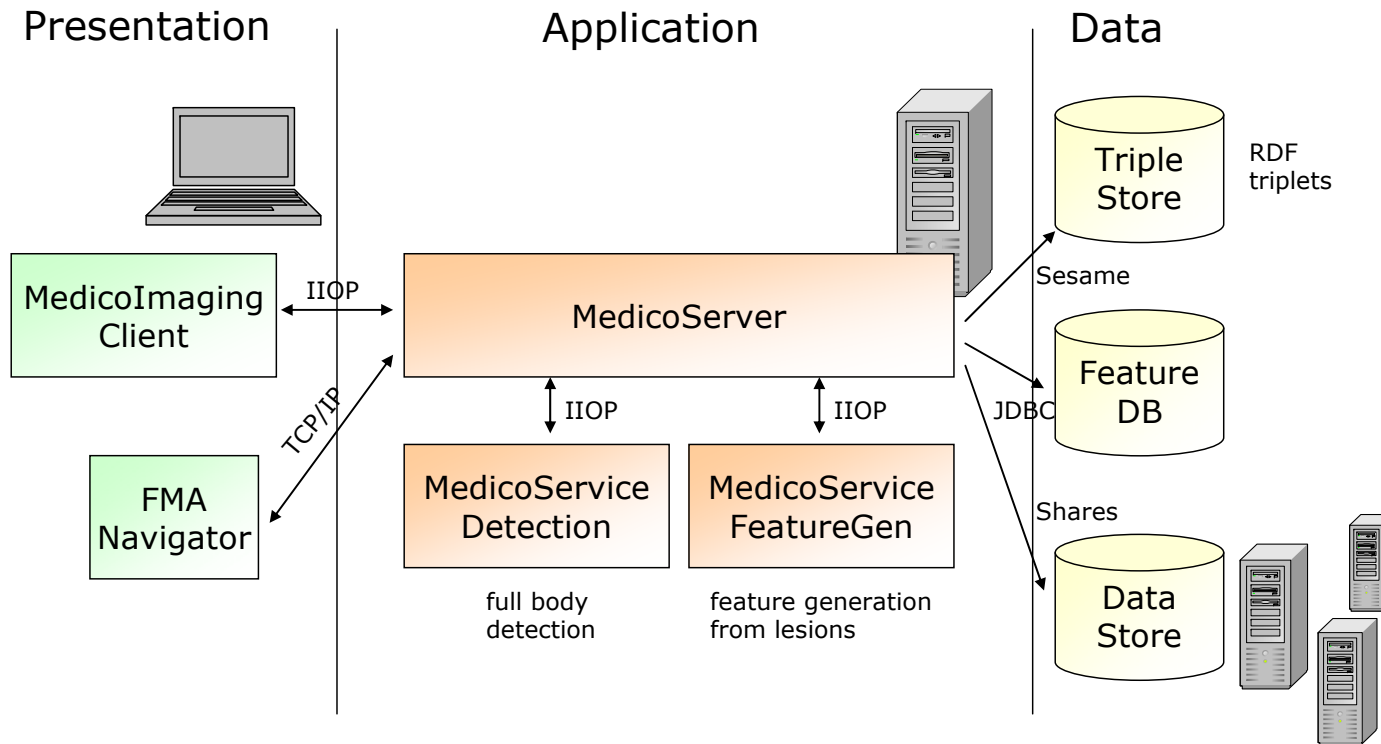
**Query, Annotation, Inference Layer**



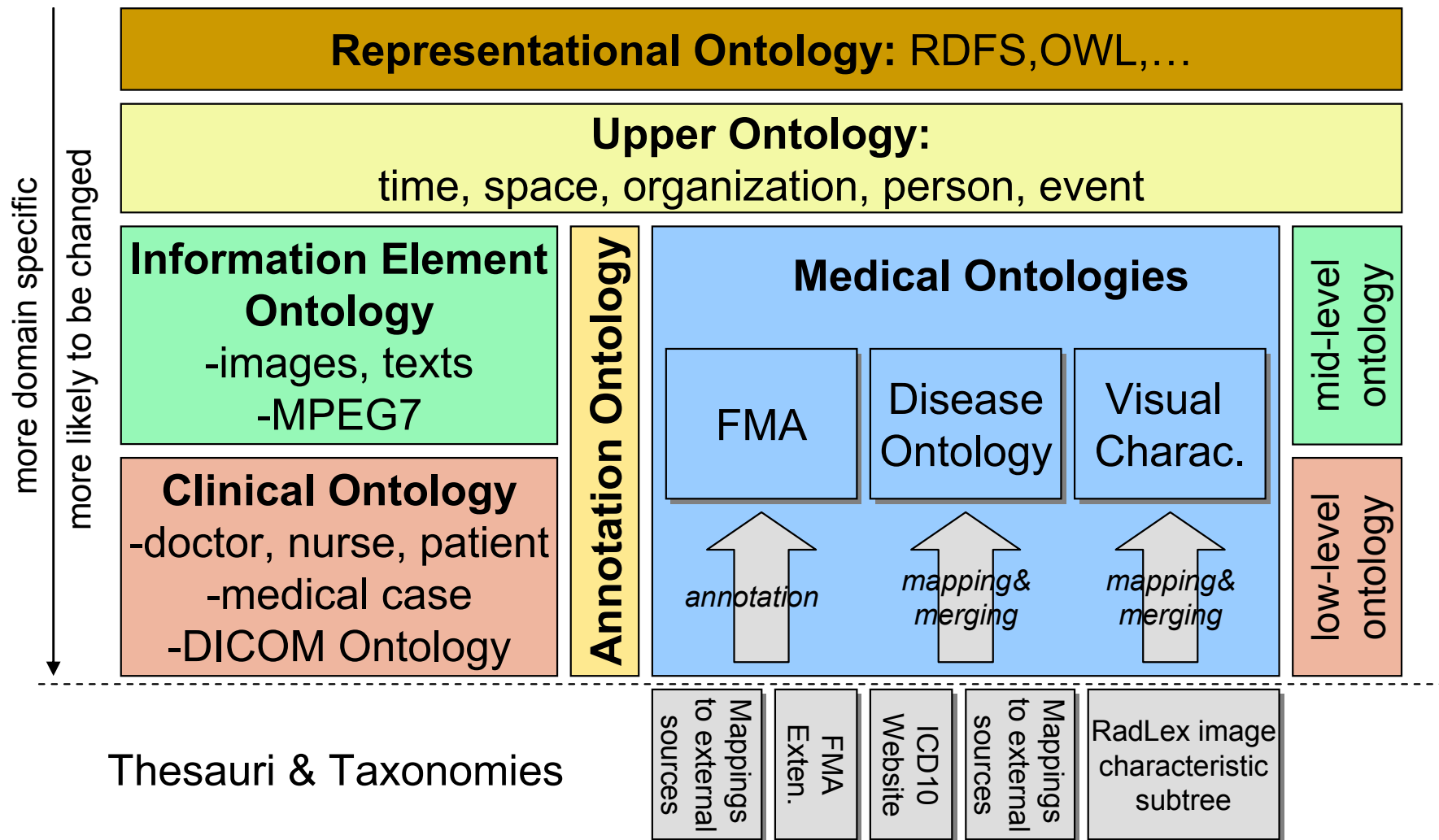
**Data Layer**



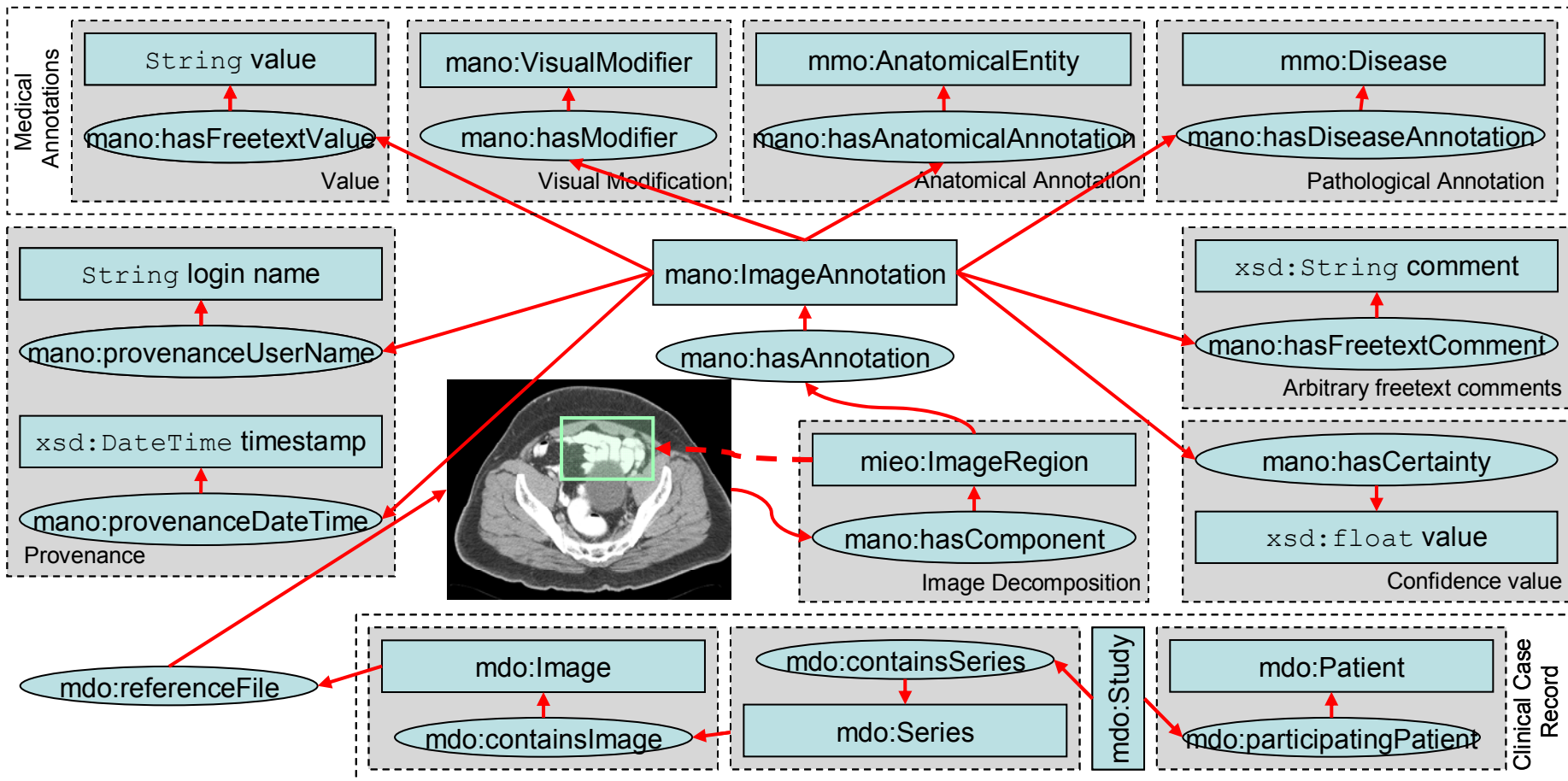
# Architecture Status



# MEDICO Ontology Hierarchy



# Schema for Semantic Image Annotations



- Why medical ontology alignment?
  - Medical image contents contain knowledge along 3 related domains: anatomy, radiology, diseases
  - This machine processable knowledge is available in domain ontologies
  - Integration is necessary
    - for obtaining a coherent view of the domain
    - for image annotation and for subsequent search
  - The integration is not straightforward
    - Conceptual heterogeneity: different conceptualizations (views), same knowledge
    - Terminological heterogeneity: different naming conventions, same concepts
  - Medical ontology alignment explicitly states the heterogeneity via mappings
    - help reduce semantic ambiguity
    - information loss

## What do clinicians and radiologists search for?

**Goal:** Predict meta information relevant for annotating medical data

### Domain sources

- Proprietary
- Publicly available
- Unstructured
- Semi structured



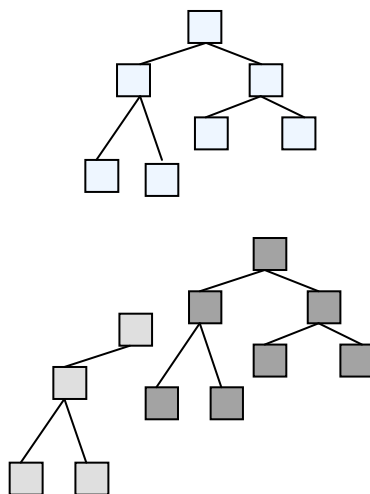
PubMed

RIS Reports



### Semantic sources

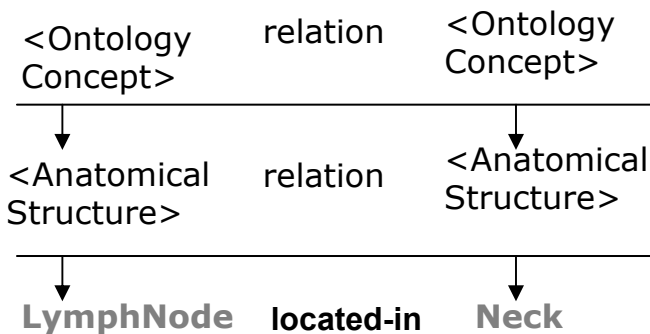
- FMA Ontology-Human Anatomy
- RadLex Terminology- Radiology
- NCI Cancer Thesaurus
- Features from medical images



### Predicting Clinical Queries

**Query Patterns =**

- most frequent concepts in domain corpora
- +their interrelations



How big is the enlargement of the **lymph node** in the **neck**?

[Recent work: German radiology reports]

- Some particularities of the radiology reports
  - no well-formed sentences, lacking for examples verbs, and few punctuation signs
  - a lot of abbreviations and specific patterns (temporal information, spatial information used describing the position and the dimension of parts of the contents of the X-Ray, etc).
- Current WIP: extraction of
  - relevant terms and relations within the document
  - negative findings
  - spatial information that describes the content of the X-Ray
  - temporal information that indicates a development of the disease, also with links to former examinations of the patient (anonymised)
  - as a side effect: possibility to extend available terminological and semantic resources in the field (for example the German version of Radlex)

## Diagnostic Findings (German „Befund“)

**Normal** liver **size** with two sufficiently indicative lesions **in segment 7** with a **diameter** of app. **1,5 cm** (image 5) and **1 cm** (image 11)...**No former** records. ...Normal wide heart shadows...aorta sclerosis...Trachea is **not** compressed. ....**On the left** many small round densifications....

### in German (original)

Leber **normal groß** mit zwei signalreichen Läsionen im **Segment 7**, die einen **Durchmesser** von ca. **1,5 cm** (Bild 5) und **1 cm** (Bild 11) haben.... **Keine** Voraufnahmen. ....**Normal breiter** Herzschatten. Aortensklerose. Trachea **nicht** eingeengt .... **linksseitig** mehrere kleine rundliche Verdichtungen...

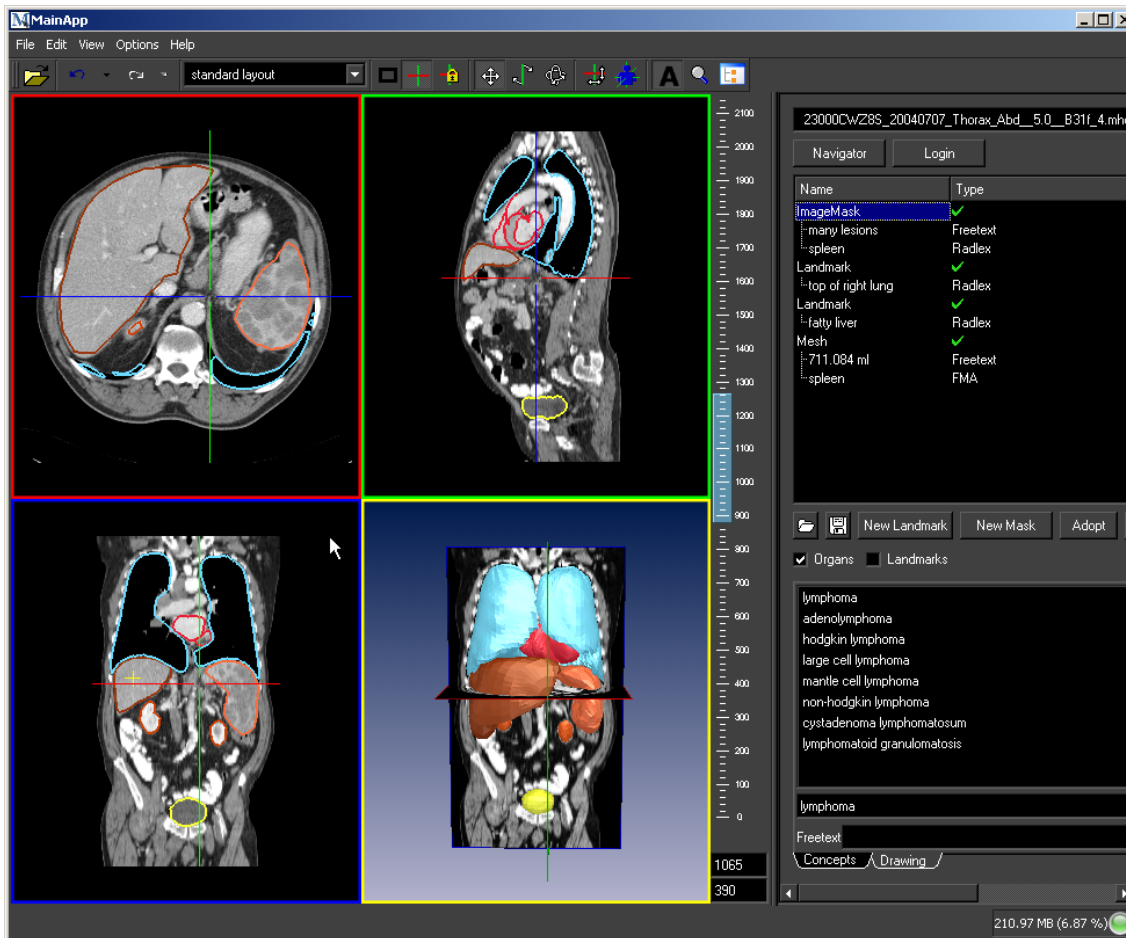
## Assessment (German „Beurteilung“)

In comparison to the pre-MRT on **03.03.2009** **no change** in the **number** and **dimension** of liver lesions in segment 7....**No** lymphoma manifestations **in the region** of investigation...**no** infiltrate... Executions in left Hilus....it is recommended to compare the relevance on the basis of **previous** records.

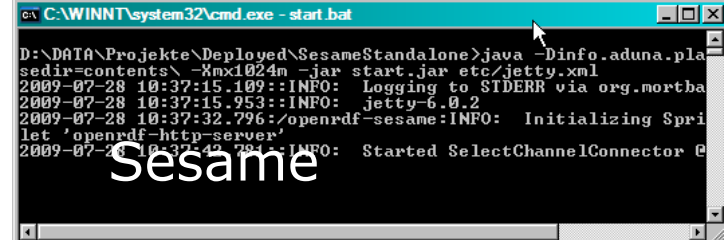
### in German (original)

**Im Vergleich zur** Vor-MRT vom **03.03.2003 unveränderte Zahl** und **Größe** der Leberläsionen im Segment 7, .....**Keine** Lymphommanifestationen im Untersuchungsgebiet....**Kein** Infiltrat, ...Pneumothorax. Verrichtungen am Hilus **links** .....Relevanz Vergleich mit **Voraufnahmen empfohlen**.

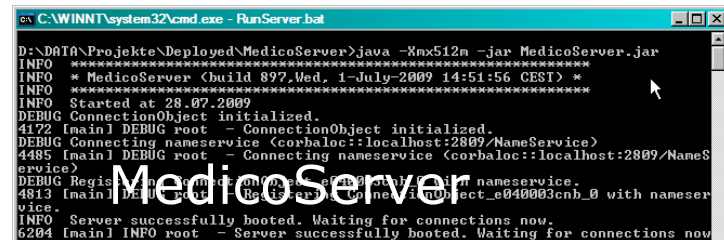
# Screenshots



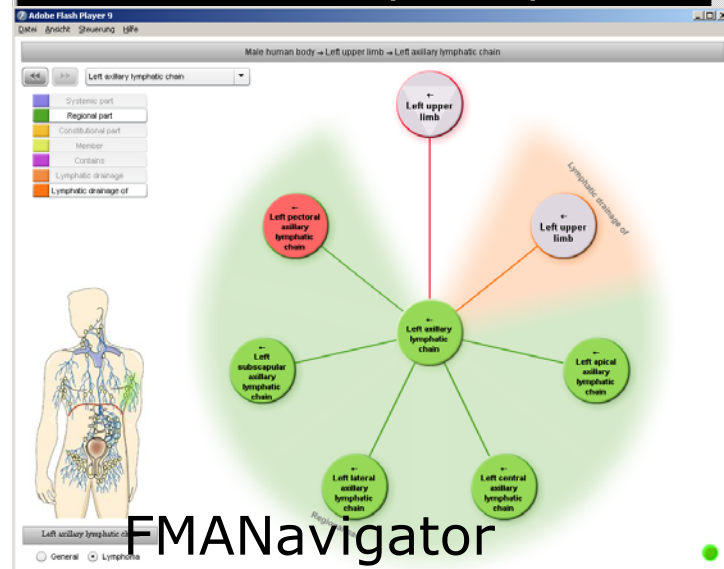
MedicoImagingClient



Sesame



MedicoServer



FMANavigator

basic

file://C:/Documents%20and%20Settings/saikma00/My%20Documents/workspace/RadSem/src/ma

Contrast Windowing

Body Region

Search the Web


ClinicalTrials  
PubMed  
Wikipedia

Special Functions

Automatic Annotation  
Body/Non-Body

Metadata

Show  
Time Line



Regions of Interest

Type	Anatomy	Characteristic	Disease	AnnotatedBy	Comment	T
Rectangle	sternum	hypodense		saikma00		200

Add Remove Anatomy Characteristic Disease

Image with annotations

Visual Query Composer

Anatomy Observation Disease Patient Search Configuration

Anatomical Concepts sternum Search

anatomic entity

chest wall pelvis abdominal wall skeletal muscle of trunk

sternum

Add Term In Search


Search With Annotations

Freetext Query anatomy:"sternum" name:"Joe" Search

Visual Query Composer

Search Results


2D Image



<file://C:/Documents%20and%20Settings/saikma00/M/>  
Semantic distance: exact match  
Anatomical annotations: [Sternum](#)

[Metadata] [Explanation]

Image Volume



<urn:mpeg:mpeg21:2003-120bf6-5461d-7f17-11>  
Semantic distance: ...  
Anatomical annotations: [Head of the right humerus](#), [Cusp point at the left hip bone](#), [Bronchial bifurcation](#), [Top of right lung](#), [Cusp point at the right hip bone](#), ...  
Disease annotations:

[Explanation]

Search Results

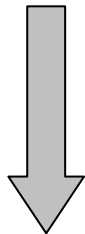
# Image Parsing

## challenges

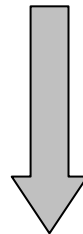
many  
anatomical  
structures

many  
modalities

large data  
volume



generic  
extensible



scalable



efficient

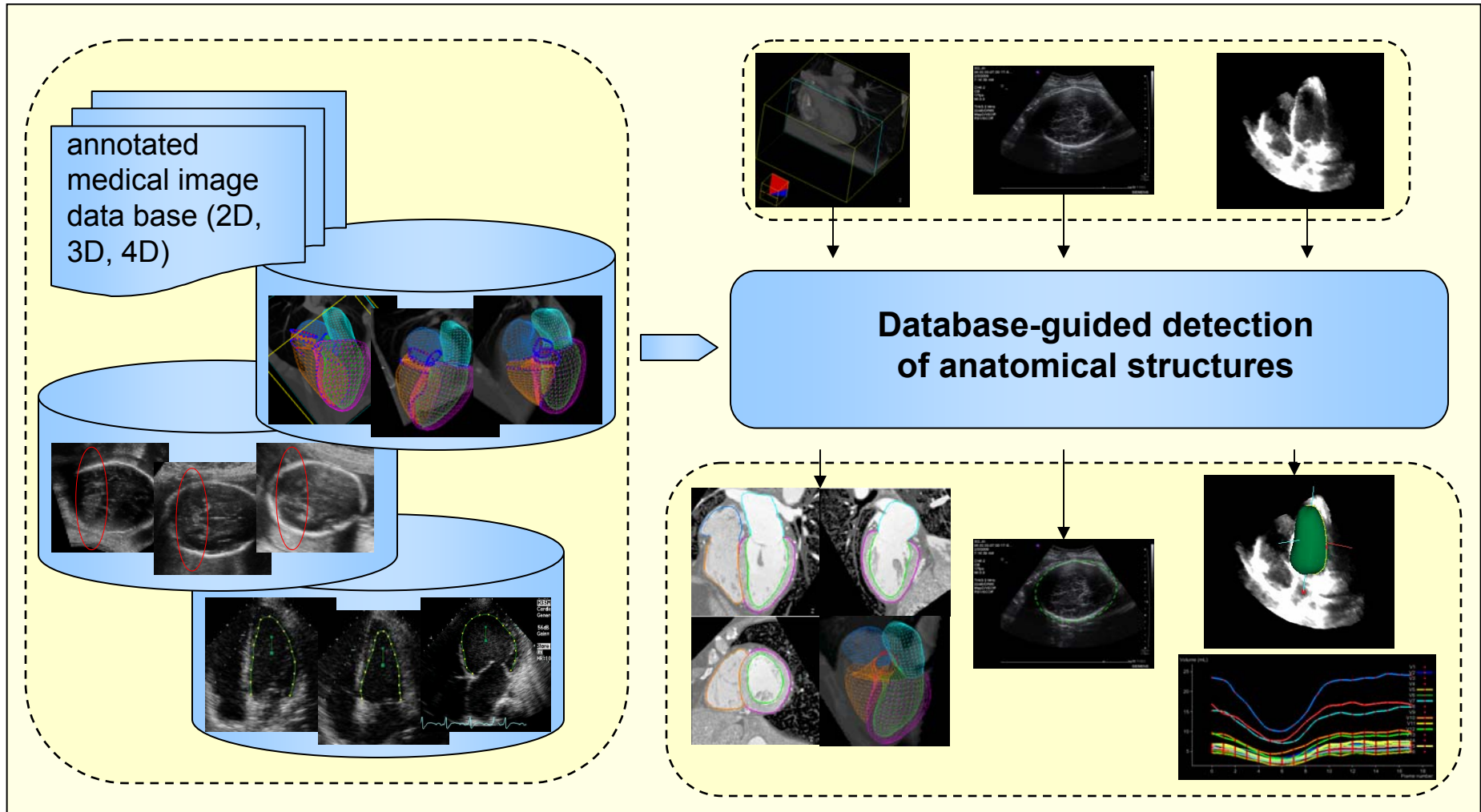
modular  
design

machine  
learning

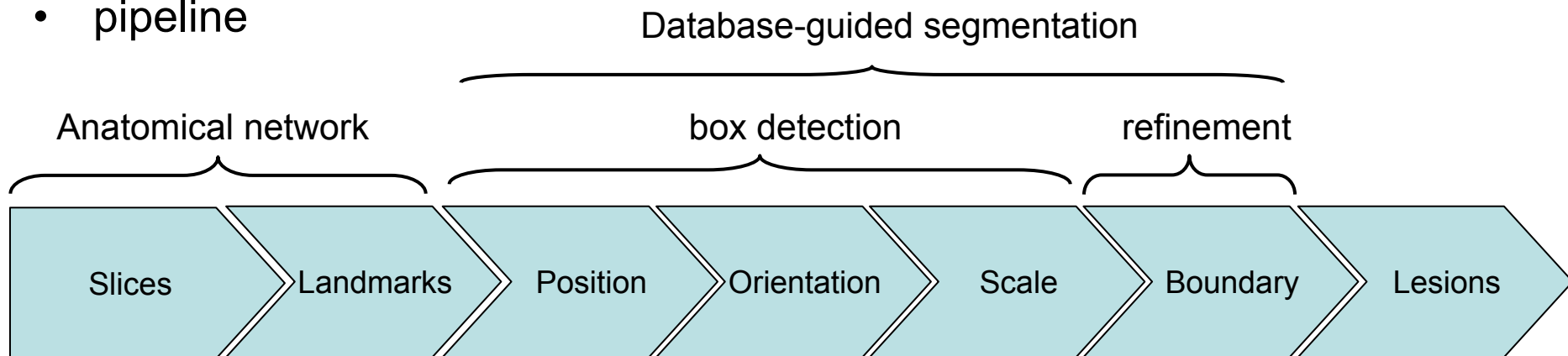
pyramid  
multi-tiered

## solutions

# Detection Technology

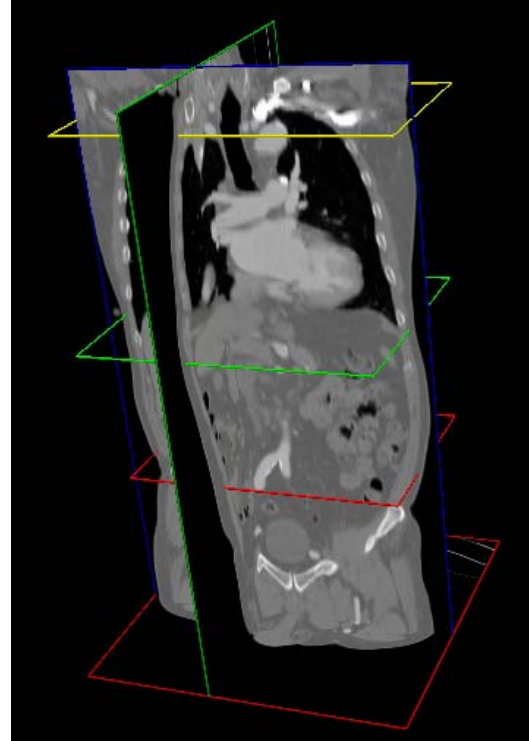


- objective: given a CT scan (e.g. whole body), we want to automatically abstract as much information as possible, about:
  - **body region**
  - **landmarks**
  - **organs and tissues**
  - **lesions**
- **pipeline**



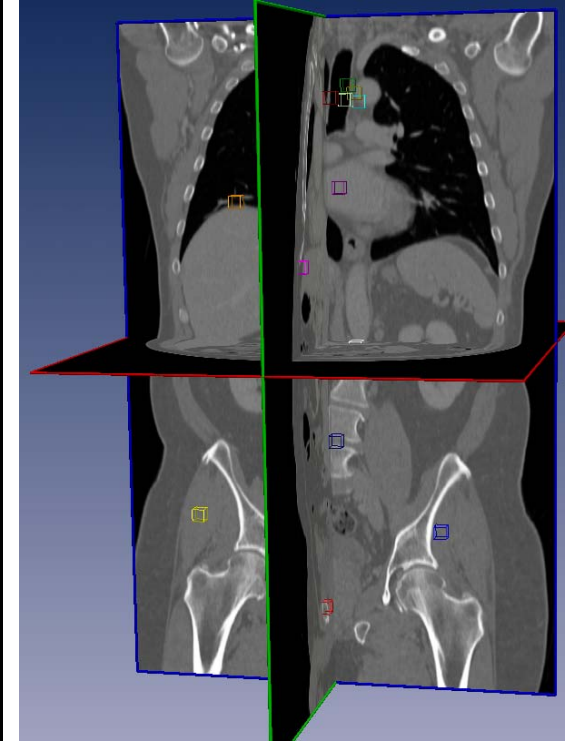
[S. Seifert, A. Barbu, K. Zhou, D. Liu, J. Feulner, M. Huber, M. Suehling, A. Cavallaro, and D. Comaniciu. Hierarchical Parsing and Semantic Navigation of Full Body CT Data, SPIE Medical Imaging, 2009]

- Technologies
  - Marginal Space Learning (MSL)
  - 2D/3D Haar-like features
  - Steerable features
  - Discriminative Anatomical Network (DAN)



## Performance Body Region Detection

- 99,7% accuracy
- 380ms computation time



## Performance Landmark Detection

- 19 body landmarks
- <4mm average error
- 14.7sec

- Technologies
  - Constrained MSL
  - Hierarchical Active Shape Models
  - Patch-based Deformable Models
  - Trainable Boundary Detector
- Performance
  - 7 organ, total <1min

<b>3-fold</b>	<b>min</b>	<b>median</b>	<b>max</b>	<b>std</b>	<b>mean</b>
Kidney Right	0.61	1.00	14.60	1.30	1.31
Kidney Left	0.76	1.14	7.91	0.79	1.35
Spleen	1.15	2.10	16.63	2.22	2.80
Bladder	0.71	2.34	10.41	1.92	2.96

<b>1-fold</b>	<b>min</b>	<b>median</b>	<b>max</b>	<b>std</b>	<b>mean</b>
Lung Left	0.86	1.25	2.23	0.24	1.30
Lung Right	1.13	1.56	3.25	0.29	1.58
Prostate	1.13	1.89	3.34	0.61	2.16



Speed: 53 sec for 9 organs (detection + refinement)

**Thank you for your attention!**