


MEDICAL INFORMATION ANALYSIS & RETRIEVAL


Tutorial on searching text and images in the medical domain

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MIE 2012, Pisa, Italy


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The screenshot displays the khresmoi search interface. At the top, under 'Queried image(s)', a protein structure image is shown. Below, the 'Results' section shows a grid of search results. Each result includes a thumbnail image, a similarity score, and a 'Show dedicated Article' link. The results are organized into two rows. The first row shows results with similarity scores of 1.0, 0.92841, 0.89808, 0.89112, and 0.87702. The second row shows results with similarity scores of 0.87702, 0.87702, 0.87702, 0.87702, and 0.87702.


MEDICAL INFORMATION ANALYSIS & RETRIEVAL

Overview

- Improving search in the medical domain
 - Allan and Henning
- Searching for medical images
- Who searches for medical images and how?
- Combining text and visual search
- Challenges for search
 - Allan and Henning

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Improving search in the medical domain

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Scenario

- A close **friend** of yours has her **5-year-old** daughter diagnosed with **Leukemia**
- As you are regarded as a medical professional in the largest sense they ask you to help **find more information** on the disease
 - **How** do you search for this information, what are the **strategies**?
 - What **type** of information are you targeting?
 - How can you assure that **trustful** information is being transferred?
 - How do you explain it to the 5-year-old?
 - What are difficulties and disadvantages of this approach?

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Search target?



- Is a **document** searched for?
- Or an answer to a specific **question**?
- Maybe an **expert** in the domain?
- Educational material?
 - Maybe **videos**, or nice pictures also for children?
- Description of the disease vs. symptoms, treatments, chances of survival?
 - With the goal of making a choice of treatment, for example, comparing various options for the choice

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Trustfulness



- How can we make sure that information is **correct**, or at least not totally wrong?
 - Sometimes differing opinions exist, knowledge changes over time
 - Cross check several sources, but this can also lead to wrong ways
 - **Quality labels** or certificates of trust can help
 - HONcode
- **Classification** of web pages into several classes
 - What are the characteristics
 - Success needs to be monitored closely (spam filtering)



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Level of understanding



- Different target groups have a totally different **level of information** that is required
 - Also physicians between a specialist and a GP
- What about **children** and the **elderly**?
- Level of understanding changes the more we read about a specific topic, we become experts
 - Not a fixed thing ...
- Users can give more information to get **personalized results**
- Cyberchondria

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Document and page ranking



- Should **wikis** and **blogs** be rated highest?
 - Google does this but for medical information several studies show that this might not be the best strategy
- Most queries are short (1-2 terms) and thus **not specific** at all, how to deal with this?
- Is the search target known?
- Users want advanced search options but then these are rarely used in practice
- Go beyond ranking, explore the content space

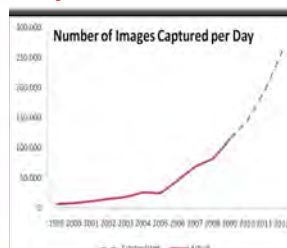
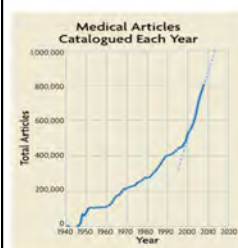
8

Searching for medical images

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Motivation

- Medical imaging is estimated to occupy **30% of world storage capacity** in 2010!
- **Mammography** data in the US in 2009 amounts to **2.5 Petabytes**



Riding the wave – how Europe can gain from the rising tide of scientific data, report of the European Commission, 10/2010.

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Retrieval of images



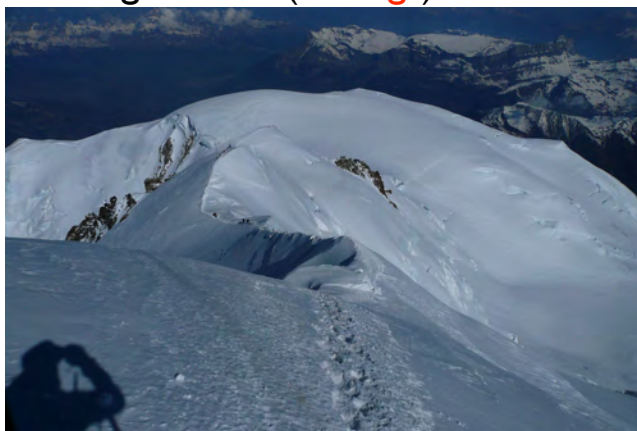
- **Text** retrieval of images
 - Is there any text attached to the images?
 - Doing this manually is expensive, subjective, **language** dependent, ...
 - Take text close to the images (such as captions)
 - Semantic **concepts** could help in some cases
- **Visual** retrieval of images
 - Using automatically extracted visual features
 - Content-based image retrieval (**CBIR**)
 - Query by Image Example(s) (QBE)
- **Multimodal** retrieval (text+images)

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Types of annotation

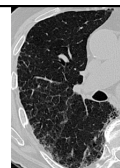
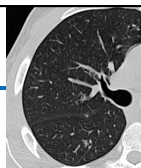


- What is **in** the image?
- What is the image **about**?
- What does the image evoke (**feelings**)?



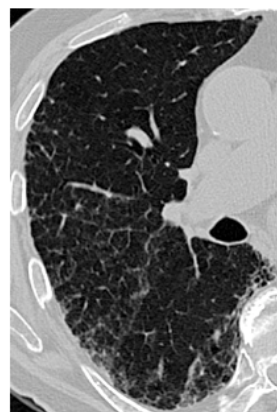
Content vs. context

- Most often text around images does not describe the image content itself
 - Unless specifically annotated for retrieval
 - Text often gives the **context** in which the images were taken (private, also medical)
- Image **content** is rarely described precisely and completely with text
 - Visual features describe the pure content
 - Low level of semantics
- Content and context are **complementary** for search



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Age matters



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Types of information needs/searches



- Known-item search (i.e. telephone number, ...)
 - Question answering
- Exploration, exploitation, informational
 - Topic search or **open ended** search
- Comparison search (between things)
- **Expert** search, person search, entity search
- Geographical search
- Literature search
- **Multimedia** search (increasingly given as results)
- Browsing, no specific goal



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Types of image searches

- **Recent** (time) pictures (journalists)
 - Date, given with camera
- Pictures of specific **places**, monuments
 - GPS in many cameras
- Pictures with particular **persons** (private search)
 - Face detection, recognition (Facebook, Picasa)
- Pictures with particular **objects**, types of images
- Pictures evoking specific **feelings**
 - Fear, joy, happiness, ...
- **Similarity** search/browsing (Medicine, journalism)



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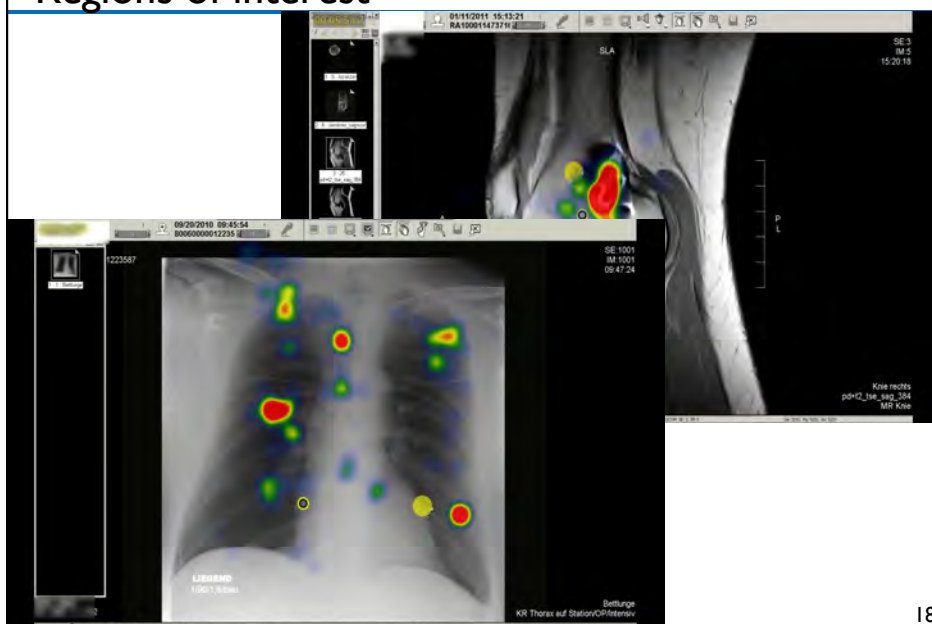
Visual information for retrieval

- Object **detection**
 - Then potentially mapping the objects to an ontology
 - Usually works well for a small number of objects
- Image **classification**
 - Training data, limited set of classes
 - **Global** classification of images vs. **local** classification of pixels, regions
- Similarity **retrieval** of images
 - Global image information, regions of interest (ROIs), small
 - No training data, relevance as criterion for quality



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Regions of interest

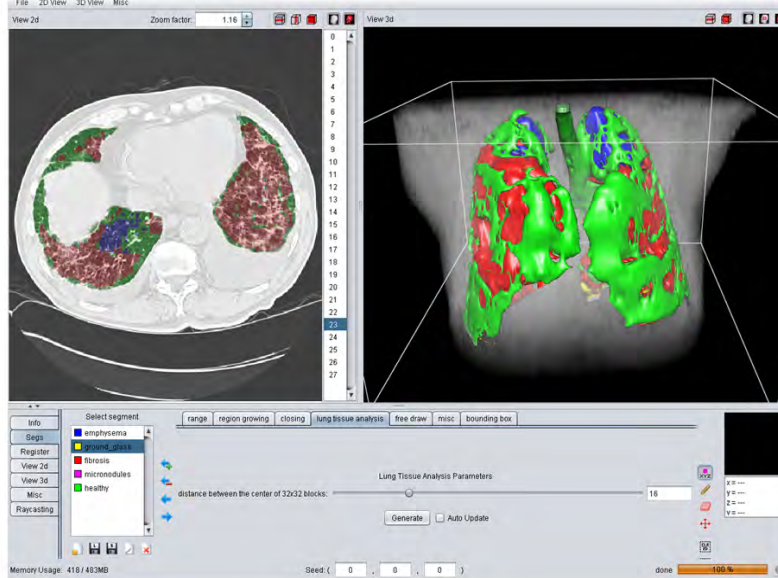


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Visual classification and retrieval

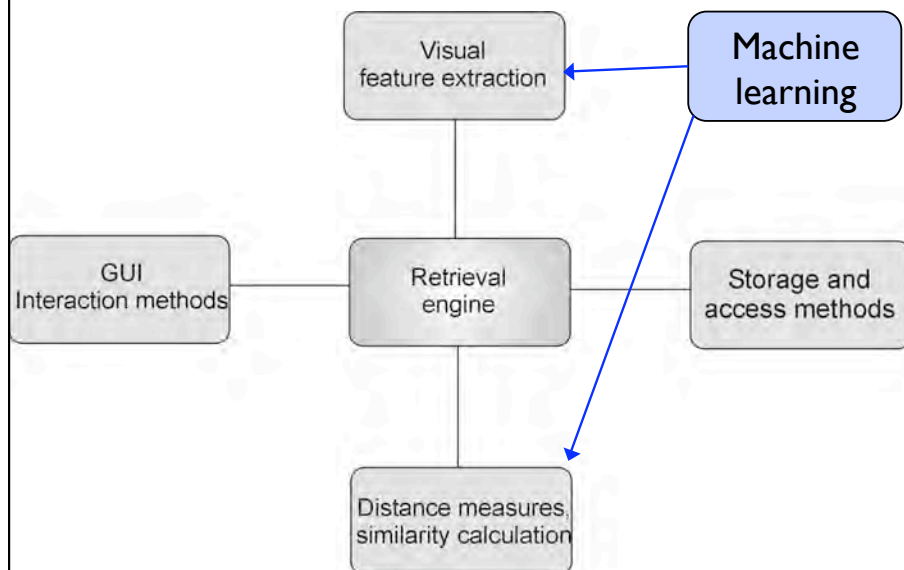


<http://www.youtube.com/watch?v=cMoONC0Tz2c>

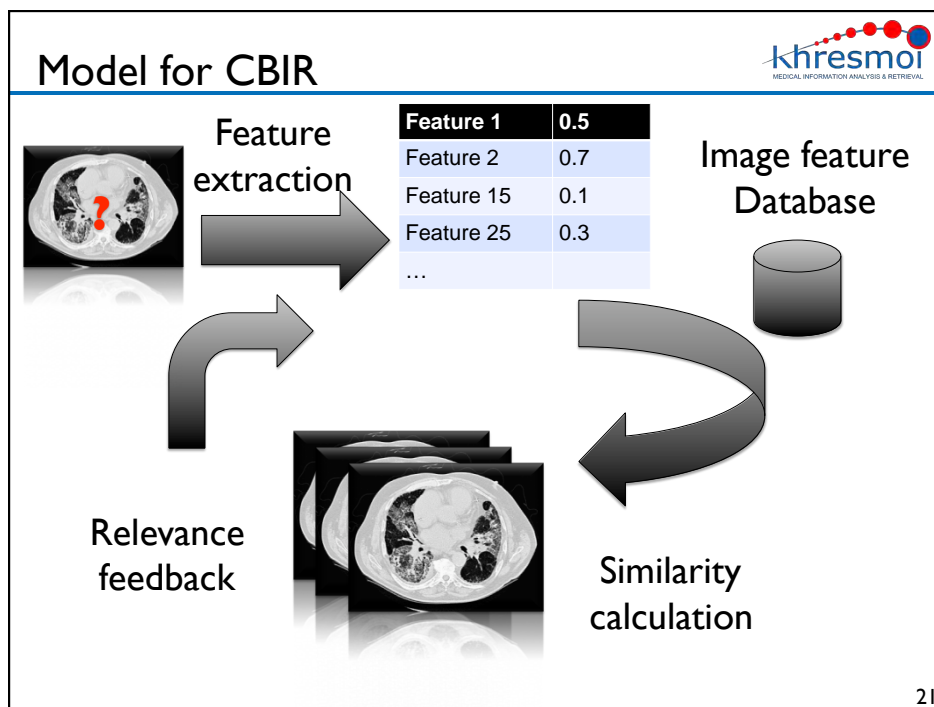


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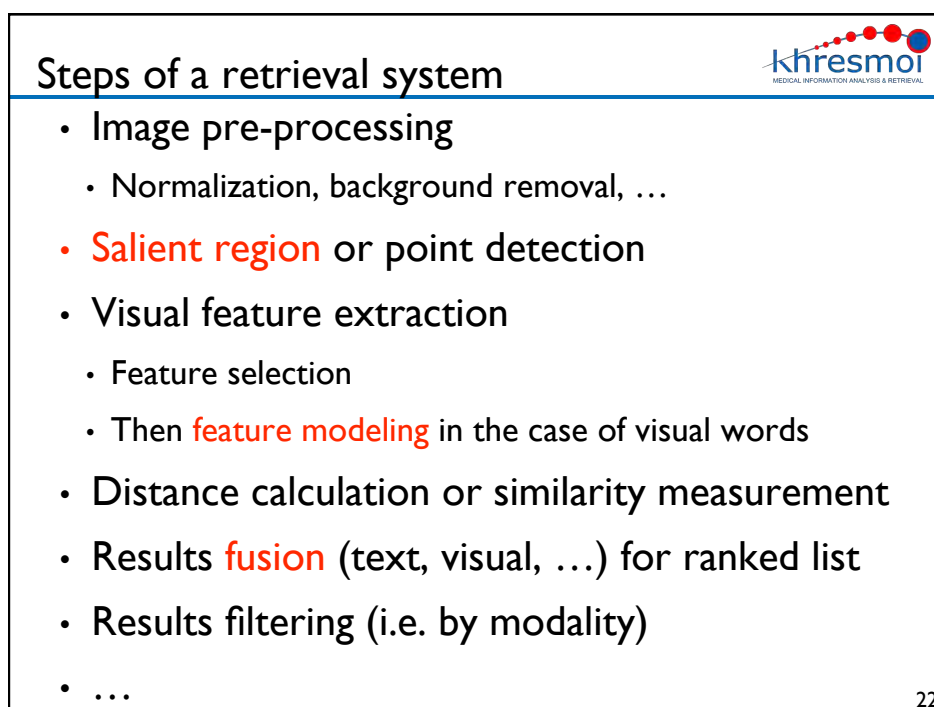
Components of image retrieval systems



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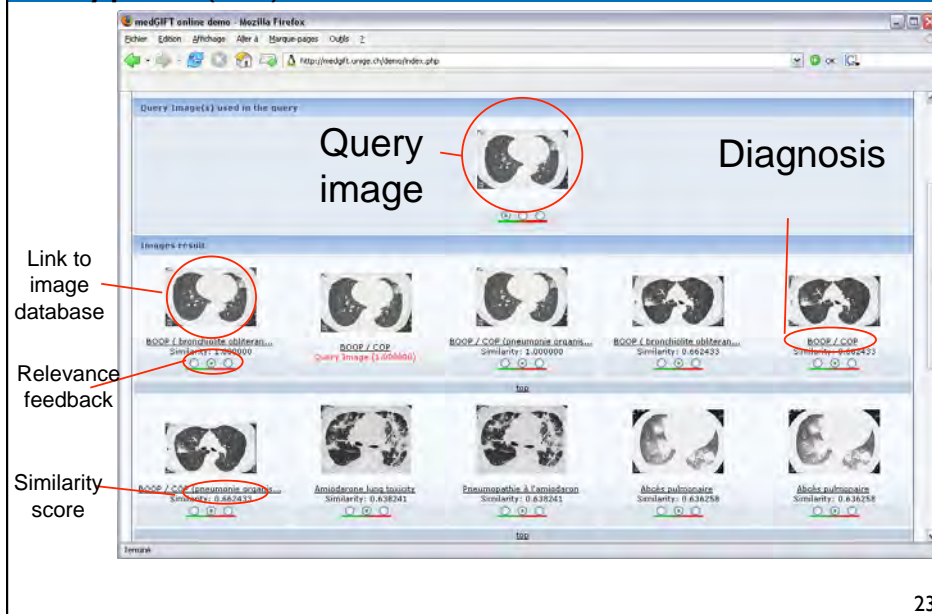


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A typical (old) interface



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Classifying visual features (Eakins)

- Level 1: **primitive** features
 - Color, texture, shape, spatial organization
- Level 2: **derived** features
 - Individual objects or persons (Eiffel tower, Britney Spears)
 - Objects of a specific type (Volkswagen car)
- Level 3: **abstract** attributes
 - High level reasoning about meaning and purpose
 - Emotional or religious significance
 - Find images of “suffering”

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Visual words

Salient regions
All pixels, grid, high gradient
Original feature space

- N-dimensional feature vector for each salient region

Quantization of the feature space

- Division of the feature space into M groups: visual words
- Clustering (k-means)
- Cluster centers are words

Visual words space

- Optimal number of words needs to be found
- For each image a histogram can be created
- Analogy to text words

Bag of Visual Words

- Histogram of words for an image or an image region based of the salient points
- M-Dimensional feature vector

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www.springerimages.com (3.3 mio)

SpringerImages - Search: lung ct with fibrosis

SpringerImages

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lung ct with fibrosis Search caption [Show advanced options](#)

REFINE MY SEARCH

Search within these results

IMAGE TYPE what's this?

☒ Image ☒ Table

☒ Line Art ☒ Video

☒ Color ☒ Black & White

☐ Only accessible images (free + subscribed)

SUBJECTS what's this?

Medicine & Public Health	40
Imaging / Radiology	22
Diagnostic Radiology	17
Neuroradiology	16

SEARCH RESULTS

41 RESULTS >> [Save this search](#)

You searched for: lung ct with fibrosis [REMOVE](#)

Zoom: Sort by: Relevancy Display: 25 | 50 | 100

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SAVED SEARCHES

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Goldminer.arrs.org (249,000 images)



GoldMiner About Us Advanced Search GoldMiner Global "Top 40" Images

270 images Filter: Modality Age Sex Reset 1 - 10 Next »

CT Recurrent malignancy. Image from a 74-year-old woman with history of middle lobe NSCLC cancer 4 years ... (74y F)
Proc Am Thorac Soc Prognosis and reevaluation of lung cancer by positron emission tomography imaging.

CT CT-scan, mediastinal window. -- The bifurcation of the pulmonary artery appears distended and enlarged probably due to the ... (57y M)
EuroRAD Right Heart Failure in Idiopathic Pulmonary Fibrosis.

CT CT-scan, lung window. -- The subpleural and peribronchovascular interstitium exhibits emphysema with multiple bullae. (57y M)
EuroRAD Right Heart Failure in Idiopathic Pulmonary Fibrosis.

CT CT-scan, lung window. -- Multiple central and peripheral traction bronchiectases are clearly demonstrated in both lungs. (57y M)
EuroRAD Right Heart Failure in Idiopathic Pulmonary Fibrosis.

CT CT-scan, lung window. -- Lung window shows diffuse interstitial thickening of pulmonary apex in both lungs. (57y M)
EuroRAD Right Heart Failure in Idiopathic Pulmonary Fibrosis.

CT Axial cross-section HR-CT images (right side) -- HR-CT images show extensive fibrosis at the base of the right lung.

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medgift.hevs.ch/, demos (300,000 images)





[Detection of emphysema progression in alpha 1-antitrypsin deficiency using CT densitometry: Methodological advances](#)
2008-2-13 Respiratory Research
Computer tomography (CT) densitometry is a potential tool for detecting the progression of emphysema but the optimum methodology is uncertain. The level of inspiration affects reproducibility but the ability to adjust for this variable is facilitated by whole lung scanning methods. However, emphysema is frequently localised to sub-regions of the lung and targeted densitometric sampling may be more informative than whole lung assessment.






[View full abstract](#) [Article in PDF-Version](#) [View all images / Visual search](#) [Similar articles](#)
Authors: David G.Pam Martin Severnoka Chunqin Deng Berend C Staal Robert A Stockley
<http://respiratory-research.com>


[Bronchiolitis obliterans organizing pneumonia \(BOOP\) after thoracic radiotherapy for breast carcinoma](#)
2007-1-03 Radiation Oncology
Common complications of thoracic radiotherapy include esophagitis and radiation pneumonitis. However, it is important to be aware of uncommon post-radiotherapy complications such as bronchiolitis obliterans organizing pneumonia (BOOP). We report on two patients with carcinoma of the breast who developed an interstitial lung disease consistent with BOOP. BOOP responds to treatment with corticosteroids and the prognosis is generally good despite the need for long-term administration of corticoids...

[View full abstract](#) [Article in PDF-Version](#) [View all images / Visual search](#) [Similar articles](#)
Authors: Robin Cornelissen Suresh Senan Imogen E Antonisse Hauw Liem Youke K Aerts
<http://www.ro-journal.com>



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www.yottalook.com (70,000 images) 

Yottalook
Images


Web Images Journals Books Anatomy

lung CT with fibrosis


Detailed Thumbnails Only

Related terms: pulmonary - (powered by Yottalook)


Radiograph: 0 CT: 554 MR: 0 NM: 0 US: 0 [Show All](#) No Subscription Mode: [ON](#) | [OFF](#) 1 to 10 results out of 554 for lung CT with fibrosis

 Fig. 6B -51-year-old man after lung transplant for cystic fibrosis. Patient had free air on routine chest radiograph and no abdominal symptoms and normal laboratory results-benign cause of pneumotosis intestinalis (PI). Digital abdominal radiograph (A) and abdominal CT images (B and C) show free air (arrows, A and B) and...


From ASP: [Pneumotosis intestinalis in the Adult: Benign to Life-Threatening Causes](#) | [View all images from this article](#)


 Fig. 6C -51-year-old man after lung transplant for cystic fibrosis. Patient had free air on routine chest radiograph and no abdominal symptoms and normal laboratory results-benign cause of pneumotosis intestinalis (PI). Digital abdominal radiograph (A) and abdominal CT images (B and C) show free air (arrows, A and B) and...

From ASP: [Pneumotosis intestinalis in the Adult: Benign to Life-Threatening Causes](#) | [View all images from this article](#)

 Figure 9a. Focal interstitial fibrosis in a 40-year-old woman. (a) Thin-section CT image at the level of the superior segmental bronchus shows a 25 mm well-defined nodular ground-glass opacity with no solid component in the lower lobe of the left lung.

From RadioGraphics: [Nodular Ground-Glass Opacity at Thin-Section CT: Histologic Correlation and Evaluation of Chance at Follow-up](#) | [View all images from this article](#)

 Figure 14a. Pseudonodule in a 56-year-old woman who underwent a previous percutaneous lung biopsy. (a) Thin-section CT image obtained at the level of the aortic arch shows a 9 mm well-defined nodular ground-glass opacity (arrow) in the right upper lobe.



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Who searches for medical images and how?

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Background



- Health professionals' **image search behavior** has been subject to several surveys and log file analyses (MedLine, HONmedia, Goldminer)
- **Goldminer** log files of over 200'000 searches most comprehensive so far
- Khresmoi project performed a **survey among radiologists** to develop first prototypes
- Results change over time as user requirements change with the generation of physicians
 - Current medical students grow up with Google, Facebook and iPhones

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Methods of Khresmoi survey



- Survey among radiologists, mainly in Geneva and Vienna University hospitals
 - Paper and electronic version
 - Survey filled in with a person explaining the goals
 - Survey took approximately 1 hour, research/clinical /teaching work separated with same questions
- **26 radiologists** answered, 13 from **Austria**, 9 from **Switzerland**, form only sent on invitation
- 17 males, 9 females, mainly 26-35 years, few years of experience

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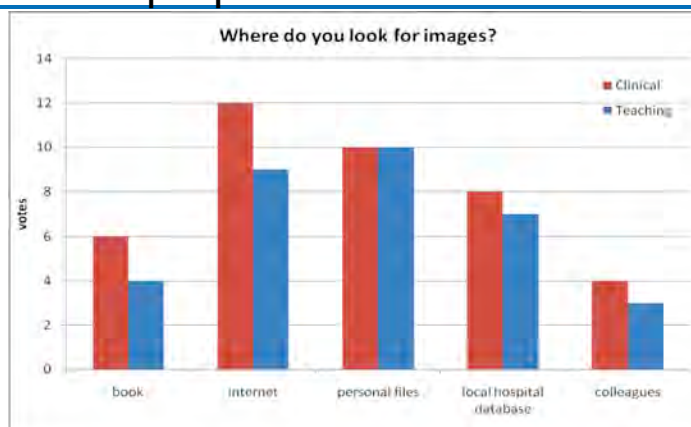
Reasons for image search



- Clinicians: Information on unclear cases, illustrate presentations, **differential diagnosis** were most frequent
- Teaching: Find **similar cases**, for example an easy, a medium and a tricky case for the same disease, problem-based learning
- Problem-based learning requires increased search skills for the students

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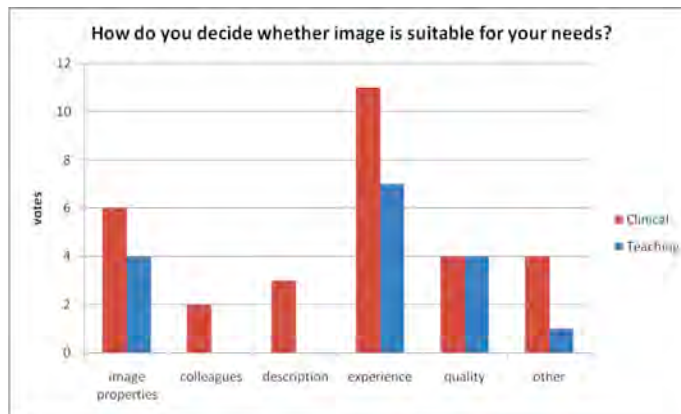
Where people search



- The **Internet** replaces books and colleagues
- Personal files are not always optimal

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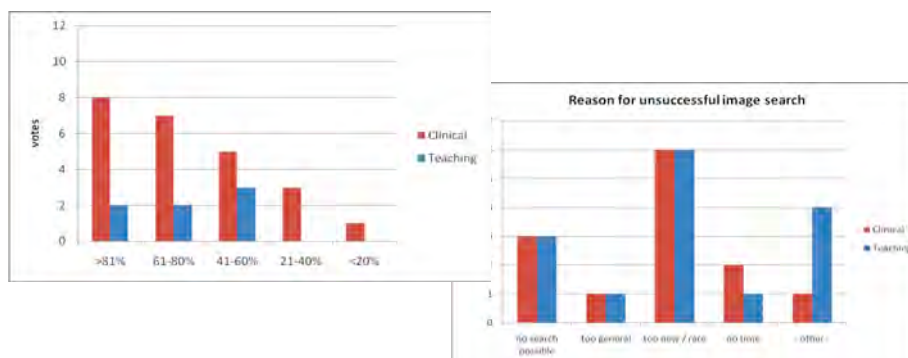
Determination of relevance



- Experience determines relevance
- Often additional **proof** such as biopsies or other clinical tests are requested

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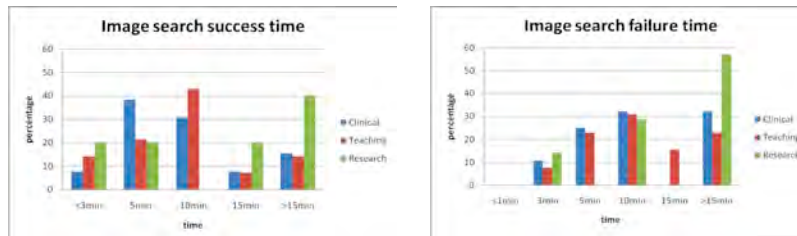
Success rates



- For teaching success rates are higher
- Clinical work might have less well defined tasks, average of success at 60%

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Search time



- 70% of successful searches less than ten minutes
- Failure often after over 15 minutes
- Less time available for clinical search than research/teaching
- Could a **faster and more targeted** image search system help?

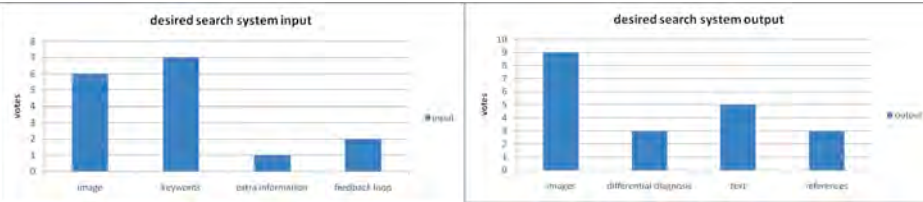
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Useful additions

- Search by
 - pathology (13 times)
 - modality (10 times)
 - patient demography (6 times)
 - **similar images** (8 times)
- Other comments:
 - Multilingual retrieval
 - Pathology classification (using **ontologies**)
 - Search in 3D data
 - Confidence in the diagnosis

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A perfect search system



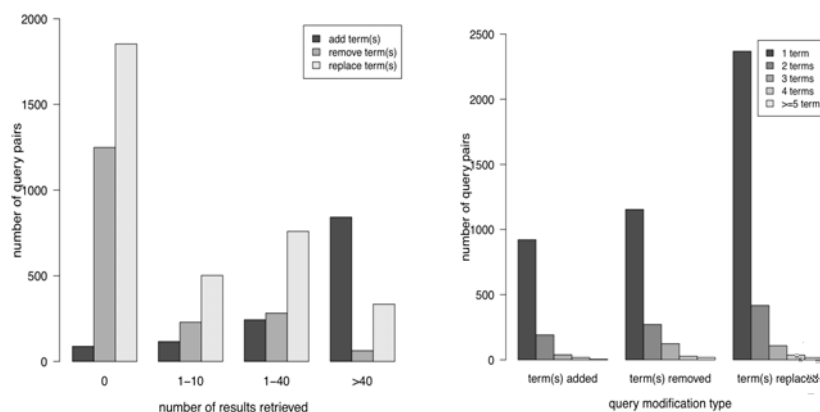
- Many free comments
 - Like Google but DICOM and text
 - Structure information and confidence in diagnosis
 - Search by **regions of interest**
 - Social networking, comments of other physicians
 - Search for **similar cases**
 - **Quantification** of structures (size, volume)

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Goldminer log files



- Monday 12h15, talk on the analysis
- 25'000 consecutive queries



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Combining text and visual search

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Background



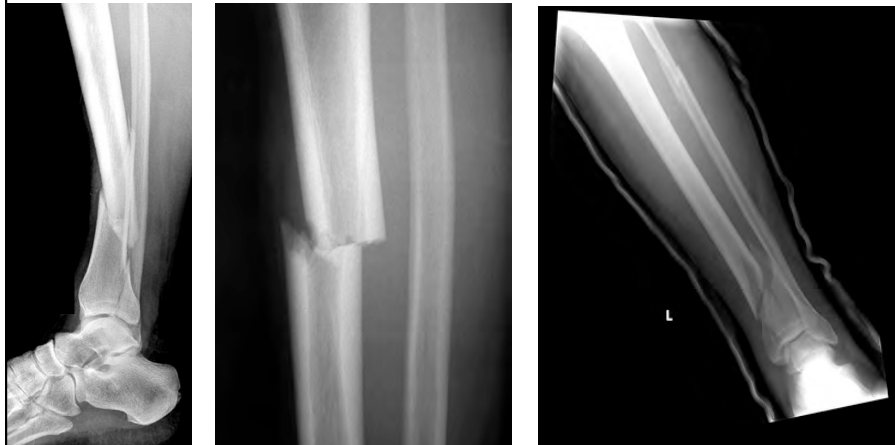
- ImageCLEF image retrieval benchmark has been run each year since 2004
- 12-20 research groups compare their tools and approaches on the same tasks and DBs
 - Visual, textual and combined approaches are used
 - Multilingual approaches are also possible
- Sometimes visual, sometimes textual and sometimes mixed approaches perform best
 - No clear outcome
 - Combination of results can be delicate, instable

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Example search topic



- Show me x-ray images of a tibia with a fracture.
- Zeige mir Röntgenbilder einer gebrochenen Tibia.
- Montre-moi des radiographies du tibia avec fracture.



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Visual vs. semantic vs. mixed searches



- Experts can **predict** what **type of technique** will most likely perform best
 - Can this prediction be modeled automatically?
 - If results were visually relatively homogeneous **visual** search can work
 - Same anatomic region, same view, same modality
 - If results are expected to be very different (no modality given), **text** would work best
 - **Combinations** often work best when some common aspects but some variability as same modality
- Visual and text retrieval are complementary

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Early vs. late fusion



- **Early fusion**
 - **Feature** spaces are directly combined, so visual features and textual words treated in the same way
 - Number of features needs to be similar to avoid bias
- **Late fusion**
 - **Results** of systems are combined, not features
 - Each system can have a varying number of features
- For text/visual combinations late fusion is often simpler to employ and works better
 - When using visual words both could be used

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Score based vs. rank-based fusion



- **Score-based fusion**
 - Score of the single systems is used for the combination of the results sets
 - Score needs to be normalized, potentially to have similar characteristics
- **Rank-based fusion**
 - The rank of an element is used to calculate fusion
 - Can be linear or logarithmic or in another form
 - Avoids the bias that very differing results sets of system can have
 - Often have better results when visual and textual systems are combined

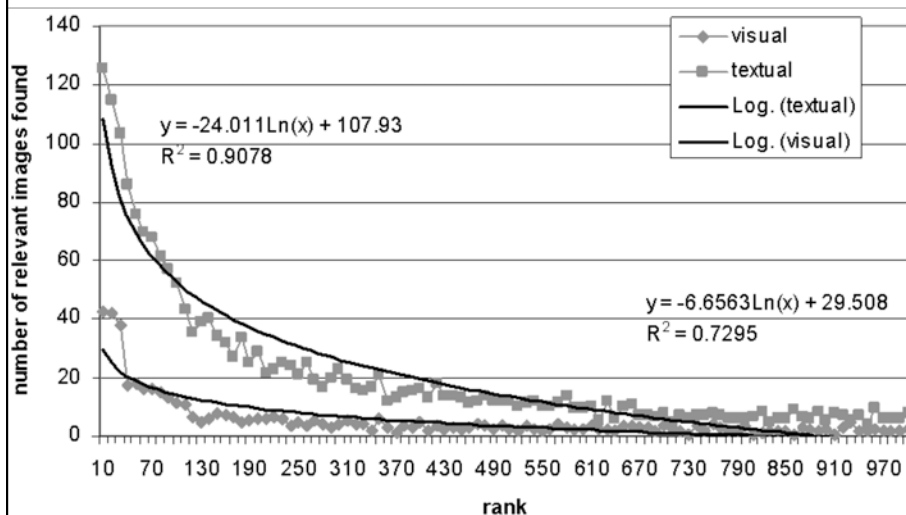
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Types of fusion techniques

- Many types of fusion techniques exist
 - combSUM : $V_{\text{combSUM}}(i) = \sum_k V_k(i)$
 - combMAX : $V_{\text{combMAX}}(i) = \text{argmax}(V_k(i))$
 - combMNZ : $V_{\text{combMNZ}}(i) = f(i) \cdot V_{\text{combSUM}}(i)$
 - Where $f(i)$ is the frequency of image i in the results
- At the ICPR 2010 conference a **competition on fusion** techniques was organized using the best ImageCLEF runs
 - Rank-based techniques using logarithmic decrease performed best in a variety of different approaches

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Distribution of relevant documents



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Other combinations



- Modality detection (using visual techniques or text of the captions) can work very well (80+%)
- Allowing to select the **target modality** can improve image search
 - Tests with all runs of ImageCLEF 2009
 - Many search engines allow for this such as Goldminer
 - This can be used for tabbed browsing as well
- **Exclusion criteria** for images can be chosen based on the text
 - Age group, gender, ...

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Combinations for **case-based** retrieval



- **Mix** of free text, structured data, images, and many other forms
- **Interactions** of the data can vary strongly between patients and diseases, also over time
- More **complex combinations** for images need to be found
 - Match images between case to match for similarity
- Currently text is better than most fusions
- Case description including images without diagnosis, find images for differential diagnosis

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Some ImageCLEF lessons learned



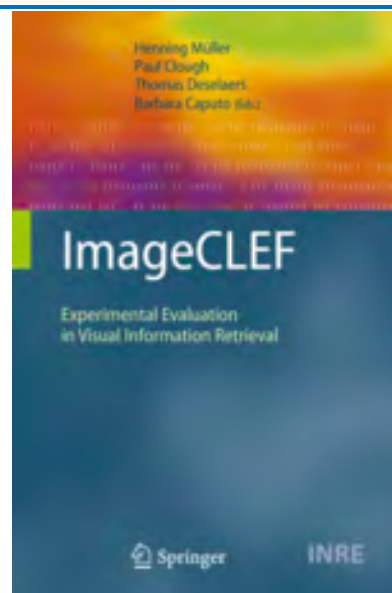
- **Text** retrieval techniques are **stable** and deliver **good** results (i.e. Lucene is above average)
- Visual has had less evolution than text retrieval
 - **GIFT** (old!) has still relatively good results
 - Semantic gap is very present
 - **Visual words**-based approaches can be much better when using high quality training data
- **Interactive** retrieval can improve visual retrieval
- Many features combined deliver best results
- Mapping of images and text to ontologies can help
 - Improve **semantic** retrieval

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Attention: advertisement



- ImageCLEF book
- All on **image retrieval**
 - Methods of evaluation
 - Task overviews
 - Participant reports
 - The best techniques
 - Industrial requirements
 - Industry perspectives
 - Specific techniques such as **fusion**



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Challenges for search?

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BIG data

- How can **scalability** be assured when treating extremely large amounts data?
 - 250'000 images per day in Geneva ...
 - 150 TB of images in Catalonia archive
 - Extremely large scales allow solving many new problems
 - Rare diseases
 - Sufficiently large training data sets
- **Hadoop/Mapreduce** as is also used by Google, Yahoo or Facebook
- Use of **cloud** computing
 - Costs, confidentiality, also bandwidth ...

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Confidentiality



- Can patient records be made **available**?
 - Maybe partly, anonymized, only internally?
 - Could the data warehouse be used for this
 - Secondary use of data
- Availability for data mining not a specific very limited scenario (as ethics committees request)
- Can **interoperability** be assured using the same semantic standards
- How to link the literature with specific cases
 - Images not in the same quality, much more than just case descriptions, ...

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Search for medical cases not images



- Combine **several data sources**
 - Importance of each source is not fully clear
 - Interaction between content importance is complex
 - Different media from free text, structured data to semantics, signals or images including 3D, 4D
- Some **data** sources might be **missing**
 - Questions not asked, not documented, errors
 - How to deal with missing data
- What is a case exactly?
 - Limited period of time? Or on a patient basis including old data?

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Diversity in the results



- Having a list of almost identical texts as result is not useful
 - Google filters out near duplicates
- **Consistency** vs. **diversity** have limits
- Some search systems cluster results and the present each cluster in a first step
- Diversity can favor **data exploration** and user relevance feedback
- Understand links between documents and content in the results

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Retrieval from social networks



- People share data in social networks
 - Blogs, facebook, ...
 - Sometimes more than any physician would share
 - People with rare diseases are sometimes desperate ...
- People can **comment** on data
- Goals of comments are not always clear
 - **Spam** can create problems
- Some metadata is available, so free text, semi-structured metadata, images
 - Can semantics help with this?

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A medical blog on movement disorder



MONDAY, MARCH 7, 2011

A pleasant genetic appointment!



Bertrand takes his official ring bearer training VERY seriously!

Bertrand's "good news" roll continues! At today's genetic/metabolic follow-up, Bertrand was found to be "improved", much to the puzzlement and pleasure of his geneticist.

WEIGHT CHALLENGE

05/16/11 - 36lbs. 10oz.
04/11/11 - 37lbs. 10oz.
03/14/11 - 38lbs. 10oz.
03/07/11 - 39lbs. 10oz.

STANDER CHALLENGE

Since April - 1-2 hrs. daily!
04/03/11 - 53 min.
03/29/11 - 0 min.
03/28/11 - 23 min.
03/27/11 - 105 min.
03/26/11 - 0 min.
03/25/11 - 36 min.

ABOUT BERTRAND

Born in December 2007, Bertrand is a charming, serious, young man. He lives in Salt Lake City, UT and has global developmental delays (0-6 months-old), leukodystrophy, intractable multifocal epilepsy (Doose Syndrome), peripheral neuropathy, liver fibrosis, gastroesophageal reflux

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Patientslikeme



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Visceral project



- VISual Concept Extraction challenge in RAdioLogy
 - Most likely as a MICCAI workshop in 2013 and 2014
- Two challenges
 - Identify organs in 3D data sets
 - Find similar cases using 3D data and radiology reports
- Very large amounts of data (~10 TB)
 - Data distribution via the cloud
 - Participants will get a virtual machine for free
 - Creation of a gold and silver standard

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LinkedIn Khresmoi group



Most Popular Discussions



Alan
Unfollow

Why is medicine often not evidence based? (Ben Goldacre)
Many reasons are given, but the following paragraph applies to what KHRESMOI is aiming to do:
"while we do make an effort with ..."



Why is medicine often not evidence based?
bengoldacre.posterous.com
posted February 2, 2011

SarathChandra Kambhatla · 1 day ago · SarathChandra likes this.



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30% of world storage is estimated to be medical imaging
According to an EU report by now 30% of worldwide data storage is estimated to be medical imaging, more to be read in <http://cordis.euro...>
posted 27 days ago

Ali HOSSEINZADEH VAHID · 18 days ago · Ali likes this.



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Big data - and the access to them for scientists
The fact that companies often keep big data sets private but publish with them causes some problems for science.



works on a common policy for data sharing and citing data resources.
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Henning Müller started a discussion: WebMill - a tool for collaborative labeling of medical images
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A few references



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- ...

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Conclusions



- Medical information **search and access** is an important technique in medicine
 - And this includes images!!
- Image information is most often complementary to text
- **Visual information** such as regions of interest can be used to **formulate queries**
 - Radiologists request this increasingly instead of searching in books and discussing with colleagues
- There is still much to be learning for combining visual and textual techniques

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Questions?



- More **information** available from
 - <http://www.imageclef.org/>
 - <http://khresmoi.eu/>
 - <http://medgift.hevs.ch/>
 - **Contact** henning.mueller@hevs.ch



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