REPRESENTATION AND INDEXING OF MEDICAL IMAGES*

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Abstract: The interpretation of an image by the computer is a highly complex task. There is a huge gap between the human and computational understanding of images and its interpretation. In this paper we present some of the concepts involved in the representation, indexing and interpretation of computerized images, focusing on medical imaging. The representation of images by low-level features (such as color and texture) is described as well as the use of high-level features such as ontologies.
Keywords: Image representation; indexing; ontologies; image processing.

Título: REPRESENTACIÓN E INDIZACIÓN DE IMÁGENES MÉDICAS.
Resumen: La interpretación del significado de una imagen por el ordenador es una tarea muy compleja. Hay una brecha entre la comprensión humana y la comprensión computacional de su significado. En este trabajo se presentan algunos de los conceptos necesarios para la interpretación, representación e indización de imágenes computacionales, centrándose en imágenes médicas. Se describe la representación de imágenes con características de bajo nivel (como color y textura) y el uso de características de alto nivel, tales como ontologías.
Palabras clave: Representación de imágenes; indización; ontologías; procesamiento de imágenes.

1. INTRODUCTION

An image is typically a representation of the objects present in a real life scene. Film photography, for example, is the result of a chemical reaction between the light reflected from the subjects at the scene and the light-sensitive emulsion of the film. In the process of image acquisition, much of the original information present on the real object is lost. In

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a portrait, for example, three-dimensional information is not present. Also, fine details of the object are missing, because of the limited resolution of any camera. So, the image is only an *approximation* of a real object and there is always an error that separates the image and the real object.

Images can be used to infer information about the real object. For example, in industry it is common to perform the automatic inspection of products, such as printed circuit boards, LCDs and transistors, using images (this is called Automated Optical Inspection or AOI). In order to be able to perform a computational processing of images it is necessary first to convert them into digital format.

This is done by representing the image as a set of discrete numbers in a particular order. In a digital photo, the image is represented as a matrix of values, called pixels. Mathematically, an image can be represented as a function I = f (x, y). That is, the image intensity (I) is a function that varies with the position (x and y). In Figure 1 a graphical representation of the matrix is shown.

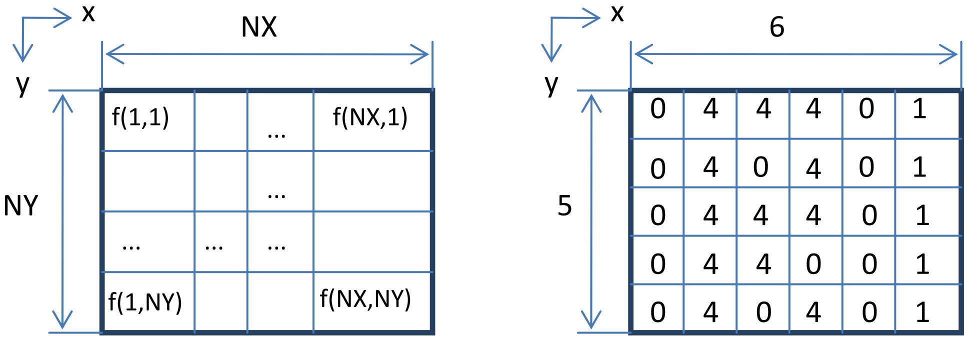


Figure 1. (L) Mathematical representation of an image. Nx is the dimension in the x axis and Ny is the dimension in the y axis (R) Sample of a 6x5 image.

With the popularity of digital cameras and recording devices there is a growing number of images stored, which creates the problem of how to find a particular image or set of images in the middle of thousands and perhaps millions of images. This problem also happens in companies and industries that have images as their main focus (e.g., television). The solution is to index the images. Indexing is the technique of creating shortcuts that allow images to be found more easily. The most traditional way to index images is to manually add labels or keywords for each image. Through the use of labels it is possible to find a whole set of images of interest (e.g.: all images labeled ‘cat’). However, when several people are indexing a large set of data, some problems arise:

a. Vocabulary. Each person has a tendency to use a certain vocabulary, which can vary over time. Thus, a person can, for example, classify an image as a "car" in one day and "vehicle" in another day. This can be minimized with the adoption of standardized vocabularies.

b. Object of interest. If an image is initially classified as "car" and in a future search the desired object is "Volkswagen’s car", then the entire set of images must be reindexed.
c. Volume. If images are mass produced, a lot of people are necessary to index them, which increases the probability of error and raises the costs, maybe even making it impractical to do the manual indexing.

These difficulties naturally led for the search of techniques for automatic image indexing. There are many ways to perform automatic indexing, and they can be roughly grouped into three categories:

a. Indexing metadata. It is applied when the image has an associated text that can be used to index it. A typical example is the indexing of images from the Internet, which often have a text describing or referencing them. The name of the image can also be used as a search key.
b. Indexing features of the image. In this category only the characteristics of the pixels are taken into account for the indexing task. Search samples are: find images with size 300x400 pixels, whose predominant color is red; find images that are similar to a particular example.
c. Composed indexing. Uses both meta-information and features to index the images. An example is shown in Figure 2. Google images allow textual search and provide refining using characteristics of the image, such as color and size.

The automatic indexing of images is beneficial in certain cases, but it is not as accurate as manual indexing. The main reason is due to the gap between the semantic representation of the computer image and its meaning (SMEULDERS, 2000). As an example, Figure 3 shows two representations of the same digital image. On the left the intensities are displayed as gray levels while on the right the intensities are displayed as amplitudes in the z axis. The image on the left is immediately understood and interpreted by the brain, while the other can hardly be interpreted, despite the fact that it contains the same information.

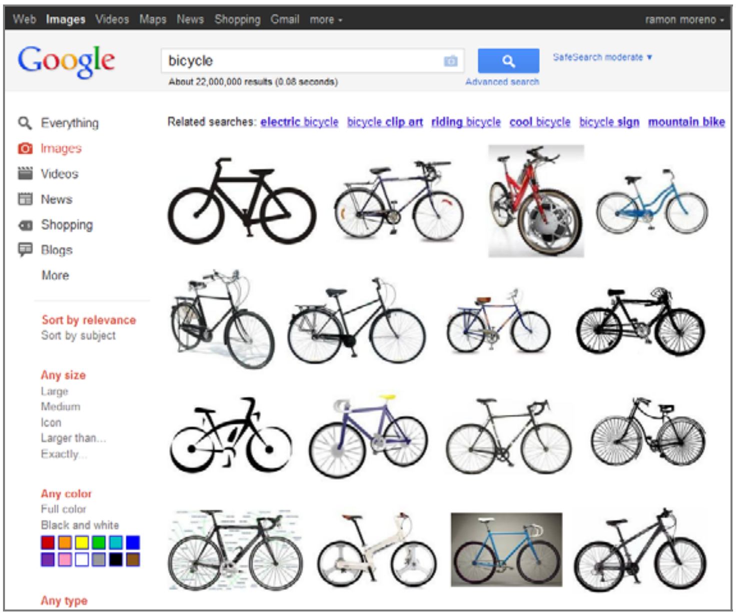


Figure 2. Advanced image search offered by Google Images™.

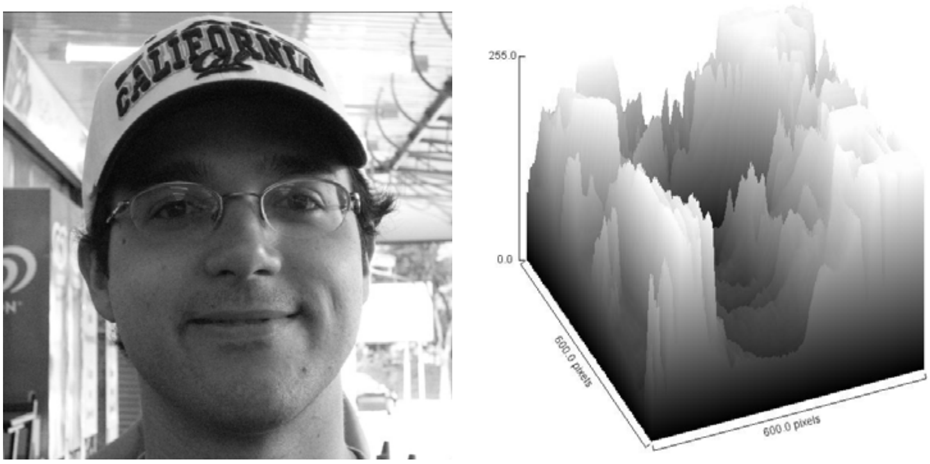


Figure 3. Same image shown in two different ways: (L) intensities represented as gray levels; (R) intensities represented as amplitudes in the z axis (image generated using ImageJ[1]).

This difference occurs because the process of interpretation of an image depends on pre-established information (i.e., prior knowledge). Thus, the first image is recognized by the reader because throughout his life there was a process of learning to recognize this pattern, which does not happen with the second image. The same challenge exists for the computer that only sees the images as numbers without an immediate understanding of its true meaning, making the indexing of the information difficult.

Another issue that influences the indexing of images is the user expectation regarding the response of a query. This can be seen, for example, when performing searches for the word "java". Figure 4 shows the result of the search in the Google search engine, whose main results are related to the programming language called Java and software built using this language. However, if the user was looking for information about the Indonesian island Java there is a disappointment with the results obtained.

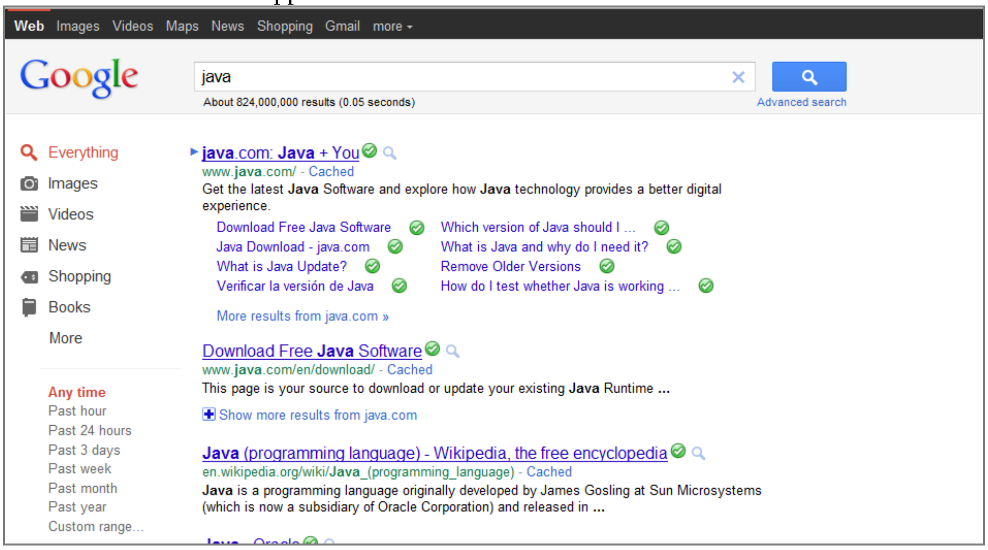


Figure 4. Search results of Google Search ™ using the word "java".

In this example, the user can easily disambiguate the results by introducing the term "island" in the search. A problem that arises when the indexing is performed using image features is the difficulty to know which parameter should be used to disambiguate the result of a search. For example, if the user wants to search for images of Volkswagen' cars it is difficult to decide which parameter separates the images of general cars and cars from Volkswagen.

One solution adopted to minimize the problems with the automatic indexing of images is to limit the scope of the application. Thus, instead of indexing any type of image, it is possible to index, for example, only images of cars. When the scope is limited, it is possible to insert *a priori* knowledge in the indexing tool. In the example of cars, this could be done by searching for the Volkswagen "W" symbol or another specific shape, and try to categorize the type of car according to the chosen feature.

Another way to reduce the semantic gap is to use the technique of relevance feedback. In this technique the user selects among the items returned by the search those he or she considers the most relevant to the search. Based on the user's feedback, the search is refined, thus trying to increase the number of relevant results.

One of the most important elements for indexing and retrieving of images is effectively determining the similarity between two images. The similarity can be determined by:

a. Definition of criteria of similarity
b. Definition of characteristics to be compared
c. Establishing metrics to compare the features

For example, in Figure 5 images of a cat, a dog and a possum are presented. If one considers the similarity criterion as the presence of four feet, then three images are highly similar. On the other side, if the criterion is the shape of the tail, the images are considered different.

Figure 5. Definition of similarity for images. How similar are the three images? (L) Siamese cat[2]. (C) German Shepherd; (R) Possum.

Computationally, the similarity between images can be defined by using mathematical tools to extract image features that can be used as elements of comparison (BUENO, 2002). A simple feature that can be used to represent an image is its histogram, which is a graph distribution of the intensities in an image. The intensity values that occur in the image are represented in the x-axis while the y-axis shows the number of times each value occurred in the image. Figure 6 depicts the histograms corresponding to the three images of Figure 5, with images resized to be the same size and converted to grayscale.

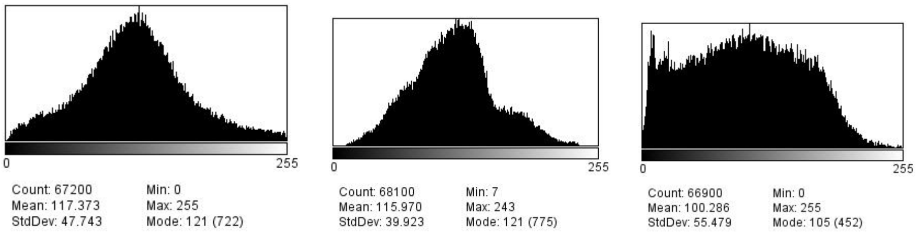


Figure 6. Histograms of the images from Figure 5, calculated using the ImageJ program. In order to obtain the graphs, the images were resized to the same size and converted to grayscale. (L) Cat histogram; (C) Dog histogram; (R) Possum's histogram.

Besides defining how to represent an image it is also important to establish a metric to determine quantitatively the difference between the features chosen for the task, in this case two histograms. A possible metric can be created by computing the sum of absolute differences between the histograms, as represented visually in Figure 7, in which the distance is given by the sum of the differences hatched (rightmost graph).

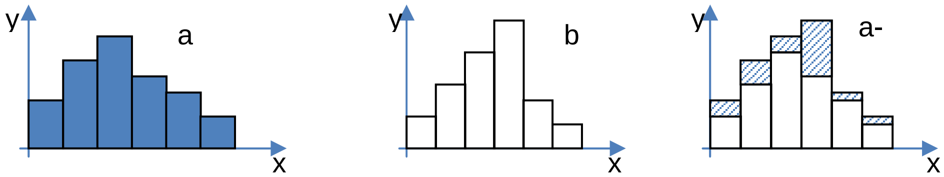


Figure 7. Sample of a metric to calculate the similarity between two histograms. (L) Histogram A; (C) Histogram B; (R) Difference between histograms A and B.

As the comparison is made between images with different distributions of intensity, it is necessary to normalize the histograms in order to compare them in equal terms. Equation 1 presents a normalization function in which the area of the histograms is normalized to have value 1.

$$dif(a,b) = \sum_{i=0}^{N-1} \left| \frac{histA[i]}{\sum_{j=0}^{N-1} histA[j]} - \frac{histB[i]}{\sum_{k=0}^{N-1} histB[k]} \right|$$

Equation 1

The application of the previous formula to the histograms shown in Figure 6 allows the calculation of the distance between the images. The difference between the images of the cat and the dog is 0.19; between the cat and the skunk is 0.42 and; between the dog and the skunk is 0.49. This result corresponds to the visual qualitative inspection we have in relation to the histograms in Figure 6 that the images of the cat and the dog are the most similar. This distance applies to the criteria established by the histogram, but may not necessarily correspond to the result expected by the user when observing the original images.

There are numerous mathematical manipulations that can be performed on the images (using transforms, segmentation, thresholding, etc.) (GONZALEZ, 2007) as well as there are also numerous possible distance measures definitions. In order to obtain the best classifiers, usually an annotated image database (a gold standard) is used to fit the parameters that best discriminate each class present in the studied set (SILVA, 2006).

2. MEDICAL IMAGES

Medical images are representations of reality, obtained by some kind of energy that interacts with atoms and molecules of the human body and can be recorded in analog or digital media. A common example of a medical imaging procedure is the prenatal exam, where the fetus representation is obtained by using ultrasound waves.

Medical images are used by different health professionals and their main purpose is the diagnosis and treatment of patients (CHO, 1993).Usually the medical images are classified into groups, called modalities, according to the physical principle that generated them.

The main imaging modalities are (WEBB, 1993):

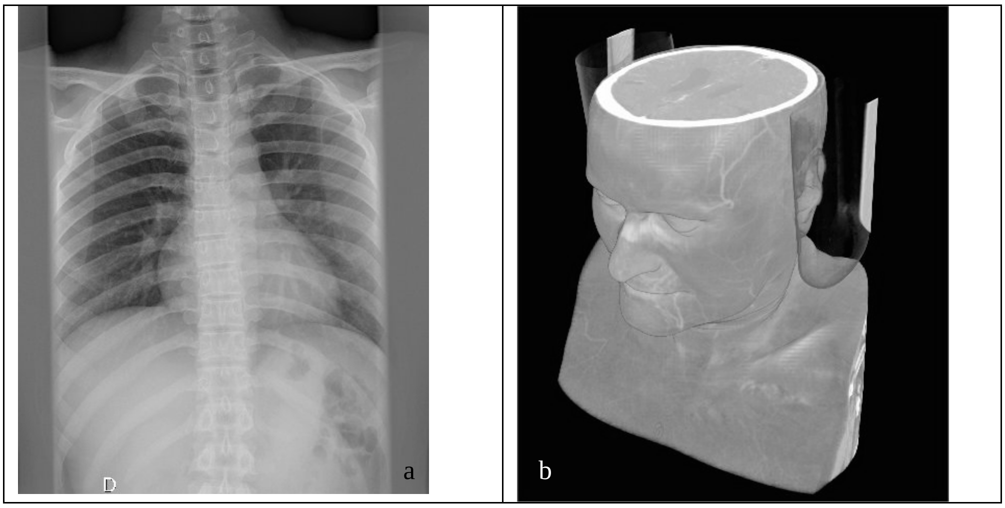
1. **X-Rays.** The x-ray is an ionizing electromagnetic radiation discovered by Röntgen in 1895. This radiation is attenuated according to the density of the material it goes through. Using this feature, it is possible to obtain information about the internal structure of an object. Ionizing radiation can damage cells and affect the genetic material (DNA). Therefore, exposure to this radiation should always be kept to a minimum. Some types of medical imaging using x-rays are: mammography, angiography and computed tomography. CT scans generate axial slices that can be reconstructed to obtain three-dimensional images of the patient. Angiography images can record dynamic images of blood vessels by means of a contrast injected into the patient.
2. **Nuclear Medicine.** Uses radioactive isotopes for diagnosis and treatment of diseases. The images are obtained with the use of radiopharmaceuticals administered to patients. Radiopharmaceuticals are substances that interact with the body and are marked by a radioactive substance. As radiopharmaceuticals are processed by the body, it is possible to obtain information about the functioning of the body (functional imaging). The main types of nuclear medicine images are SPECT (Single Positron Emission Tomography) and PET (Positron Emission Tomography).
3. **Nuclear Magnetic Resonance (MRI).** Produces medical images through the stimulation of nuclei of hydrogen through a combination of magnetic fields and radiofrequency pulses. MRI devices do not use ionizing radiation and can generate images in any orientation, unlike other techniques such as CT, SPECT and PET,

which only generate images in the axial plane. The sequence of radiofrequency pulses used can produce images with different contrasts, enhancing different structures of the body.

4. **Ultrasound.** It uses high frequency sound pulses that are sent into the body by a transducer. An echo is generated at the intersection between materials of different sound conductivity.This echo is picked up by the transducer allowing the construction of an image of the examined body part. Compared to the other imaging modalities, the ultrasound tests are less expensive and more versatile. Nowadays four-dimensional (4D - 3 spatial dimensions plus time) images can be generated in real time

Medical images can be characterized by different parameters such as resolution, dimensionality, noise type, and type of organ visualized. For example, images of conventional X-rays have high spatial resolution, 2000 to 3000 pixels and high depth, typically 12 bits, allowing up to 4,096 different gray levels. On the other side, conventional computer monitors can only display 256 shades of gray.

Figure 8 displays some examples of medical images from different modalities.



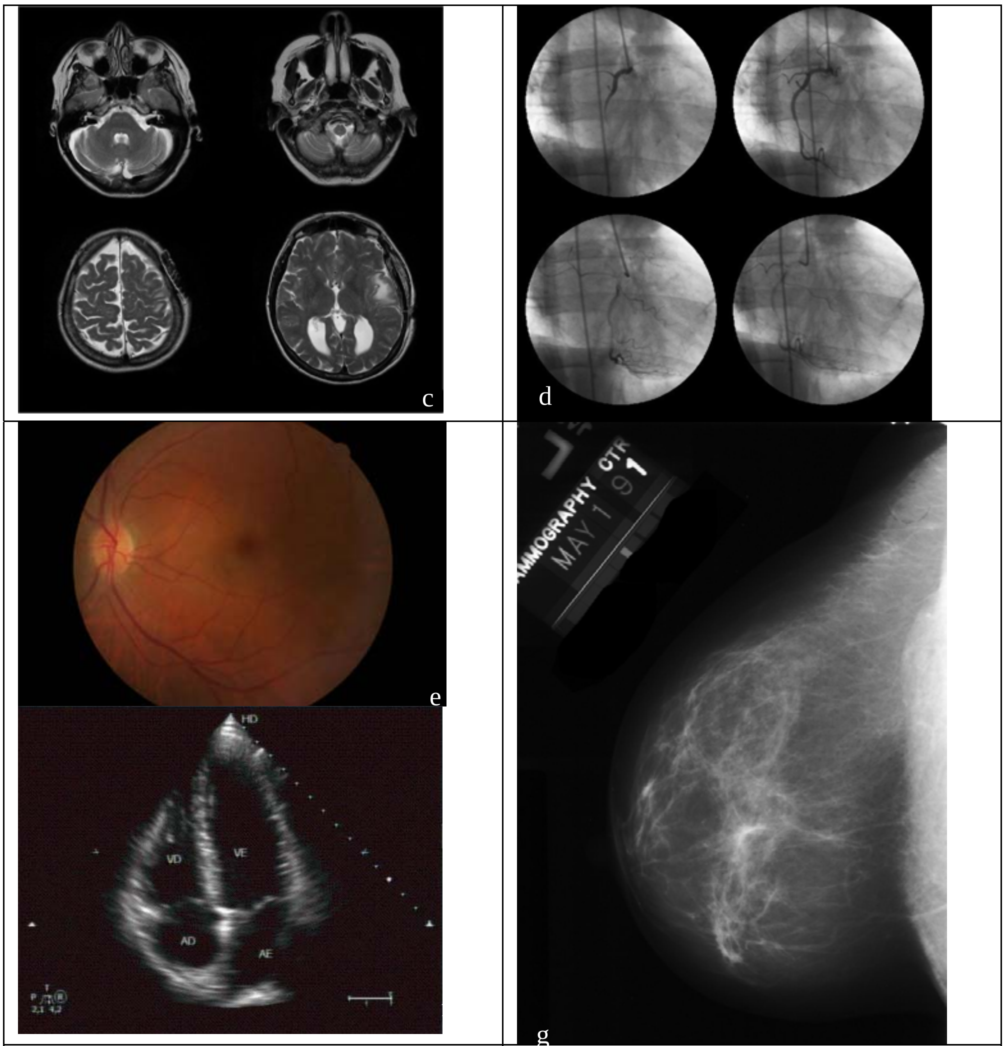


Figure 8. a) Torax X-Ray[3]; b) 3D rendering of a Computed Tomography head scan3; c) Brain axial slices of Magnetic Resonance3; d) Different time frames of an angiography3; e) Retinal scan[4]; f) Heart ultrasound; g) Mammography[5].

3. MEDICAL IMAGES WORKFLOW AND PACS

Medical images are generated by dedicated equipment and are used as part of routine inside the hospitals (MASSAD, 2003). In general the images are sent and stored on a central server through a Picture, Archiving and Communication System (PACS)

(HUANG, 2000), from which they can be retrieved for elaboration of the report or future inspections. A key point is that medical images are involved in a context of the patient care and have a precise meaning inside the flow of the hospital. The hospital's flow of information is complex and varies from patient to patient. This complexity is due to the non-trivial nature of patient care. An example of workflow in a radiology department is shown in Figure 9.

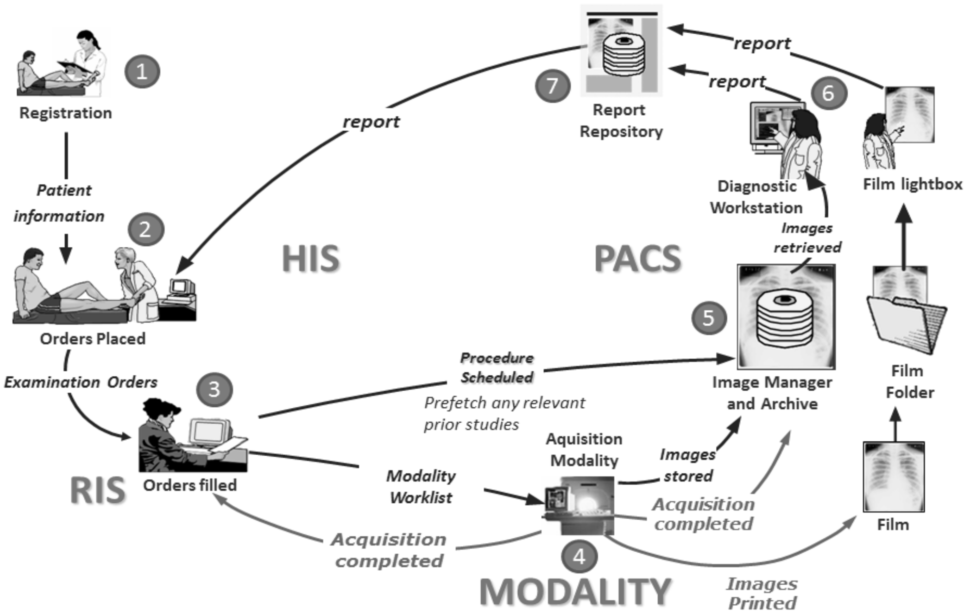


Figure 9. Workflow in a radiology department. Adapted from Andrei Leontiev IHE (*Integrating the Healthcare Enterprise*) presentation[6].

Figure 9 shows the following sequence flow: (1) the patient is admitted for a consultation; (2) The physician requests image exams; (3) The request is registered on the Radiology Information System (RIS); (4) The image exam is performed using demographic information already registered on the system; (5) The images are transmitted to the PACS; (6) the Radiologists can retrieve and visualize the patients' exam and (7) write a report for the image. This information goes back to the clinician who originally requested the exams (2), allowing him/her to diagnosis the patient or request new exams.

The acquisition workflow allows that the images have useful meta-information. Besides information about the patient such as name, age, sex, there is also information about the procedure like imaged organ, imaging protocol, image resolution. This meta-information can be used for image recovery. However, there are some cases when the meta-information is not enough for an extensive recovery or there is a need for new applications (MULLER, 2004):

a. Information fulfilled during the acquisition of the images is wrong, incomplete or not standardized, leading to errors during image recovery.
b. The use of indexing techniques by content can provide data to support certain diagnoses (for example, case-based reasoning (AAMODT, 1994) and evidence based medicine (TIMMERMANS, 2005)) that would not be found in regular searches. In this case, additional information is needed for recovery.
c. Teaching and clinical research can benefit from search by visual features. For example, it is possible to find cases where there are similarities between images, but with differences in their diagnosis.

The report associated with an imaging exam contains summarized information about the images, which can assist in their indexing. Usually the report consists of: patient history, procedure performed, results and conclusions. A report may be represented computationally in a structured or unstructured way.

The unstructured report, as the one presented in Figure 10, consists of a text in which the radiologist can type any sentence in any order he/she wants, using natural language. A common variation of unstructured report is one that is generated from pre-programmed sentences that can be changed arbitrarily by the user.

FINDINGS/INTERVENTIONS:
LEFT VENTRICULOGRAPHY: The overall left ventricular systolic function is mildly reduced. Left ventricular ejection fraction is 40% by left ventriculogram. Mild hypokinesis of the anterior wall of the left ventricle. There was no transaortic gradient. Mitral valve regurgitation is not seen.

LEFT MAIN CORONARY ARTERY: There were no obstructing lesions in the left main coronary artery. Blood flow appeared normal.

LEFT ANTERIOR DESCENDING ARTERY: There was a 95%, discrete stenosis in the mid left anterior descending artery. A drug eluting, Boston Sci Taxus RX Stent 3.0mm x 32mm stent was placed in the mid left anterior descending artery and post-dilated to 3.5 mm. Post-procedure stenosis was 0%. There was no dissection and no perforation.

LEFT CIRCUMFLEX ARTERY: There was a 50%, diffuse stenosis in the left circumflex artery.

RIGHT CORONARY ARTERY: The right coronary artery is dominant to the posterior circulation. There were no obstructing lesions in the right coronary artery. Blood flow appeared normal.

IMPRESSION:
1. Severe two-vessel coronary artery disease.
2. Severe left anterior descending coronary artery disease. There was a 95% mid left anterior descending artery stenosis. The lesion was successfully stented.
3. Moderate left circumflex artery disease. There was a 50% left circumflex artery stenosis. Intervention not warranted.
4. The overall left ventricular systolic function is mildly reduced with ejection fraction of 40%. Mild hypokinesis of the anterior wall of the left ventricle.

Figure 10. Excerpt from a non-structured report[7].

In a structured report the information is divided into several fields, arranged in a pre-definite pattern. Figures 11 and 12 present examples of structured reports. Each field of the report can be further subdivided into smaller fields or contain plain text.

The use of structured and coded reports facilitates the computational interpretation of the information contained in the report. Coded items have a well-defined meaning. For example, the code D-14800 from SNOMED[8] has a specific meaning for the diagnosis of tuberculosis while the code T-28000 refers to the anatomical location of the lung. Thus, the interpretation of the meaning of the report becomes more accurate. The computational interpretation of unstructured reports requires the use of indexing techniques such as inverse document frequency (JONES, 1972) or natural language processing (NLP) (HRIPCSAK, 1995; BACIC, 2007; CASTILLA, 2007). These techniques, however, fail to capture all the original information contained at the report.

```xml
<?xml version="1.0"?>
<report>
    <...>
    <findings>
        <finding type="LEFT VENTRICULOGRAPHY">The overall left ventricular systolic function
        is mildly reduced. Left ventricular ejection fraction is 40% by left ventriculogram.
        Mild hypokinesis of the anterior wall of the left ventricle. There was no
        transaortic gradient. Mitral valve regurgitation is not seen.</finding>

        <finding type="LEFT MAIN CORONARY ARTERY">There were no obstructing lesions in the
        left main coronary artery. Blood flow appeared normal.</finding>

        <finding type="LEFT ANTERIOR DESCENDING ARTERY">There was a 95%, discrete stenosis
        in the mid left anterior descending artery. A drug eluting, Boston Sci Taxus RX
        Stent 3.0mm x 32mm stent was placed in the mid left anterior descending artery and
        post-dilated to 3.5 mm. Post-procedure stenosis was 0%. There was no dissection and
        no perforation.</finding>

        <finding type="LEFT CIRCUMFLEX ARTERY">There was a 50%, diffuse stenosis in the left
        circumflex artery.</finding>

        <finding type="RIGHT CORONARY ARTERY">The right coronary artery is dominant to the
        posterior circulation. There were no obstructing lesions in the right coronary
        artery. Blood flow appeared normal.</finding>
    </findings>
    <conclusions>
        <conclusion>Severe two-vessel coronary artery disease.</conclusion>
        <conclusion>Severe left anterior descending coronary artery disease. There was a 95%
        mid left anterior descending artery stenosis. The lesion was successfully stented.
        </conclusion>
        <conclusion>Moderate left circumflex artery disease. There was a 50% left circumflex
        artery stenosis. Intervention not warranted.</conclusion>
        <conclusion>The overall left ventricular systolic function is mildly reduced with
        ejection fraction of 40%. Mild hypokinesis of the anterior wall of the left
        ventricle.</conclusion>
    <conclusions>
</report>
```

Figure 11. Example of a structured report in XML[9].

```xml
<?xml version="1.0"?>
<sequence>
  <element tag="0040,a160" vr="UT" vm="1" len="1038" name="TextValue">
    The patient developed a lesion in the concha of the left external ear. Recent biopsy
    confirmed this as being a squamous cell carcinoma. The patient has had a few other skin
    cancers.
  </element>
  <item card="3" len="44">
    <element tag="0008,0100" vr="SH" vm="1" len="8" name="CodeValue">M-02550</element>
    <element tag="0008,0102" vr="SH" vm="1" len="4" name="CodingSchemeDesignator">SNM3</element>
    <element tag="0008,0104" vr="LO" vm="1" len="8" name="CodeMeaning">Diameter</element>
  </item>
  <sequence tag="0040,a300" vr="SQ" card="1" len="92" name="MeasuredValueSequence">
    <item card="2" len="84">
    <sequence tag="0040,08ea" vr="SQ" card="1" len="60" name="MeasurementUnitsCodeSequence">
      <item card="4" len="52">
        <element tag="0008,0100" vr="SH" vm="1" len="2" name="CodeValue">cm</element>
        <element tag="0008,0102" vr="SH" vm="1" len="4" name="CodingSchemeDesignator">UCUM</element>
        <element tag="0008,0103" vr="SH" vm="1" len="4" name="CodingSchemeVersion">1.4</element>
        <element tag="0008,0104" vr="LO" vm="1" len="10" name="CodeMeaning">centimeter</element>
      </item>
    </sequence>
  </sequence>
</sequence>
```


Figure 12. Example of a coded and structured report (where SNM3 = Snomed versão 3; UCUM = *Unified Code for Units of Measure*)[10].

4. ONTOLOGIES

A key feature of structured reports is that they can be encoded according to some medical terminology (Figure 12) (CLUNIE, 2000). There are several different medical terminologies (e.g. RadLex[11], LOINC[12], ICD-10[13], SNOMED. They can be open (available to the public) or proprietary (created and used inside a hospital or clinic).
The medical terminologies can be organized into hierarchies or ontologies. An ontology is a formal representation of a set of concepts within a domain and the relationships between these concepts[14] (GRUBER, 1993).

Figure 13 shows part of RadLex terminology represented as an ontology. The relationships shown in the figure are of type inheritance ('subClassOf'). So 'imaging observation' is a subtype of 'RadLex Entity', inheriting all its features. Likewise 'cardiovascular disease' (CVD) is the subtype of 'imaging observation'.

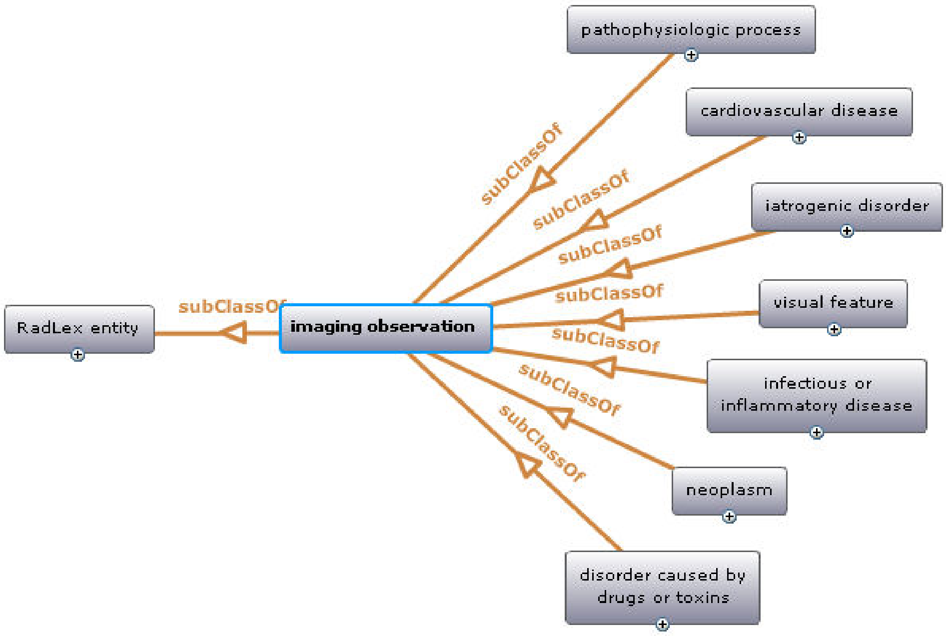


Figure 13. Example of RadLex as an ontology. Obtained from the site of NCBO Bioportal [http://keg.cs.uvic.ca/ncbo/flexviz/FlexoViz.html].

The use of ontologies allows performing more complex tasks than would be possible through a simple list of terms. It is possible, for example, to associate the ontology to a rule-base system based on inferences (Figure 14).

IF the infection is primary-bacteremia
AND the site of the culture is one of the sterile sites
AND the suspected portal of entry is the gastrointestinal tract
THEN there is suggestive evidence (0.7) that infection is bacteroid.

Figure 14. Rule example in the form IF – THEN used by the inference system. Rule extracted from the classic MYCIN system (SHORTLIFFE, 1976).

By using inference systems it is possible to obtain more complex relationships between the elements of the text, which is a particularly interesting feature for application in the medical field.

Ontologies can also be used for indexing images by combining low-level features (color, shape, size, etc.) with features of high level ('bicycle', 'car', 'red', etc.). For example, Mezaris and Kompatsiaris (MEZARIS, 2003) used an ontology of objects (Figure 15) to map low-level features with high-level features.

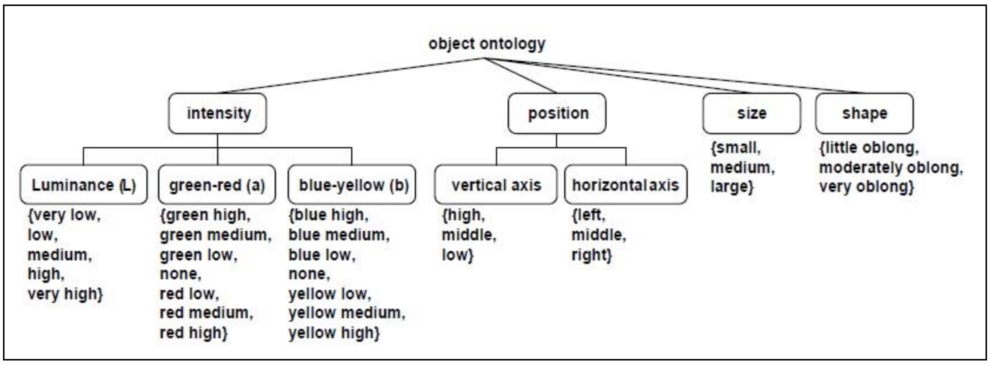


Figure 15. Object ontology developed by Mezaris et al (MEZARIS, 2003).

5. FINAL REMARKS

This text presented some forms of computational representation for images and, in particular, representation of medical images. For the careful reader it must be clear by now that the computational representation of medical images is not straightforward because there are many elements involved in its interpretation, and, so far, there are not global solutions to index all types of medical images (MULLER, 2004).

Nevertheless, the fact that medical images are almost always associated with textual elements is an important aspect that can be used to facilitate their recovery. In this sense, ontologies appear as excellent candidates for the representation of these images as well as the knowledge associated with them, being a very interesting research focus.

This text focuseed mainly in technological aspects of the activity of archiving and retrieving medical images. Nevertheless, it must be pointed out that they are interdisciplinary activities that include the participation of technicians, technologists, archivists, and health professionals in order to be successful. Another important remark to be added is that the huge work involved in the correct storage and retrieval of images helps to provide a better quality patient care and facilitates the work of health professionals.

6. ACKNOWLEDGMENT

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NOTES

[1] ImageJ. Available at <http://rsbweb.nih.gov/ij/>.
[2] Foto: Cindy McCravey, postada originalmente no Flickr sob licença Creative Commons Atribuição 2.0.
[3] Available from Osirix: <http://pubimage.hcuge.ch:8080/>.
[4] Available from Leadtools: <http://www.leadtools.com/SDK/Medical/DICOM/ltdc19.htm>.
[5] Available from DDMS: <http://marathon.csee.usf.edu/Mammography/Database.html>.
[6] Available at <http://ihe.net/Participation/upload/rad1_ihe_wkshp07_scheduled_workflow_leontiev.pdf>.
[7] From <http://www.medicaltranscriptionsamples.com/cardiac-cath-coronary-angiography/>.
[8] Systematized Nomenclature of Medicine. Site <http://www.ihtsdo.org/snomed-ct/>.
[9] EXtensible Markup Language.
[10] UCUM. Site at <http://www.regenstrief.org/medinformatics/ucum>.
[11] A Lexicon for Uniform Indexing and Retrieval of Radiology Information Resources. <http://www.rsna.org/radlex/>.
[12] Logical Observation Identifiers Names and Codes. <http://loinc.org/>.
[13] International Classification of Diseases – Version 10. <http://www.who.int/classifications/icd/en/>.
[14] See a more complete definition at <http://en.wikipedia.org/wiki/Ontology_(information_science)>.

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