Combining content-based retrieval and description logics reasoning

Christine Golbreich

Laboratoire d'Informatique Médicale
Université Rennes 1, Av du Pr. Léon Bernard, 35043 Rennes, France
Christine.Golbreich@univ-rennes1.fr

Abstract Content-based techniques have a long experience in automatic indexing and retrieval of the visual content of images. Description Logics provide powerful reasoning services for managing semantic contents. Hence, an hybrid approach combining content-based and semantic-based techniques is a compelling idea for multimedia information processing. After introducing the general approach, the paper presents two applications. The first one deals with indexing and searching multimedia documents about TV "news". The second application concerns processing medical imaging documents. We present the visual and domain OWL ontologies that are under development for supporting a system aiming at improving decisions based on a mammogram.

1 Introduction

A major challenge for the Web is to evolve towards a « Semantic Web », in which information may have explicit semantics, enabling human and machines to make a better use of information, and better integrate available data. The semantic markup of resources is a means to reach this goal. To standardize a semantic markup method, the Semantic Web proposes to rely on the one hand on a uniform formalism, e.g. XML or OWL, and on the other hand on an organization of knowledge into ontologies. Ontologies play a central role in the Semantic Web, since they define a precise and shared vocabulary for the semantic markup of the resources and their description by metadata. Ontologies are the key technology to explicitly describe the semantics of the information and enabling to exchange contents.

Nowadays, multimedia data, i.e. texts images, diagrams, music, speech, sound and video documents as well as composite documents that contain fragments of data of different types, possibly with temporal synchronization, are also widespread. Thus, multimedia information processing becomes a main issue for the Semantic Web.

There are two main approaches for multimedia documents retrieval. 'Content-based image retrieval', also often called 'retrieval by example', is a numerical approach that deals with the objective *visual* content e.g., the color, shape, texture of images or of regions of interest. The advantage is that visual descriptors can be automatically computed. However, the main problem is the semantic gap between the extracted descriptors and the users queries. The main question that arises is how to abstract a higher-level description of the semantic content of an image (or a region) from its low-level description by visual descriptors, so as to answer to high-level queries with the suited images.

In contrast, ‘semantic-based search’ is a symbolic approach that usually deals with the subjective *semantic* content of the image, most often described by keywords or text in metadata. The advantage is that symbolic descriptors carry more semantics. But the disadvantage is that such a semantic description is subject to an interpretation of the image content. Another difficulty is that keywords are often defined in a dictionary or a hierarchical thesaurus. Hence, semantic-based search is faced to the usual problems of silence and noise met with keywords, due to the hazardous feature of the annotations, to the imprecision of the keywords, and the difficulties to maintain a thesaurus consistent. The existing search engine e.g.; QBIC, WebSeek, Virage, Excalibur, ImageRover [2][3][4][5] are generally based on one of these approaches or an improvement. The problem is that none of them is really satisfying, since they most often do not provide the user with the relevant documents corresponding to his high-level query.

We present an hybrid approach connecting content-based and semantic-based techniques for multimedia information processing. Section §2 presents the principles underlying an “hybrid” approach aiming at combining content-based retrieval with description logics reasoning. Section §3 illustrates the hybrid approach experimented in the domain of RV ‘news’. Section §4 give an overview of the current project under progress for mammography interpretation and managing.

2 Hybrid multimedia information processing

The method proposed to develop an intelligent and hybrid search engine is based on ontologies and hybrid search and indexing techniques:

- **Ontology-based indexing**: the documents are indexed by ‘concepts’ from a formal ontology instead of keywords (§2.1).
- **Hybrid search**: the multimedia documents are composite (image, text) Each document is composed of an *image*, e.g.; mammogram, and a descriptive *text*, e.g.; the medical report (§4.1.1). The search is hybrid, based on the visual *and* semantic contents of the documents (§2.2).

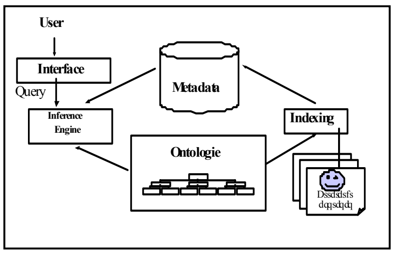


Fig. 1: Ontology-based indexing and search

An indexing hybrid tool indexes the document and stores the metadata in a database. The metadata include (1) a symbolic description of the semantic content (2) a symbolic description of the visual content, including the extracted visual descriptors numerical features. An hybrid search engine, combining an inference engine and a content-based engine is in charge of searching the documents.

2.1 Ontology-based indexing and search

In this paper the term ontology refers to a formal model of the domain representing the domain concepts and their relations in some logical formalism, e.g.; the breast imaging ontology based on the BI-RADS lexicon represented in OWL DL (§4.1.1). Using an ontology for multimedia information processing offers several advantages:

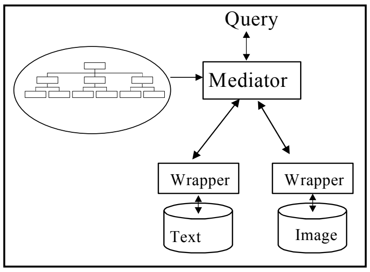
1. The ontology provides a source of shared and precisely defined terms that is used
   - to index the metadata describing the semantic content of the document
   - to express the queries
   - to describe the content of each source of documents (also called views).

2. An ontology-based approach allows more precise queries on metadata. For example, it is possible to ask for all the documents containing *" a black and white close-up of the Chinese President visiting France in October 1999"* thanks to the FOL query below:
   `Q(I):- image(I), semanticContent(I, C), agent(C, Pr), president(Pr), nationality(Pr, Chinese), action(C, visit), date(C, oct 1999 ), location (C, France),` **`close-up`**`(I),` **`black&white`**`(I)`

3. An ontology-based search is more powerful than a keywords search. The inferences that are drawn from the ontology enable to derive information that was not explicitly stated in the metadata, and thus to provide documents that would have been missed otherwise. For example, knowing from the ontology that Jiang Zemin was the Chinese President in October 1999 enables to retrieve documents indexed by 'Jiang Zemin' for the above query `Q(I)`, while they would not be retrieved by keywords indexing. If the ontology includes the fact that Jean Tiberi has spouse Xaviere Tiberi i.e. `spouse(Jean Tiberi, Xaviere Tiberi)`, and also an axiom asserting that the relation 'spouse' is symmetric then a query for documents containing 'Xaviere Tiberi and his spouse will retrieve documents indexed by Xaviere Tiberi and Jean Tiberi, as it will be inferred from this axiom that Xaviere Tiberi spouse is Jean Tiberi i.e. `spouse(Xaviere Tiberi, Jean Tiberi)`. Several examples issued from earlier experiments comparing the results obtained by our approach to those obtained with QBIC [8] showed that a concept-based query engine was more powerful than engines based on keywords §3.2.

2.2 Hybrid indexing and search

An hybrid search combining semantic and content-based search is intended to combine the advantage of each approach and compensate the shortcomings of the other one, for example to compensate the subjective *semantic* content of the metadata by the objective but semantic-less feature of the visual content. The hybrid search is based on a mediator approach [7]. Wrappers allows the interoperability required to access the data of the different databases, using the suited, numeric or DL, tool.



For example, to answer the query Q(I) above, the idea proposed is to use either a content-based engine for searching images that correspond to close-up and black and white requested features or a query engine to evaluate `close-up(I)`, `black&white(I)` from the symbolic metadata describing the visual content.

Fig. 2: Hybrid engine

3 Processing 'news' documents

This approach has been tested for processing composite documents composed of images and descriptive texts in the domain of 'news' [8] [9]. The experiment was achieved with a base of 120 images in the field of the French TV news. Indexing and search are based on (i) a formal ontology (ii) similarity (iii) and hybrid techniques.

3.1 Ontology, metadata, queries

The language used for representing the ontology, the queries, and the metadata is the description logic *C-Classic*[1].

- **Ontology (Tbox)**. As the domain of 'news' is open it was decided to restrain the modeling of the documents semantic content to six dimensions: Location, Date, Action, Agent, Object, Event. Here some examples of concepts, roles, individuals in *C-Classic.*

– **Concepts**

```
POLITICALPERSON ≡ PERSON ⊓ (∀ hasFunction POLITICALFUNCTION)
⊓ (∀ beginFunction DATE) ⊓ (∀ endFunction DATE)

REPUBLIQUE-PSDT ≡ PERSON ⊓ (∀ hasFunction REP-PRESIDENCE)

MAN ≡ PERSON ⊓ (∀ gender FILLS « male »)

OLD-MAN ≡ MAN ⊓ (∀ age INTEGER MIN 60)
```

– **Roles:** `gender, age, hasFunction, begin-function` …

– **Individuals (Abox)**

[1] This work was done before OWL language

```
Mitterand-Francois : REPUBLIQUE-PSDT
⊓ (FILLS name « Mitterand ») ⊓  (FILLS first name « Francois »)
⊓ (FILLS birthday 1916)& (FILLS death 1996)
⊓ (FILLS beginFunction May 10 1981)&(FILLS endFunction mai 7 1995)
⊓ (FILLS president-of France))

(France : COUNTRY
⊓ (FILLS official « République française »)
⊓ (FILLS continent Europe-occidentale)
⊓ (FILLS bounded-north-east Belgique Luxembourg Allemagne )
⊓ (FILLS bounded-south-east Mer-Méditerranée Principaute-Monaco)
⊓ (FILLS capital Paris) ⊓  (FILLS … ))
```

- **Symbolic metadata.** Symbolic metadata are represented by *C-Classic* individuals of the Abox. Each document is associated to symbolic metadata describing the visual and semantic content at a symbolic level. Thus, a concept CONTENT has been defined pointing to two parts:

$$\text{CONTENT} \equiv (\forall\, \text{semanticContent SemanticDescription}) \sqcap \text{ semanticContent AT-MOST 1}) \\ \sqcap\ (\forall\, \text{visualContent VisualDescription}) \sqcap \text{ visualContent AT-MOST 1})$$

The first part (Fig. 3) represents the visual content of the image at a symbolic level (Vc1); the second part represents the semantic content of the descriptive text (Sc1).

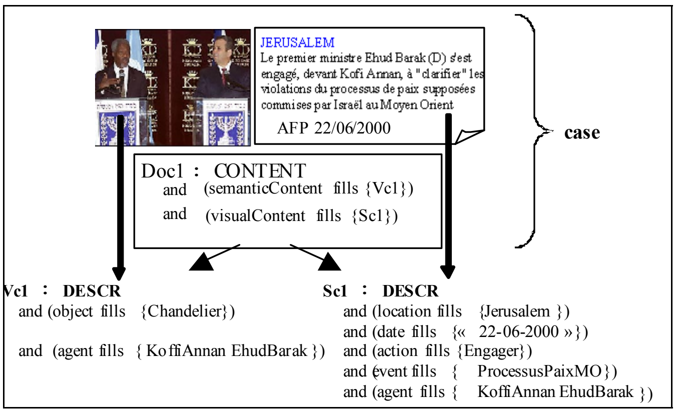


Fig. 3: C-Classic individual representing the visual and semantic content of a document[2]

- **Queries** are expressed in the ontology vocabulary. They are represented by a *C-Classic* individual, instance of the concept CONTENT.

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[2] "fills" operator specifies that a particular role is filled by the specified individuals, it corresponds to hasValue in OWL. In our experiments individuals were abstracted to C-Classic concepts.

A prototype implementation that allows CBR, grounded on DL inferences, has been achieved. The different algorithms used (LCS, DISSIM [10], ELENA+ [12]) have been implemented in Java. The method has been tested for search (3.2) and for semi-automatic indexing (3.3) on a case-base including 120 cases about various topics, mainly sport and politics. Several hybrid scenarios have been experimented on this case-base (for details about the method and experiments achieved see [8] [9]).

3.2 Search

A DL inference engine and case-base reasoning formalized in DL, support the semantic search. Two search engines, QBIC [5] and Surfimage [6], have been used for the comparison with content-based search,

Description Logics (DL) reasoning and CBR search. The semantic search combines usual DL reasoning (classification and class identification) with Case-Based Reasoning (CBR) techniques. The search is not based on an exact matching but on similarity. Each document of the case-base is represented by an individual of the Abox, instance of `CONTENT`, and the query as well. The search of the most similar cases is based on the notion of Least Common Subsumer (LCS) and is supported by algorithms (LCS, DISSIM [10], ELENA+ [12]) that allow to retrieve in the case-base the metadata that are the most similar to the query.

Comparing the results obtained by this method to those of QBIC showed that our method is more powerful than QBIC keywords search in most cases, since:

DL constructors and semantics allow expressing more precise queries.

It is possible to express a conjunction of specific features such as the wanted location, persons etc. Moreover it is possible to combine visual and semantic requests. For example, the query `(∀ visualContent (∀ agent fills {Kofi-Annan Arafat})) and (∀ semanticContent (∀ location {Syria}) and (∀ action peace-negogiate))` asking for images of 'Kofi-Annan and Arafat negotiating peace in Syria', has retrieved the single image of the base that exactly match the query while QBIC has returned several irrelevant images. To the query asking for Ehud Barak and Yasser Arafat, our tool retrieved the two relevant images of the base while QBIC returned 6 images among which 4 were irrelevant.

DL based search retrieves documents that would have been missed without the inferences of DL reasoning. For example, the query `(∀ visualContent (∀ agent fills POLITICALPERSON)) and (∀ semanticContent (∀ location MIDDLEEST))` returned all the documents about a political person, whatever the town, country, provided it takes place in Moyen Orient (Middle-East) i.e. 6 documents are retrieved from the base, while QBIC did not find any relevant document because they were annotated by a concrete location e.g. 'Jerusalem', 'Syrie' etc. and not by 'Moyen Orient' (Middle-East).

Besides, when there is no direct match, CBR enables to return the most similar documents. The approach is based on the formalization of CBR defined by [10] where case selection is performed using two criteria: *similarity* and *dissimilarity*. Similarity between two cases is characterized by, the most specific concept which subsumes the two cases (Least Common Subsumer) and dissimilarity by a concept representing properties that belong to one case but not to the other. For a new case, the first step consists in retrieving the most specific concepts it is an instance of. Next, a partial order induced by subsumption is used to select the most similar cases among the instances of their union. Next, in case of identity, dissimilarity is used ti discriminate. For example, the query asking for a Prince in the Middle East: `(∀ visualContent (∀ agent PRINCE and(∀ location MIDLEEAST))` could not be matched. Based on the ontology and DL reasoning, the most similar images of the base have been computed. The answer consists of 6 images exhibiting persons in Middle-East who are political persons such as king, president, prime minister, etc (Fig. 4).

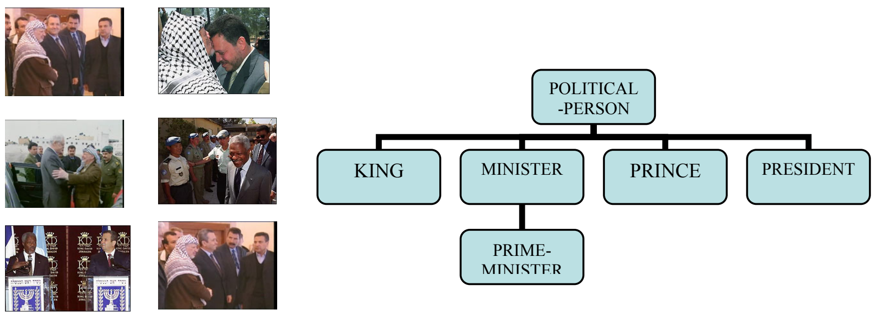

Fig. 4: Retrieval of images based on CBR for the query of a prince in Middle-East

In conclusion the DL CBR based approach is more efficient since it allows to eliminate noise and silence in many cases.

Hybrid search. Several scenarios of hybrid search have been tested, combining the DL reasoning engine and the content-based engine.

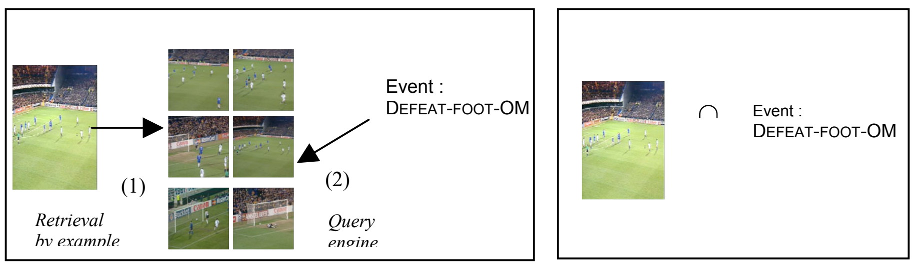

Fig. 5: Examples of hybrid search (left) and hybrid query (right)

– The first two scenarios experimented are sequential. Scenario 1 consists in making at a first step the semantic search described above, which provides documents that are the most similar to the query i.e. the most relevant documents w.r.t a wanted topic. Then, content-based search engine is done for an image from that subset used as example, so as to refine the results from visual criteria.
– Scenario 2 (Fig. 5 left) is the reverse: (1) at a first step an image example is used, (2) the semantic engine is run with a query asking for DEFEAT-FOOT-OM.

– Scenario 3 (Fig. 5 right) consists in processing an hybrid query, i.e. a query composed of an image plus an individual of CONTENT in making the intersection of the results of the two engines.

3.3 Semi-automatic indexing

A semi-automatic approach is proposed to index a new document, based on the already indexed cases. Again, the method used is based on CBR. The problem consists in inferring for a new image its semantic content SC_I. This description is inferred in using a machine learning algorithm ELENA+ [12] based on the Elena [14] and LCS [15] which allows to learn a *C-Classic* concept from positive and negative instances of the concept. The case-base is a base of images associated with the formal description of their content. The different reasoning steps are the following:

1. **Search**: the first step is a content-based search of cases in the case-base achieved for the new image as example
2. **Reuse**: at the second step, the retrieved images are classified by the user into two categories: relevant, non relevant. The formal descriptions associated to the relevant (resp. non relevant) images serve as examples (resp. contra-examples) for the ELENA+ learning algorithm, which suggests one or several possible descriptions of the new image.
3. **Revision**: the description has to be validate, possibly completed by the user in order to index the image by the learnt description.

This semi-automatic method is strongly influenced by the quality of the content-based search, as its results depend on the retrieved images. The main difference with a traditional method of 'indexing and retrieval by example' is that step 2 allows learning a new formal C-Classic concept from positive and negative examples based on the algorithm Eléna [14] and the LCS computation.
The proposed method was studied on a small case-base. It would be interesting to investigate the results with respect to precision and recall at a wider scale.

4 Medical Images Processing

Another project devoted to Medical Imaging, more precisely to breast imaging, aims at combining numerical techniques and description logics reasoning. Breast cancer is one of the leading causes of cancer death among women and is the most common cancer for women in many countries. Mammography is the best test for the early detection of breast cancer. The present project aims at improving decisions based on a mammogram in assisting experts in their tasks. The system under development is intended to assist radiologists in their decision-making process and in the management of patients based on breast imaging. The proposed approach aims at processing mammography multimedia documents thanks to (i) formal ontologies, (ii) hybrid techniques. This application requires to make a step further than the 'news' application in the representation of multimedia composite (image, text) documents.

A mammography is a composite multimedia (image, text) document composed of a mammogram (image) and of an expert report including a diagnosis (text). As previously, each document is associated to a composite description. The first part describes its semantic content (SC) issued from the descriptive report. The second part describes the visual content (VC) from the image descriptors (**Fig**. 6).

The problem is that none of these descriptions is really satisfying. On the one hand the report about a mammography, and the corresponding semantic description extracted from text, is subjective: « the wide variation of training and practice among radiologists results in significant variability in screening performance … » [17]. In addition, although the American College of Radiology (ACR) has defined a lexicon to standardize breast-imaging reporting [13], its terms are not always very precise. For example, according to the lexicon the term "microlobulated margins" means, "the margins undulate with short cycles producing small undulations." However, different radiologists may have different perceptions of what "short cycles" and "small undulation" mean. Thus, there remains a possible variability among experts in the mammography interpretation and reporting. On the other hand, the advantage of visual descriptors is that they are 'objective' and they can be automatically computed. However, the problem is how to abstract a higher-level description of the semantic content of an image (or a region) from its low-level description by visual descriptors.

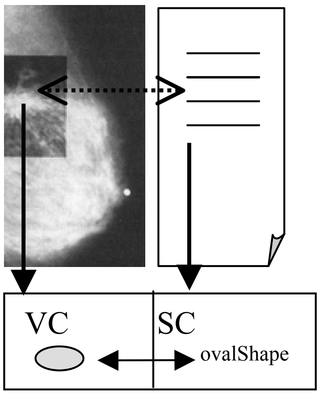

Fig. 6: Mammography: a composite image, text document

Therefore, the proposal under study is to combine the description of the visual content and of the semantic content to support hybrid reasoning. The work under progress aims at allowing a closer connection between the visual and semantic descriptions. The method proposed is based on a composite description grounded upon an image ontology (§4.1.2) and a domain ontology (§4.1.1), used respectively for describing the mammogram visual content on one hand, and the conceptual content of the mammography the report on the other hand. The key idea is to design a visual ontology whose concepts are associated with numerical descriptors and methods to compute descriptors values.

4.1 Ontology-based reasoning

The system under development includes:

(1) a domain ontology for Breast Imaging Reporting providing the concepts used for indexing the *semantic* content issued from the mammography reports.

(2) a visual ontology providing the concepts and properties for indexing the *visual* content of the images

(3) a case-base. A base of mammography is available for example from the Digital Database for Screening Mammography (DDSM) at http://marathon.csee.usf.edu/Mammography/Database.html

The visual and domain ontologies are being developed in the Web Ontology Language OWL. OWL is now the W3C recommended standard for ontologies [1]. Interoperability is a first motivation for using OWL. Also of interest is OWL higher expressiveness, and precise formal semantics. Another major advantage is the existence of powerful reasoning services, based on OWL (DL) underlying description logic $\mathcal{SHOIN}$. Based on subsumption calculus, OWL supports ontology automatic classification and consistency checking, instance retrieval (identify the class an individual belongs to). Tools such as the Protégé OWL editor (http://protege.stanford.edu/plugins/owl) and several reasoners, among which Racer (http://www.racer-systems.com/) are available.

4.1.1 The ACR domain ontology in OWL

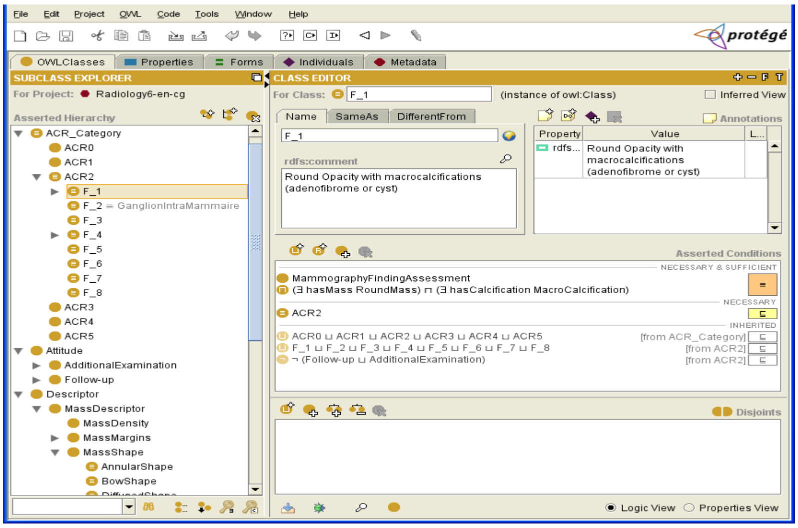

Fig. 7: The ACR domain ontology in OWL: findings of the ACR 2 category

The domain ontology (ACR) being built is based on the breast-imaging lexicon developed by the American College of Radiology (ACR) in the framework of the Breast Imaging Reporting and Data System BI-RADS™ [13]. BI-RADS contains a guide to standardized mammography reporting, including a breast-*imaging lexicon of terminology* used to describe mammogram feature distinctions, a report organization and *assessment structure* and coding system. BI-RADS lexicon describing mammographic findings includes both X-ray-specific terms such as *image descriptors* (e.g. the shape, the texture of a lesion,), *lesion types* (e.g. calcification, mass), and terms related to the *breast cancer types* and *patient management*.

A first ontology is under development in OWL [16]. It provides the main concepts and properties relevant for breast-imaging and for ACR categories assessment

Representation of the assessment categories in OWL. BI-RADS defines six ACR assessment categories depending on the mammogram observations (Fig. 8).

- Category 0: Need Additional Imaging Evaluation (ACR0)
- Category 1: Negative (ACR1)
- Category 2: Benign Finding (ACR2)
- Category 3: Probably Benign Finding? Short Interval Follow-Up Suggested (ACR3)
- Category 4: Suspicious Abnormality? Biopsy Should Be Considered (ACR4)
- Category 5: Highly Suggestive of Malignancy? Appropriate Action Should Be Taken (ACR5)

ACR 2 : benign finding that do not require follow-up or additional examination
[F_1]• Round mass with macrocalcifications (adenofibroma or cysts)
[F_2]• Ganglion intramammaire
[F_3]• Round mass(s) corresponding to a/several cysts(s) typical in echography
[F_4]• Image(s) with fat or mixt density (lipome, hamartome, galactocèle, kyste huileux)
[F_5]• Known scare(s) or calcification(s) on suture material
[F_6]• Macrocalcifications without opacity (adenofibroma, kyste, adiponecrose, ectasie canalaire secretante, calcifications vasculaires, etc.)
[F_7]• Microcalcifications with annular, bow, semi-lunar, sedimented, rhomboédriques1 shape
[F_8] • Skinny calcifications et punctiform regular diffus calcifications

Fig. 8: BIRADS assessment categories

A case has to be classified from the mammography findings into one of these categories which also provides the recommended attitude for cases in this category.

In OWL each class is either 'primitive' or 'defined'. A defined class is represented by an owl: equivalentClass axiom noted $\mathtt{A} \equiv \mathtt{Exp}$. `Exp` is an expression asserting a necessary and sufficient condition for an individual to belong to class A. In contrast, a subclass is represented by an owl : `subclassOf` axiom noted $\mathtt{A} \subset \mathtt{B}$. `Exp` is an expression asserting a necessary condition.

All the ACR categories (Fig. 8) are represented by OWL defined classes e.g., the ACR 2 class (Fig. 7). Each line from F_1 to F_8 describes a specific situation corresponding to a benign finding. Therefore they are represented as subclasses of the class ACR2 representing a specific Benign Finding. For example, line F_1 corresponds to the presence of a round mass and of a macro-calcification. F_1 is represented by a 'defined' class specified by the logical expression $(\exists \mathtt{hasMass}\ \mathtt{RoundMass}) \sqcap (\exists\ \mathtt{hasCalcification}\ \mathtt{MacroCalcification})$ expressing the presence of a round mass and of a macro-calcification. Cysts or Adenofibroma show finding of this type, hence the implication: $\mathtt{Cysts} \sqsubseteq \mathtt{F\_1}$

The ACR2 category is the union of a number of situations F_1 to F_8 that are assessed to correspond to 'Benign Finding', thus it is represented as the defined class:

$$\mathtt{ACR2} \equiv \mathtt{F\_1} \sqcup \mathtt{F\ \_2} \sqcup \mathtt{F\ \_3} \sqcup \mathtt{F\ \_4} \sqcup \mathtt{F\ \_5} \sqcup \mathtt{F\ \_6} \sqcup \mathtt{F\ \_7} \sqcup \mathtt{F\_8}$$

The axiom below asserts that mammography of the ACR2 category does not imply follow-up or additional examination

$$\mathtt{ACR2} \sqsubseteq \neg(\mathtt{Survellance} \sqcup \mathtt{ExamenComplementaire})$$

Ontology-based processing mammography. The method proposed to assist the radiologist in the assessment of the relevant category for a new case, is supported by DL reasoning services based on the representation of the ACR ontology in OWL (*classification* and *instance retrieval*). A DL reasoner, e.g.; Racer is used to automatically classify the ACR ontology. Racer also enables to identify for a new case its relevant ACR category from the mammographic findings. *Instance retrieval* allows the automatic classification of all the cases in the different categories, from the finding observed on the mammogram. For example, a mammogram exhibiting a round mass and a microcalcification is represented by an individual of the class `MammographyAssessmentFinding`. This individual is automatically classified into the category `ACR2` "Benign Finding", as it fulfills the conditions asserted to be necessary and sufficient for belonging to that class. Then the relevant attitude is deduced. Indeed from the necessary condition expressed by the axiom `ACR2 ⊑ ¬(Survellance ⊔ ExamenComplementaire)`, it is derived that the case does not require follow-up or additional examination. In the future, when no class can be assessed, case-based reasoning such as described §3.2 will be performed so that to present the most similar cases to the radiologists.

4.1.2 The visual ontology in OWL

The 'Image' visual ontology is intended to be used for indexing the *visual* content of images or of regions of interest in medical images. The idea is to have two complementary descriptions of the visual ontology concepts, the first one corresponding to a *numerical description* and the other one to a *semantic description*. For example, for the numerical description, the "round shape" concept can be represented as suggested in [15] by a numeric vector couple: an average vector and a standard deviation vector, which values will be computed from an input training mammogram set according to a very simple and weakly-supervised approach (e.g. the dominant color descriptor average value and its variation will be determined from a cluster of benign mammograms given by experts). On the other hand, the symbolic description of the visual descriptors is needed to help experts in their mammography analysis.

The OWL visual ontology under development is issued from the Visual Descriptor Ontology based on MPEG-7 visual descriptors. The Visual Descriptor Ontology (VDO) aceMedia Visual Descriptor Ontology v9.0 developed within the aceMedia project contains representations of MPEG-7 visual descriptors such as color space descriptor, dominant color descriptor, etc., and models concepts and properties that describe visual features of objects. However, the current version of VDO is not enough for this application. A richer ontology, especially for the visual descriptors such as color, shape and texture, is required. The goal is to extend the current VDO ontology.

First, new *subclasses* will be defined concerning the visual descriptors such as color, shape and texture, so as to allow mapping to concepts of the domain ontology. For example, specific Shape3D descriptors, including usual 3D shapes such as SphericShape3D, EggedShape3D, elliptical etc. are needed to map them to predefined masse shapes e.g.; round, lobular, defined in BI-RADS lexicon (Fig. 9). *New classes* may also be specified. As pointed out by [15] the region based descriptor ART

(Angular Radial Transformation) is useful for retrieval by example. But the generic circularity, the area and perimeter of a region of interest may also be useful to estimate the size which may be a discriminant feature to distinguish benign and malign calcifications (which are usually smaller).

1	Round:	A mass that is spherical, ball-shaped, circular or globular in shape.
2	Oval:	A mass that is elliptical or egg-shaped.
3	Lobular:	A mass that has contours with undulations.
4	Irregular:	The lesion's shape cannot be characterized by any of the above.

Fig. 9: Extract from BI-RADS Lexicon

Additionally, *several numerical representations* might be considered for a concept, for example, the ‘round shape’ concept may be simply characterized by its angle and its ray or by Fourier coefficients. Besides, *new descriptors* and related properties might be defined so as to allow using different mehods. For example, there are other methods for characterizing the texture, e.g.; grey level cooccurrence matrices that might be used instead of Gabor method, perhaps more useful in medical imaging [15].

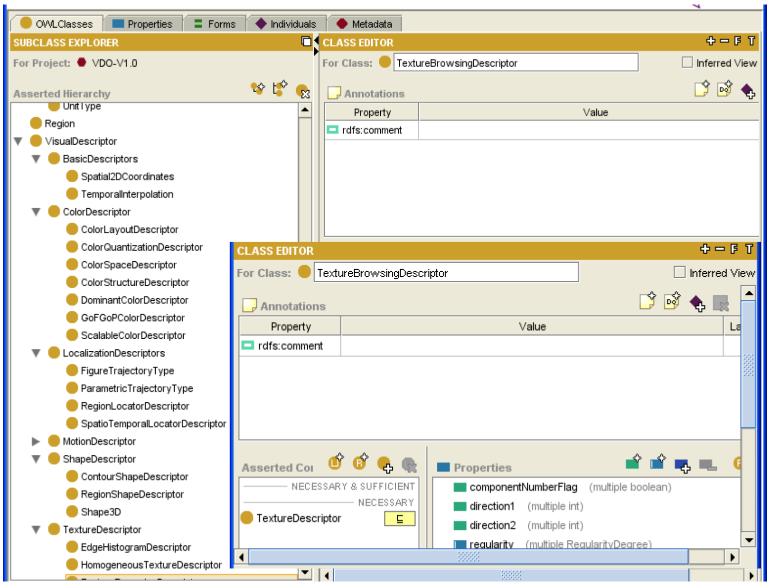

Fig. 10: The VDO ontology converted into OWL

At a first step, we have converted the original VDO ontology from the original RDFS representation into OWL respecting its original model (Fig. 10). The present goal is to provide a more precise description of the concepts in OWL. At a next step, we aim at reusing the general ontology and enriching it, so as to provide the appropriate concepts needed to describe the visual content of medical images, e.g. a region of interest exhibiting a suspicion of “*mass*”, defined by BIRADS as “a space occupying lesion seen in two different projections” at the visual level, or of “*calcification*” etc.

4.2 Connecting the ACR and the VDO ontologies

Mass

– hasMargin : **Margin**
  - circumscribed
  - microlobulated
  - obscured
  - indistinct
  - spiculated

– hasShape : **Shape**
  - round
  - oval
  - lobular
  - irregular

– hasDensity : **Density**
  - high
  - -

Fig. 11: Extract from BI-RADS Lexicon

The connection between the visual ontology and the medical domain ontology is a major requirement of the application. BI-RADS provides 43 descriptors organized in a hierarchy. Mapping the BI-RADS descriptors of the ACR ontology and the visual descriptors of the visual VDO ontology is crucial for supporting the hybrid approach. For example, the `RoundShape` concept of the ACR ontology (Fig. 7) should be mapped to the `SphericShape3D` visual descriptor of the VDO extended ontology (Fig. 10). The connection will rely on the two levels description of the visual ontology concepts.

5 Perspectives

At the moment, the classification of the documents only relies on the symbolic description of the semantic content issued from the descriptive text of the mammogram. Tools are under development to extract the semantic description from the texts driven by the ACR ontology. In the future, the system is intended to exploit not only the information issued from the reports, but also the 'visual' features characterizing the mammogram observations. For example, "benign calcifications" are usually *larger* than calcifications associated with malignancy. They are usually *coarser*, often *round* with *smooth margins* and are much *more easily seen*. The idea is (1) to describe the semantic content by the facts extracted from the reports, being driven by the ACR ontology, e.g.; round mass, (2) to describe the visual content from the mammogram, e.g. a 'large opacity round with smooth margins' thanks to image analysis techniques assisted by the Visual Descriptor Ontology, (3) to combine both information so as to infer the corresponding ACR category for a case and finally to derive the corresponding recommendation from the ACR classification. The first issue to be addressed is how to connect the domain ontology and the visual ontology. The key idea to support it is the description of the visual ontology concepts at two levels both at a numeric and symbolic level. Another point is how to define the mapping. In [15] we suggest investigating a many-to-many relation. For example, the BI-RADS lexicon defines mass shapes as *round* (i.e. a mass that is spherical, ball-shaped, circular or globular in shape), *oval* (i.e. a mass that is elliptical or egg-shaped), etc. If the numerical tool identifies a 'nearly' round region of interest in the mammography, it may be more interesting to associate the mass not only with *round* but also with *oval* with certain accuracy degrees. Fuzzy logics may help to manage this

Combining content-based and semantic-based techniques is a promising perspective to process multimedia information. The first experiment achieved for 'news' documents shows that combining content-based retrieval and description logics reasoning is more powerful than using each technique in isolation. The 'mammography' project under progress highlights that a main challenge is the connection between the domain and the visual ontology. Future work will address the two levels description of the visual ontology concepts.

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