An Ontology of Image Representations for Medical Image Mining

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***Abstract*—Ontologies are an effective means to formally specify and constrain knowledge. They have proved their utility in various data mining applications, especially in annotating text to render it machine interpretable. More challenging research perspectives arise when ontologies are used to annotate images where the information is encoded in numeric pixel values rather than in words and language grammar. Current approaches to bridge the gap between the pixel-based foundational representation and high level image semantics include the utilization of taxonomies describing 2D spatial relations between the depicted objects and hence linking image features with semantics. To this direction we present a novel ontological approach that formalizes concepts and relations regarding image representations for medical image mining. It provides descriptors for pixels, image regions, image features, and clusters. It extends previous approaches by including assertions of spatial relations between clusters in multidimensional feature spaces. The relational assertions enable the linkage between a given image, image region and feature(s) to the object they represent. The proposed approach is more general than most current approaches and can be easily extended to support multimodal data mining.**

***Index Terms*—Image mining, medical images, ontologies, semantics, description logics, owl.**

I. Introduction

ONTOLOGIES are formal and hence computer interpretable representations of the invariant properties of the entities in a domain. In order to emphasize the use of a formal language in domain representations, we here subscribe to the notion of formal ontologies [1], understood as theories that attempt to give precise representations of the types of entities in reality, of their properties and of the relations between them, using axioms and definitions that support algorithmic reasoning. Furthermore we make a clear distinction between knowledge representation artifacts and ontologies proper, along the traditional philosophical distinction between epistemology and. ontology [2].

Since the beginnings of this decade many studies have considered ontologies as a means for semantic image annotation [3]. An imaging application ontology had been proposed by [4], which creates links between the radiology imaging vocabulary RadLex and the Foundational Model of Anatomy [5]. A different approach is pursued in [6] by delineating the FMA as a source for image entity descriptors, whereas in [7] an ontology for annotation of radiographic images (AIM) has been proposed.

Ontology-based semantic image annotation can contribute in image management tasks such as indexing and sharing of medical images and regions of interest by providing a common semantic reference to align and query the heterogeneous data available in different repositories [8]. However, the enhancement of image mining tasks with axioms from formal ontologies is a major challenge indicated in various studies [9]-[12]. In content-based image retrieval, ontologies are usually considered as a link between the high level image semantics, such as our understanding of real-world objects, and the low level features of their imaging manifestations, such as their intensity, texture and shape. In this context, modeling of 2D spatial relations between the depicted objects has also been considered [9]. Ontological approaches proposed for the formalization of low level features include the ontology of MPEG-7 visual descriptors (VDO) in multimedia [10], and the COMM ontology [11] which has been used for the description of low level features in [12].

In [13] a definition of an image ontology was realized indicating four specifications: a) spatial relations between the depicted objects, b) uncertainty of the concepts and their media properties, c) associations between low level features and higher level semantic properties of the images, and d) an associated probabilistic reasoning service which can use available feature observations and concept likelihoods to infer probabilities for other concepts in presence of uncertain relations.

A recent study [14] proposes an ontology of fuzzy 2D spatial relations between depicted objects, such as “Left of” and “Close to”, for the guidance of semantic image interpretation. This approach was motivated by the importance of structural information in image interpretation, and by the intrinsically ambiguous nature of most spatial relations. Its utility was demonstrated for the annotation and analysis of brain structures in magnetic resonance images.

Motivated by the afore-mentioned studies, in this paper we present an ontology of image representations to support content-based mining of medical images. This is realized by extending the concept of spatial relations described in [14] from

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the 2D image space to multidimensional feature spaces, allowing the definition of spatial relations between clusters of feature vectors that represent properties of image regions. It is rooted in BioTop [15], an upper ontology for the life sciences formulated in OWL-DL [16]. BioTop was chosen due to its more than 700 logical axioms, and its compatibility with the upper level ontologies DOLCE [17],[18], BFO [19] and the OBO relation ontology [20].

The presented endeavor aims to fulfill the following goals:

- To reduce the ambiguity in recognition of image content objects in medical images;
- To use automated reasoning for classifying image content and sceneries;
- To search and retrieve images based on their explicit - and due to the reasoning ability even to implicit - semantic content.

The rest of this paper consists of four sections. In Section II we outline requirements for an ontology for image interpretation. Section II describes the implementation of the needed entities in a proposed ontology. Section IV discusses the contribution of this work in comparison with similar works in the literature, and the last section summarizes initial conclusions of our study.

II. Discriminating Real World Objects and their Representations

Interpreting medical images requires knowledge about canonical and abnormal body structures that is matched against the pixel data. From an ontological perspective we have categorically different kinds of entities, which are, however, often intermingled in discourse. So is it common to talk about "an opacity observed in a lung", although the opacity is not in the lung but in the image of the lung (and may correspond to, e.g. a tumor in the lung). The main source of confusion is mistaking the anatomical entities that are represented for the representation itself, i.e. the corresponding image. As an example, the term "right margin of heart" does not describe anything tangible in human anatomy, since 3D objects like hearts do not have margins. Instead, such descriptors refer to a representational entity, i.e. in a radiological image or a drawing. This example sheds light on the important ontological notion of *representation* as the relation between representational entities and the objects they represent [21].

In BioTop a representational entity is any entity that is an agent in a representation. With regard to images we narrow our view to so-called information artifacts as introduced by OBI [23]. The same information artifacts can inhere in different bearers, e.g. data media such as a computer disc or a hardcopy, just as a text that can be on paper and encoded in a PDF file.

III. Formalization of Image Representations

We here present the Image Representations Ontology (IROn), which extends BioTop to cover the realm of the medical image representations abundantly used in image mining. We distinguish between the subject matter of medical imaging, image-related entities, vector space-related entities, diagnostic interpretations, and concrete domains.

A. Representations of Subject Matter of Medical Imaging

This encompasses everything represented by parts or features of one or more images but is not part of the image itself. The representation of the subject-matter is not part of IROn itself, as these classes can be provided by numerous biomedical vocabularies, including SNOMED CT, RADLEX, and FMA [22],[6].

We distinguish between the following types of entities. An image feature or region represents **iron:subjectMatter** of one of the following types:

1) Anatomical Entities such as lung, heart and diaphragm, but also *Devices*, such as pacemakers and catheters, reside under **biotop:MaterialEntity**.

2) Spaces and Boundaries such as the mediastinal space and the lung boundaries, reside under **biotop: ImmaterialPhsyicalEntity**.

3) Pathological or Interventional Processes such as a course of bacterial infection or the insertion of a catheter, reside under **biotop:Process**.

4) Static Properties of Anatomical Entities such as an infiltration of the lung tissue, reside under **biotop:State**.

5) Metabolic or Biochemical Activities of Certain Biologic Structures **i**nclude entities that are realized in virtue of their bearer's physical makeup [19], and they reside under **biotop:BiologicalFunction**.

B. Image-related Entities

Images are represented directly by the following entities:

1) Whole Images, subsumed by **biotop:InformationEntity**.

2) *Pixel*, as the atomic building block of an image, subsumed by **biotop:InformationEntity**.

3) Image Regions of Interest (ROIs) that consist of self-connected regions of pixels. These regions can have arbitrary shapes, e.g. the ROI "left lung" (representation of the left lung), "heart" (representation of the heart)[1], also subsumed by **biotop:InformationEntity.**

4) Image Features, as emerging properties of ROIs, images or image collections such as time-series images, subsumed by **biotop:Quality**. Features considered include i) descriptors of *intensity* (*opacity*) such as grey-level histograms, ii) descriptors of *texture* such as Gabor energies, iii) descriptors of *shape*, such as curvature, iv) *position*, and v) *size*; all subsumed by **biotop:Quality**.

5) Image Attributes, such as the DICOM attributes as **biotop:Quality** and their values as **biotop:QualityRegion** describing the whole image together with the process of the capture of the image.

C. Vector Space-related Entities

The following kinds of entities are included:

[1] Note that often the same terms are used for denoting anatomical structures (in reality) and the image feature representing the anatomical structure.

1) Vector spaces, regardless of their dimensionality. In BioTop they are subsumed by **biotop:SpatialRegion**.

2) Vectors that can be formed by a set of image features, such as the grey-level histograms. They are subsumed by **biotop:InformationEntity**.

3) Clusters of feature vectors extracted from an image region, also subsumed by **biotop:InformationEntity**.

D. Diagnostic Interpretations

The basic idea of diagnostic relations is that for a person (interpretant) an image entity (a sign) represents some kind of reality outside the image (an object), according to Peirce's Theory of Signs [24]. We distinguish between representational relation assertions (RRAs) and spatial relation assertions (SRAs). Both are not modeled as object properties but as more complex classes like the reifications used in [14], being subclasses of **iron:ImageInterpretation**, a subclass of **biotop:Process**.

1) RRAs: relate a given image, an image region, an image feature, or a set of features to the object it represents. For example, such an object can be the opacity in a chest radiograph with a tumor in a patient's lung. RRAs bear probability values that vary according to the suspected pathologic condition, the image features, and the interpretant's knowledge.

iron:RRA equivalent-to **iron:ImageInterpretation** and
has-agent some **biotop:Human** and
has-participant some
(**iron:ImageFeature** and
represents only **iron:SubjectMatter**) and
has-probability **iron:ProbabilityRange**

2) *SRAs*: relate clusters to each other. Such relations can also include vectors since a single vector can be considered as a cluster of unitary cardinality. With the proposed ontology, clusters can be defined in *n*-dimensional (*n*D) feature spaces, where $n>0$; therefore, directional relations referring to a two-axes coordinate system ($n=2$), like "Right of", "Left of", "Above" and "Below" or even to a three-axes system (n=3) that includes "Front of" and "Behind from" as proposed in [14] are inadequate to describe their relative positioning. To this end, for each of the *n* axes we define directional relations between the clusters indicating whether one cluster is on the right or on the left of another cluster across axis *m*, where $m=1, 2, ...n$. Such relations are denoted as "Right of across *m* axis" and "Left of across *m* axis". There are also two-valued and three-valued SRAs (e.g. "A is between B and C across axis *m*").

iron:SRA equivalent-to **iron:ImageInterpretation** and
has-agent some (**biotop:Human** and
has-direct-participant =1 **iron:Cluster** and
has-indirect-participant =1 **iron:Cluster**

As in [14], SRAs subsume also *distance relations*, such as "Close to" and "Far from", and *topological relations*, such.as "Intersects with", "Is interior to" and "Is exterior to". Based on the same paradigm the SRAs can be enhanced by fuzzy logic so that the vagueness of the real world relations is captured.

E. Concrete Domains

Concrete domains like numeric values are not expressible in OWL-DL. Many interpretation classes and features require the reference to some kind of numeric value. As suggested in [14] this can be represented OWL-DL using XML schema. As an alternative we consider the introduction of a subtype of **biotop:quality**, called **iron:OrdinalQuality** that projects into an **iron:OrdinalQualityRegion**, a subtype of **biotop: QualityRegion**. Rounded probability values can be represented in such an ordinal quality region as OWL classes like **iron: 0.05_Probability**, **iron:0.1_Probability**, etc. Together with intervals like **iron: 0.3_Probability_or_less** inferences regarding order relations can be drawn. In IROn ontology ordinal qualities are exemplified for probability intervals and feature values. The drawback of this method is the huge number of classes necessary, especially for very fine-grained descriptions. Although these can be easily created automatically they inflate the ontology and have a negative impact on the performance.

IV. DISCUSSION

Comparing our approach with published image ontologies, we claim that it is the one that most forcefully implements principles of formal ontology. This is rather an exception than the rule, because with the popularity of the Semantic Web and its ontology language OWL we frequently observe that vocabularies or thesauri are being carelessly "ontologized" regardless of the strict semantics OWL imposes. An example of this is the OWL representation of RadLex, which intermingles the language level with the object level: it allows to relate the same kind of entities via *synonym_of* and *tributary_of*. Although we do not advocate to re-use the RadLex owl file like done in [7], we base our architectural principles on those earlier approaches. Just as Marwede et al. [4] and Mejino et al. [6] we propose to maintain the domain of anatomy and the domain of imaging separately. What we name "Diagnostic Interpretation" is similar to the "reporting layer" introduced by Marwede et al., who, however do not present a solution of how to express diagnostic certainty. Another difference is their use of Protégé Frames, which is semantically not as explicit as OWL. Mejino et al's proposal to selectively re-use an anatomy ontology as a source for what corresponds to image regions of interest is principally useful to avoid redundancies between the image entity and the subject-matter sub-ontologies. However, we disagree with their way to transfer spatial relations from real anatomy to medical images: whereas in a living organism every heart (anatomy) is located in some thorax (anatomy) not every heart (image) is located in some thorax (image). So there is no region of interest in a coronary angiography image that has any correspondence to the patient's thorax.

IROn was mainly inspired by the idea of using a formalization of 2D spatial relations to resolve ambiguities in image interpretation as described in [14]. However, the 2D spatial relations between the depicted objects can be defined by visual observations, whereas the spatial relations in a multidimensional space cannot be visually observed. In IROn this information can be provided by the so called 'ground truth' information extracted from images annotated by domain experts. For example, a radiologist can annotate two ROIs in a chest radiograph: region *A* that belongs to an abnormal tissue and region *B* that belongs to a normal tissue. The relations between the cluster of feature vectors extracted from *A* and the cluster of feature vectors extracted from *B* can be considered as ground truth relations described by IROn in the feature space.

IROn can also be used to describe image content with 2D spatial relations similarly to the current imaging ontologies, e.g. by using the pixel coordinates as features. Therefore, IROn is more generally applicable than current imaging ontologies.

Furthermore, considering that feature space representations can be derived from data of other modalities, the applicability of IROn extends beyond the image domain provided that modality-specific data representations are included.

V. Conclusion

We presented IROn, an ontology formalizing fundamental concepts and relations regarding image representations used in medical image mining. This ontology builds on previous work to establish more formal links between low level image representations and high level semantics. Its major advantage over state of the art approaches is that it can be used for the description of the spatial relations between clusters of image feature vectors in multidimensional feature spaces.

The proposed ontology will be integrated in a multimodal data mining system utilizing image evidences to extract information about the presence and the progress of infections. The purpose of such a system will be to improve patients' safety by the prevention of adverse events related with antibiotherapy. For example, pulmonary infiltrates visible in a plain chest radiograph can be evidences of a pulmonary infection. By extracting information about the evolution of the infiltrates in time one can derive conclusions about the progress of the disease, responding to a prescribed antibiotherpy or not.

Our immediate research objectives include the experimental application of the proposed ontology for various medical image mining tasks and its extension to support multimodal data mining.

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