doi: 10.1515/itms-2014-0013
Information Technology and Management Science
2014 / 17

Ontology-based Image Representation

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Abstract **– This article presents an overview of ontology based digital image representation. An ontology is a specification of a conceptualization to create a vocabulary for exchanging information, where conceptualization mean a mapping between symbols used in the computer (i.e., the vocabulary) and objects and relations in the real world. In this paper, digital image semantic annotation by ontology and a novel ontological approach that formalizes concepts and relations with respect to image representations for data mining – the Image Representations Ontology (IROn) – are examined.**

Keywords **– Digital image, IROn, ontology.**

I. Introduction

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. 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. An image is typically a representation of the objects present in a real life scene [1]. In the process of image acquisition, much of the original information present on the real object is lost (e. g., third dimension, motion), there is mixture of several factors in the value of a pixel (e. g., texture, lighting, geometry), introduction of false values (e. g., noise, chromatic aberration), and alteration of the original information (e. g., geometric distortion, blurring) [2]. In addition, fine details of the object are missing because of the limited resolution of any camera. Therefore, the image is only the 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 [1]. Image content does not make sense by itself. An image is inherently ambiguous and does not provide information about its content. Without a subject matter, an image does not allow making a distinction between relevant and irrelevant information. What is relevant for one application may be irrelevant for another. Furthermore, there is no intrinsic relevant information. For example, apparently simple information such as object edges is difficult to accurately extract without knowledge about the scene. Edges are usually modeled as sharp changes in image intensity, but this is also the case for noise, shadows, and texture elements [2].

In order to be able to perform the 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

$$I = f(x, y) \tag{1}$$

where I is the image intensity, f is a function that varies with the position x and y in matrix [1].

Image processing is the low-level part of a more global image analysis and computer vision system. Then high-level part uses image-processing results to perform interpretation, visualization, storage, or transmission of the image data. Image processing includes many categories of mathematical manipulations, such as image restoration, image enhancement, image compression, image reconstruction, image segmentation, and object detection. An image class is a set of images that share many features, on condition that these features are meaningful for the application [2].

Remote sensing images are used in many decision-making domains. The addition of semantics to geographical information management is critical for the improvement of semantic interoperability and the usability of this type of images. An important step to strengthen the semantic interoperability of these images includes making clear the semantics associated with geographical information [8]. The semantic representation of geographical data provides a formal semantic description that cannot be expressed in current models of geographic data [6].

For example, an image analysis can be used for analysis of long-term agricultural or forest landscape changes [7]. The same landscape area is compared year by year, always at the same season, to detect changes of area. The image class is created of color satellite images of landscape with the same spatial resolution. The objective of the image processing here is to segment the input images to isolate each potential vegetation area into a unique region. The resulting regions or classes will then be transmitted into a classifier, which is trained to identify various categories of geographic objects: field, forest, hedge, city, etc. [9]. The performance of the classifier distinctly depends on the accuracy of the image segmentation. To obtain the best classification results, usually an annotated image database is used to fit the parameters that best separate each class presented in the data set [2].

II. Basic Ontology Concepts

Several different terminologies (e. g., RadLex, LOINC, ICD-10 and SNOMED) are available and can be used for digital image semantic annotation. The 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 [10]. Therefore, ontologies are an effective means to formally specify and constrain knowledge, so ontologies can be viewed as a means for semantic image annotation. The use of ontologies allows performing more complex tasks than it would be possible through a simple list of terms. They have proved their utility in various data mining applications, especially in annotating text to make 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. Ontology-based semantic image annotation can contribute to image management tasks such as indexing and sharing of images and regions of interest by providing a common semantic reference to align and query the heterogeneous data available [1].

Current approaches to bridge the gap between the pixel-based foundational representation and high-level image semantics, such as content-based image retrieval (CBIR), include the utilization of taxonomies describing 2D spatial relations between the imaged objects and hence linking image features with semantics [3]. Therefore, indexing of images is implemented by combining low-level features (intensity, texture, color, shape, size, etc.) with features of high-level image semantics, such as our understanding of real-world objects. For example, an ontology of objects (Fig. 1) can be used to map low-level features with high-level features of image [1].

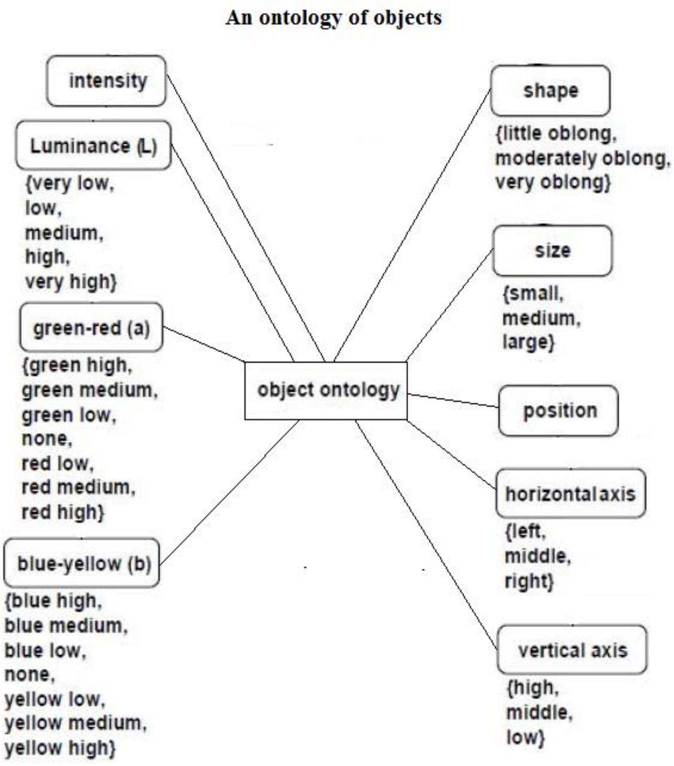

Fig. 1. Ontology-based image representation.

Ontologies must be clear both to humans for semantic annotation and to machines for cogitative and error checking, unintuitive rules for image processing give errors. Common rules allow for alignment ontology with other ontologies and, therefore, enable cross-domain operation with data. A reference ontology or domain ontology tries to optimize representational suitability to its subject matter. An application ontology is constructed for specific practical objectives.

Relational entity is anything that exists, including things, processes, functions, qualities, beliefs, actions, images, etc. The basic idea of relational entities is representation: for a person or interpretant an image entity represents some type of reality outside the image – an object, therefore, they connect viewers to reality. Instances represent what particular exists in reality – exists in numerous instances, e. g. databases, inventories, images. Types are connected to their instances and exist in objective reality – types of image, types of imaging process, etc. Types are ontologies, terminologies, catalogs, etc. Images are continuous representations – they represent instances in reality, but ontologies represent types in reality and the relations between these types.

Top-level ontologies proposed for the formalization of low level features include the VDO ontology, the COMM ontology, FMA, OBO ontologies, FuGO, SNOMED, UMLS Semantic Network, NCI Thesaurus, ICF, ISO Terminology Standards, HL7-RIM, BFO, DOLCE and other ontologies. Top-level ontologies have been shown to work in many different domains. Top-level ontology structure is shown in Fig. 2.

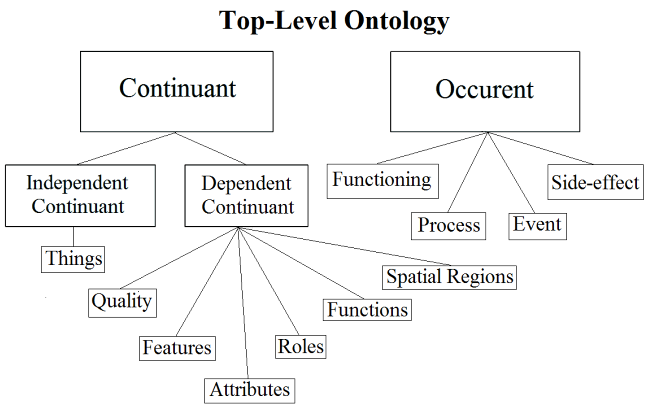

Fig. 2. Top-level ontology.

The ontologies are divided into two versions: continuant ontologies, and occurrent ontologies. Continuants are something existing in time and they preserve their identity through a change. Occurents are temporal parts, they unfold themselves in successive phases and they exist only in their phases [12]. Subtypes of continuants include independent continuants, dependent continuants, spatial regions and environments. All occurents are dependent entities – they are dependent on continuants as their carriers. Some dependent entities are monadic – they have one single independent carrier, but other dependent entities are relational – they have more than one independent carrier. Some dependent continuants are also realizable.

III. Ontology-Based Image Representation

Images are complex representations, but they are not made of representational units. Representational units are terms, icons, bar codes, alphanumeric identifiers etc., which relate to entities in reality and which are not made of additional sub-representations; therefore, representational units are the smaller parts in the domain of representations. The sub-representations of an image are regions. For an image, annotation terms representing types to detect knowledge about specific instances are used:

- This image as a whole;
- Regions in the image;
- Qualities of these regions;
- That part of the world the image represents as representative of a type as this specific instance.

Image interpretation is the mapping of regions (image segments) to pairs (instance, type) or the image segmentation to instances in reality identified as instances of specific types. Actual entities present in the image are regional segments created by delineation. These entities are the so-called image patterns. In addition, other kinds of segmentations exist, such as segmentations according to quantitative and qualitative spatial coordinates [4].

The image class definition can be done either by means of sample images or through a linguistic description. A priori information is represented by sample image parts. Two types of sample image parts are taken into account: clusters (blobs) that represent a region in the image, which delineates one object of interest or an image area and patches that separate one characteristic part of one object of interest. Therefore, an object of interest is described by a series of patches with their spatial relations. A priori information can also be represented by a linguistic description. The description language is generally made over a domain ontology. Therefore, the description of an image class is an application ontology [2].

The semantic representation of remote sensing images is characterized by the semantic definition of geographical objects presented in the image and respective relations [6]. The spatiotemporal relationships are used to obtain space and time related information of an image. The image contents are analyzed, and the relationship between the content (image objects) is obtained by means of spatial relationship. If the spatial and the temporal dimensions are included into the part of ontology, the image representation level is raised to the new dimension. The spatial information describes the regions of space. The digital image consists of various objects (or pixels), and these objects are linked by using spatial relationships.

The Region Connection Calculus (RCC) is used for representing high-level (qualitative) information in spatial representation. The Region Connection Calculus takes regions rather than points as a fundamental notion. The RCC abstractly describes regions in Euclidean space (or in a topological space) by their possible relations to each other. The RCC includes eight basic relations that can exist between any two regions. These basic relations are as follows:

- X is disconnected from Y (DC);
- X is externally connected with Y (EC) ;
- X is equal to Y (EQ) ;
- X partially overlaps Y (PO) ;
- X is tangential proper part of Y (TPP);
- X is tangential proper part of Y inverse (TPPi);
- X is non-tangential proper part of Y (NTPP);
- X is non-tangential proper part of Y inverse (NTPPi).

DC (disconnected) means that the two regions do not have a common point. EC (externally connected) means that the two regions have only common point borders. PO (partially overlapping) means that the two regions have common interior points. But TPP (tangential proper part) means that one region is a subset of the other region and they have some common points along the margins [5]. Fig. 3 shows eight basic relations of the Region Connection Calculus (RCC).

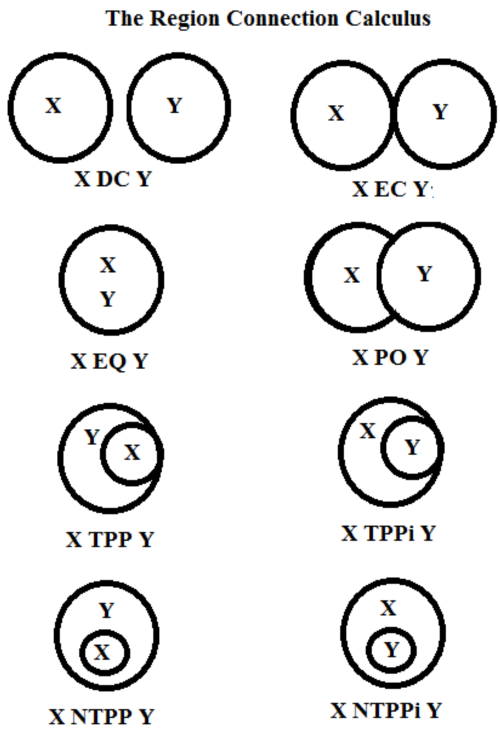

Fig. 3. The region connection calculus.

The association between geographic objects is represented in the image; knowledge takes into account the recovery process, and the topological relationships between the objects are represented [6]. The topological relationship is also used to tender quantitative information in spatial representation. The relevant topological relationships are as follows:

- Proximity describes how close two or more objects are;
- Orientation describes the location and direction of an object;
- Connectivity means how two objects are linked with each other;
- Adjacency explains whether two objects are next to each other or not;
- Membership means whether an object belongs to a particular group or not.

Temporal relationships are described by instances of relations, whose validity is a function of time [5]. Fig. 4 shows a hierarchy of temporal relationships using an event.

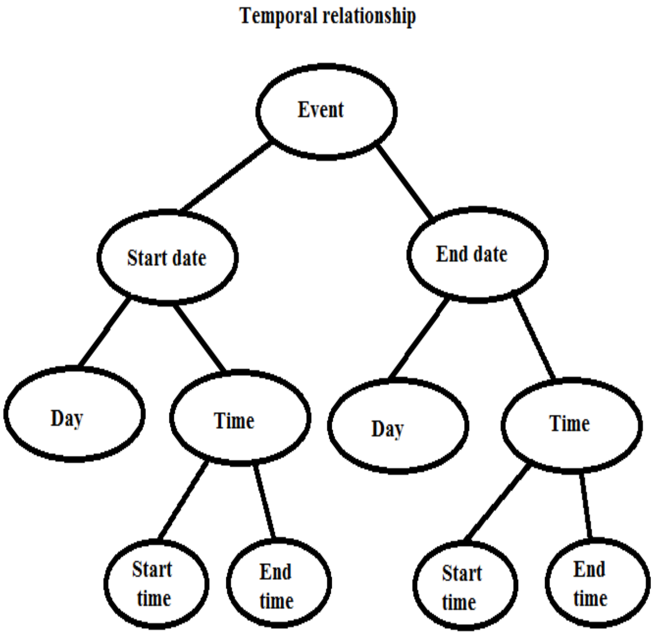

Fig. 4. Temporal relationship.

IV. The Image Representation Ontology (IROn)

In paper [3], a novel ontological approach that formalizes concepts and relations with respect to image representations for image mining – the Image Representations Ontology (IROn) – was presented. It provides descriptors for pixels, image regions, image features, and clusters. This approach continues previous ontology approaches by including application of spatial relations between clusters in multidimensional feature spaces. The subject matter of images, image-related entities and vector space-related entities were used.

Images can be represented by the following image related entities:

- Whole images;
- Pixel, as the smaller part of an image;
- Image regions of interest (ROIs) that include self-connected regions of pixels, where these regions can have arbitrary shapes;
- Image features as properties of ROIs, images or image collections such as time-series images. Features include descriptors of intensity (histograms, mean, standard deviation, skewness, kurtosis), descriptors of texture (energy, entropy, contrast, homogeneity, correlation, variance, Laplacian transformation, gradient transformation, angular second moment, flat texture, inverse difference moment, etc.), descriptors of shape (curvature, area, perimeter, etc.) [11], position, and size;
- Image Attributes (DICOM attributes, gamma values, background color, textual metadata information), and their values as describing the whole image together with the process of the capture of the image.

The following vector space-related entities were included:

- Vector spaces with any dimensionality;
- Vectors that can be created by a set of image features, such as histograms;
- Clusters of feature vectors extracted from an image region.

Two kinds of relations: Representational Relation Assertions (RRAs) and Spatial Relation Assertions (SRAs) were used. The both of them were not modeled as object properties but as classes that are structure that is more complex. RRAs relate a given image, an image region, an image feature, or a set of features to the object it represents. SRAs relate clusters to each other. Such relations can also include vectors because a single vector can be viewed as a cluster of unitary number of elements. With the proposed ontology, clusters can be defined in n-dimensional feature spaces, where $n>0$. Directional relations between the clusters indicate when one cluster is on the right or on the left of another cluster across axis m. Such relations are marked as “Right of across m axis” and “Left of across m axis”, where $m = 1, ..., n$. There are also two-valued and three-valued SRAs (for example, “A is between B and C across axis m”). SRAs include also distance relations, such as “Close to” and “Far from”, and topological relations, such as “Intersects with”, “Is interior to” and “Is exterior to”. The SRAs can be improved by fuzzy logic so that the ambiguity of the real world relations can also be captured.

Concrete domains like numeric values cannot be expressed in Web Ontology Language with DL class (OWL-DL). Many interpretation classes and features require the reference to numeric values. This can be represented by OWL-DL using XML schema. Comparing approach in [3] with published image ontologies it has been claimed that it is the one that most strictly implements principles of formal ontology. IROn was mainly coined based on the idea of using the formalization of 2D spatial relations to prevent uncertainty in image interpretation. However, the 2D spatial relations between the imaged objects can be defined by visual observations, while the spatial relations in a multi-dimensional space cannot be visually observed. In IROn this information can be provided by the “ground truth” information extracted from images annotated by domain experts. The “ground truthing” refers to the process of gathering the proper objective data. IROn can also be used to describe image content with 2D spatial relations similarly to the current imaging ontologies; for example, by using the pixel coordinates as features. Therefore, IROn is in general more used than current imaging ontologies.

V. Conclusions

In this paper, digital image semantic annotation by ontology and a novel ontological approach that formalizes concepts and relations with respect to image representations for data mining – the Image Representations Ontology (IROn) – were examined.

An image is typically the representation of the objects present in a real life. The interpretation of an image by the computer is a highly complex task. To be able to perform the computational processing of images, it is necessary first to convert them into digital format. More challenging research perspectives arise when ontologies are used to annotate images where the information is encoded in numeric pixel values. An ontology is a specification of conceptualization to create a vocabulary for exchanging information, where conceptualization means mapping between symbols used in the computer (i. e., the vocabulary) and objects and relations in the real world.

Therefore, ontologies can be viewed as a means for semantic image annotation. Ontology-based semantic image annotation can contribute to image management tasks such as indexing and sharing of images and regions of interest by providing a common semantic reference to align and query the heterogeneous data available. Current approaches to bridge the gap between the pixel-based foundational representation and high level image semantics such as CBIR include the utilization of taxonomies describing 2D spatial relations between the imaged objects and, hence, linking image features with semantics and, therefore, indexing images by combining low-level features (intensity, texture, color, shape, size, etc.) with features of high level image semantics, such as our understanding of real-world objects.

The basic idea of relational entities is representation: for a person or interpretant an image entity represents some type of reality outside the image – an object, therefore they connect viewers to reality. Instances represent what general exists in reality – exists in numerous instances, e. g. databases, inventories, images. Types are connected to their instances and exist in objective reality – types of image, types of imaging process, etc. Types are ontologies, terminologies, catalogs, etc. Images represent instances in reality, but ontologies represent types in reality and the relations between these types.

A novel ontological approach that formalizes concepts and relations with respect to image representations for image mining – the Image Representations Ontology – was examined. It provides descriptors for pixels, image regions, image features, and clusters. This approach extends previous ontology approaches by including application of spatial relations between clusters in multidimensional feature spaces: representational relation assertions and spatial relation assertions. In addition, the subject matter of images, image-related entities and vector space-related entities were used in this approach.

Comparing the Image Representations Ontology with published image ontologies it has been claimed that it is the one that most strictly implements principles of formal ontology.

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Artūrs Stepčenko, Arkādijs Borisovs. Uz ontoloģiju bāzēta attēla reprezentācija
Attēls parasti reprezentē reālās pasaules objektus. Attēla interpretācija ar datora palīdzību ir sarežģīts uzdevums, un, lai, būtu iespējams veikt skaitļošanas darbības ar attēlu, vispirms tas ir jāpārveido digitālā formātā. Digitālais attēls ir divdimensionāla matrica, kuru veido diskrētas vērtības, ko sauc par pikseļiem. Ontoloģija ir konceptualizācijas specifikācija, lai izveidotu vārdnīcu informācijas apmaiņai, kur ar konceptualizāciju tiek saprasta reālās pasaules objektu un to attiecību attēlošana ar datorā izmantojamo simbolu (vārdnīcas) palīdzību. Tādējādi ontoloģiju var apskatīt kā līdzekli attēla semantiskai anotācijai. Pašlaik, lai mazinātu plaisu starp uz pikseļiem bāzētu attēla reprezentāciju un augsta līmeņa attēla semantiku, izmanto taksonomiju, kas apraksta divdimensionālas telpiskās attiecības starp attēla objektiem, un tādējādi sasaista attēla īpašības ar semantiku. Attēlus var indeksēt,, kombinējot attēla zema līmeņa īpašības (intensitāte, tekstūra, krāsa, forma, izmērs) ar attēla augsta līmeņa semantikas īpašībām, kā, piemēram, reālās pasaules objektu izpratne. Telpiskās un īslaicīgās attiecības raksturo attiecības starp attēla objektiem. Telpiskā informācija apraksta telpā esošos reģionus. Īslaicīgas attiecības tiek aprakstītas ar instanču attiecībām, kuru darbības ilgums ir funkcija, kas atkarīga no laika. Rakstā tika apskatīta jauna ontoloģiskā pieeja – Attēla reprezentācijas ontoloģija (ARO). Tā nodrošina aprakstītājus pikseļiem, attēlu reģioniem, attēlu īpašībām un klasteriem. Šī pieeja paplašina iepriekšējās ontoloģiskās pieejas, iekļaujot telpisko attiecību pielietošanu starp klasteriem daudzdimensionālās attēlu īpašību telpās. Arī attēlu temats, ar attēlu saistītās vienības un ar vektoru telpu saistītās vienības tiek izmantotas šajā pieejā. Salīdzinot Attēla reprezentācijas ontoloģiju ar iepriekš publicētajām attēlu ontoloģijām, tika secināts, ka šī ontoloģija ļoti strikti īsteno formālas ontoloģijas principus.

Артур Степченко, Аркадий Борисов. Представление изображения на основе онтологии
Изображение обычно представляет объекты реального мира. Интерпретация изображения с помощью компьютера - сложная задача, и чтобы можно было совершать вычислительные операции с изображением, во-первых, изображение надо представить в цифровом формате. Цифровое изображение является двумерной матрицей, которая состоит из дискретных значений, называемых пикселями. Онтология является спецификацией концептуализации, цель которой - сделать словарь для обмена информацией, где под концептуализацией понимают отображение объектов реального мира и их отношений с помощью символов, используемых в компьютере (словаре). Поэтому онтология может рассматриваться как средство для семантической аннотации. Изображения могут быть индексированы, комбинируя свойства изображения низкого уровня (интенсивность, текстура, краска, форма, размер) со свойствами семантики изображения высокого уровня, как например понимание объектов реального мира. Пространственные и кратковременные отношения описывают отношения между объектами изображения. Пространственная информация описывает регионы, которые находятся в пространстве. Кратковременные отношения описываются с помощью отношений инстанций, продолжительность которых является функцией, зависящей от времени. В статье был рассмотрен новый онтологический подход, который формализует понятие и отношение для представления изображений – Онтология Представления Изображения (ОПИ). Она обеспечивает средства описания для пикселей, регионов изображений, свойств изображений и кластеров. Этот подход дополняет существующие онтологические подходы, включая применение пространственных отношений между кластерами в многомерных пространствах свойств изображений. В данном подходе также используются темы изображения, связанные с изображением единицы и пространством векторов единицы. Сравнивая Онтологию Представления Изображения с ранее опубликованными онтологиями изображений, был сделан вывод, что эта онтология очень строго соблюдает принципы формальной онтологии.