Semantic understanding of Image content

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***Abstract*—Large amounts of spatial data are becoming available today due to the rapid development of remote sensing techniques. Several retrieval systems are proposed to retrieve necessary, interested and effective information such as key-word based image retrieval and content based image retrieval. However, the results of these approaches are generally unsatisfactory, unpredictable and don't match human perception due to the well gap between visual features and semantic concepts [1]. In this paper, we propose a new approach allowing semantic satellite image retrieval, describing the semantic image content and managing uncertain information. It's based on ontology model which represents spatial knowledge in order to provide semantic understanding of image content.**

Our retrieval system is based on two modules: ontological model merging and semantic strategic image retrieval. The first module allows developing ontological models which represent spatial knowledge of the satellite image, and managing uncertain information. The second module allows retrieving satellite images basing on their ontological model. In order to improve the quality of retrieval system and to facilitate the retrieval process, we propose two retrieval strategies which are the opportunist strategy and the hypothetic strategy.

Our approach attempts to improve the quality of image retrieval, to reduce the semantic gap between visual features and semantic concepts and to provide an automatic solution for efficient satellite image retrieval.

Keywords- Semantic image retrieval; scene interpretation; knowledge representation; ontology merging; semantic similarity.

I. INTRODUCTION

Content-Based image retrieval (CBIR) systems are usually based on the description of images by low-level (colors, gray shades, textures), and middle-level (contours, regions, shapes) features [2], [3]. A retrieval algorithm matches these descriptions with a user query according to some similarity metric. The effectiveness of a CBIR system depends on the choice of the set of visual features and on the choice of the metric that models the user's perception of similarity. Several systems are proposed to improve the retrieval quality and to provide semantic in retrieval process such as relevant feedback [4], semantic template [5], machine learning [6] and ontology [7], etc.

Our retrieval system is based on two modules: ontological model merging and semantic strategic retrieval. The first module allows developing ontological models which represent spatial knowledge of the satellite image. In addition, it manages uncertain information and resolves conflicts situations using a fusion algorithm for merging ontological models which represent satellite image knowledge. The second module allows retrieving satellite images basing on their ontological model. In order to improve the quality of retrieval system and to facilitate the retrieval process, we propose two retrieval strategies which are the opportunist strategy and the hypothetic strategy. These strategies allow reducing the ontological model base and facilitate the retrieval process.

II. IMAGE RETRIEVAL SYSTEMS

Image retrieval systems are developed such as text based image retrieval and content-based image retrieval. In the text-based approach, the images are manually annotated by text descriptors (keyword) which are then used in the retrieval process. But, this approach requires a considerable effort for manual annotation, and the keyword does not necessarily describe image content. In addition, the user may know little about the domain, and thus can't specify the most appropriate keywords for image retrieval [8]. To overcome the above disadvantages in text-based retrieval system, content-based image retrieval (CBIR) was introduced in the early 1980s. In this approach, images are indexed by their visual content, such as color, texture, shapes, etc [9]. To retrieve images, users provide image query or sketched figures; then, the system changes these examples into its internal representation of feature vectors. The similarities between the feature vectors of the query example and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image

database [1]. However, the similarity measures between visual features do not match human perception [8]; for example, two images can be very similar in color, size, and shape, despite containing different objects. Thus, the retrieval results of low level features based retrieval approach are generally unsatisfactory and often unpredictable.

While [10] and [11] based their solutions on visual features, argued that in many domain specific applications, such as medical image databases, the semantic content is more desirable. They also introduced the I-Browse histological image retrieval system. I-Browse associates semantic meaning, visual properties, contextual knowledge and textual annotations into a single framework for retrieving histological images. Two major techniques may be used for building the retrieval engines:

• Retrieval using visual features.

• Retrieval using semantic features

A. The semantic gap

The approach first classifies a query using the features that best differentiate the Level 1 classes and then customizes the query to that class by using the features that best distinguish the Level 2 classes within the chosen Level 1 class. Level 1 class corresponds to seven main disease classes and Level 2 classes correspond to the Level 1 subclasses. The discriminating features for each level are automatically chosen from 256 visual features for image color, texture and geometry. In order to derive high-level semantic features, machine learning techniques have been introduced in CBIR such as neural network for concept learning, Bayesian network for indoor/outdoor image classification and SVM for image annotation.

III. ONTOLOGY

Ontologies now play an important role for many knowledge-intensive applications for which they provide a source of precisely defined terms. The term "ontology" can be defined as an explicit specification of conceptualization. Ontologies capture the structure of the domain, i.e. conceptualization. This includes the model of the domain with possible restrictions. The conceptualization describes knowledge about the domain, not about the particular state of affairs in the domain. In other words, the conceptualization is not changing, or is changing very rarely. Ontology is then specification of this conceptualization - the conceptualization is specified by using particular modeling language and particular terms. Formal specification is required in order to be able to process ontologies and operate on ontologies automatically. Three kinds of inter-relationships are generally represented in an ontology: “IS-A”, “Instance-Of”, and “Part-Of”. These relations correspond to key abstraction primitives in object based and semantic data models. “Instance-Of” relation shows membership between concepts, while “Part-Of” shows composition relationships. “IS-A” relation shows concept inclusion, it used in similarity comparison in ontology-based image retrieval. When concept has an “IS-A” relation to another concept, this means that the second concept is more general than the first concept. If concept A has relation “IS-A”to concept B, we call concept A sub-concept and call concept B a super-concept. One characteristic of “IS-A” relation is that all the attributes of a super-concept can be inherited by its sub concepts. Sub-concepts normally have more attributes than super-concepts and as a result, correspondingly sub-concepts are more specific.

A. Measuring similarity between ontological models:

The measures for similarity computation can be divided into two general groups [13]; namely, lexical measures comparing entity labels, and structural measure comparing taxonomic hierarchy. In [13], seven criteria are extracted for deciding that two entities are similar:

- Their direct super-entities (or all of their super-entities) are already similar.
- Their sibling-entities (or all of their sibling-entities) are already similar.
- Their direct sub-entities (or all of their sub-entities) are already similar.
- All (or most) of their descendant-entities (entities in the sub-tree rooted at the entity in question) are already similar.
- All (or most) of their leaf-entities (entities, which have no sub-entity, in the sub-tree rooted at the entity in question) are already similar.
- All (or most) of entities in the paths from the root to the entities in question are already similar.
- All (or most) of relative entities to the entities in question using properties are similar.

IV. THE MAIN APPROACH

We propose an ontology approach for satellite image retrieval as shown in figure 1. The proposed system contains two main modules: ontological model merging and semantic strategic retrieval.

A. Module 1: Ontological model merging

1) Ontological modeling of the scene: Scene modeling consists of creating an ontological model describing features and spatial relations between them. This process contains two steps as shown in figure 2: the treatment step and the modeling step.

In the first step, we classify the satellite image, and extract objects from these classes. In the second step, we develop an ontological model representing extracted objects and spatial relation between them: The sensor ontological model, the scene ontological model and the spatial relation ontological model. The sensor ontological model allows representing the types of sensor according to their functioning mode. The scene ontological model allows representing objects in the satellite scene and their semantic hierarchy. The spatial relation ontological model allows representing spatial relation, position, direction and distance between objects.

2) Merging ontological models: The developed ontological models given by the first module cannot represent all objects of the real scene. Each model gives a particular aspect of the scene. For example, acquired by an optic sensor is clearer than a radar sensor. In addition, there are many conflicts situations: a scene feature can have many significations. For example, a line object in a scene can be interpreted as a road in a satellite image, and a River in another image.

3) Probabilistic method for merging ontological models: An approach for merging uncertain information is presented in [14]. It allows merging structured reports in XML document by using fusion approach such as probabilistic method, evidence method and possibility method. Our ontological model is formalized in OWL language. This language is based on XML/RDF. Therefore, we propose to adapt this approach in our fusion module by adding a specific attribute representing and managing uncertain information. Especially, we add the probability attribute to the object of the Ontological model. For example, Scene feature is a cultivated parcel with probability value of 80%, and forest with probability value of 20%.

B. Module 2: Semantic strategic retrieval

This module allows retrieving satellite images basing on their ontological model. The retrieval system contains a scene base composed of satellite images, and an ontological model base composed of ontological models which correspond to these satellites images. The idea is to retrieve satellite images basing on their ontological models; two images are similar if their ontological models are similar. In order to improve the quality of retrieval system and to facilitate the retrieval process, we propose two retrieval strategies which are the opportunist strategy and the hypothetic strategy.

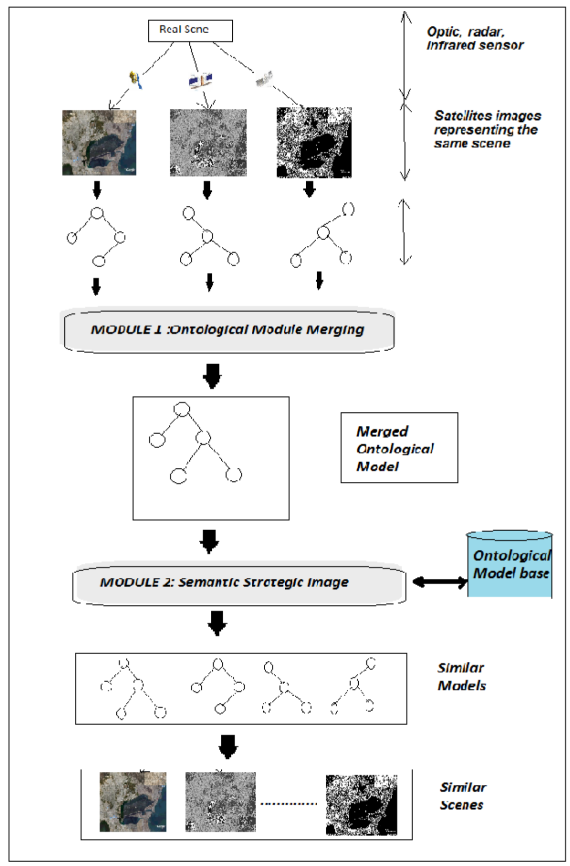

Fig. 1 The main conceptual diagram

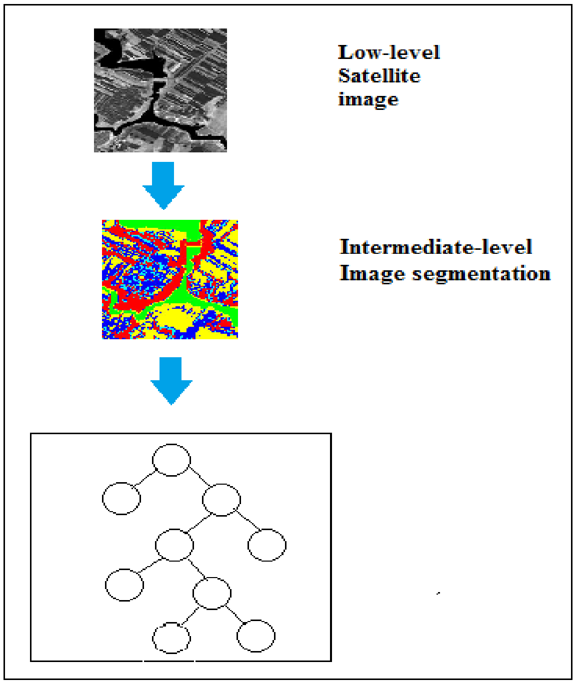

Fig. 2 Ontological modeling process

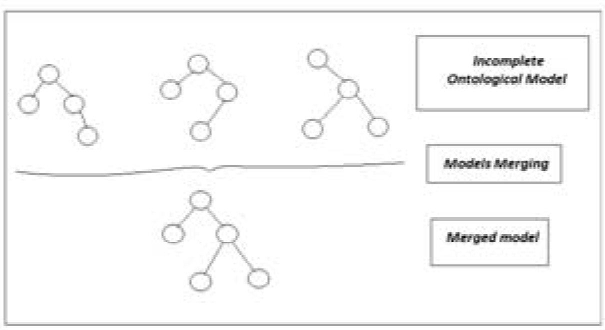

Fig. 3 Ontological model merging.

1) The opportunist strategy: This strategy is based on *atypical* objects which are the eminent and distinguished objects in the satellite image. It composed by two steps which are ontological model analysis and ontological model retrieval. The first identifies atypical objects from the merged ontological model. The second retrieves ontological models which contain *atypical* objects from the ontological model base. The result of this step is a set of accepted ontological models and another of rejected model. This strategy allows reducing the ontological model base and facilitates the retrieval process. We consider an ontological model which contains a cultivated parcel and a lake as atypical objects and adjacency as spatial relation between these objects. The result of this strategy is the set of ontological models which contains these atypical objects.

2) The hypothetic strategy: This strategy is based on the result of the opportunist strategic and the merged ontological model. It establishes the similarity degree for each model in the ontological model base according to its conformity with the query model. The result of this strategy is a set of ontological models ordered by their similarity degree. The similarity between ontological models is based on several levels such as the lexical similarity and the structural similarity.

V. CONCLUSION

In this paper, we presented an ontology approach for semantic retrieving satellite image taking into account the representation of spatial knowledge and based on two main modules: ontological models merging and semantic strategic retrieval. Our approach permits to overcome the obstacles of keyword-based approach. It has the potential to fully describe the semantic content of an image. Besides, it manages uncertain information and resolves conflicts situation by fusion algorithm that allows developing an ideal and reliable ontological model describing satellite scene. This work contributes the methodologies for the semantic representation, and the retrieval processes using ontology approach.

REFERENCES

[1] E. Hyvönen, A. Styrman, and S. Saarela. “Ontology-based Image Retrieval”, HIIT Publications Number 2002-03, pp.15-27.
[2] Y. Rui, T. S. Huang, and S.-F. Chang, “Image retrieval: Current techniques, promising directions, and open issues,” *J. Vis. Commun. Image Repres.*, vol. 10, pp. 39–62, 1999.
[3] A. Smeulders, M.Worring, S. Santini, A. Gupta, and R. Jain, “Contentbased image retrieval at the end of the early years,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 12, pp. 1349–1380, Dec. 2000.
[4] Y. Rui, T.S. Huang, “Optimizing learning in image retrieval”, Proceedings of the IEEE International Conference on Computer Vision and Pattern Recognition, June 2000, pp.1236-1243.
[5] Y. Rui, T.S. Huang, S.-F. Chang, Image retrieval: current techniques, promising directions, and open issues, J. Visual Commun. Image Representation, 1999, pp.39–62.
[6] A. Vailaya, M.A.T. Figueiredo, A.K. Jain, H.J. Zhang, Image classification for content-based indexing, IEEE Trans. Image Process, 2001, pp.117–130.
[7] N. Ruan, N. Huang, W. Hong, “Semantic-Based Image Retrieval in Remote Sensing Archive: An Ontology Approach”, Geoscience and Remote Sensing Symposium, 2006. IGARSS 2006, pp. 2903-2906.
[8] W. Zheng, Y. Ouyang, J. Ford, Fillia S. Makedon “Ontology-based Image Retrieval”, WSEAS MMACTEE-WAMUS-NOLASC 2003, Vouliagmeni, Athens, Greece, December 29-31, 2003
[9] Y. Liua, D. Zhanga, G. Lua,W.Y. Mab, “A survey of content-based image retrieval with high-level semantics”, The journal of the recognition society, pp. 262-282, 2007
[10]”Exploring the Semantic Gap in Content-Based Image

Retrieval: with application to Lung CT"Omar Karam, Ahmad Hamad, and Mahmoud Attia *Faculty of Computer and Information Sciences, Ain Shams University, Cairo, Egypt* .

[11] O. H. Karam, A. M. Hamad, S. Ghoniemy, S. Rady, "Enhancement of Wavelet-Based Medical Image Retrieval through Feature Evaluation Using an Information Gain Measure," *Proceedings of the 2003 ACM symposium on Applied computing Melbourne, Florida*, pp. 220 - 226

[12] J. G. Dy, C. E. Brodley, A. C. Kak, C. Shyu, and L. Broderick, "The Customized-Queries Approach to CBIR using EM," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition,* June 1999.

[13] B. B. Hariri, H. Abolhassani, A. Khodaei, "A New Structural Similarity Measure for Ontology Alignment", in the Proceedings of 2006 International Conference on Semantic Web and Web Services (SWWS'2006), Las Vegas, USA, June 2006.

[14] A. Hunter and R. Summerton. "Fusion rules for context-dependent aggregation of structured news reports". Journal of Applied Non- Classical Logics, pp. 329-366, 2004.

[15] Natalya Noy and Mark Musen. "Anchor-PROMPT: Using non-local context for semantic matching". In Proc. IJCAI 2001 workshop on ontology and information sharing, Seattle (WA US), pp.63–70, 2001.

[16] J. Zhong, H. Zhu, Y. Li, and Y. Yu, "Conceptual graph matching for semantic search," in Proceedings of Conceptual Structures: Integration and Interfaces (ICCS-2002), 2002, pp. 92–106.

[17] S. Melnik, H. Garcia-Molina, and E. Rahm, "A versatile graph matching algorithm," in Proceedings of ICDE, 2002.

[18] J. Euzenat and P. Valtchev, "An integrative proximity measure for ontology alignment," in Proceedings of Semantic Integration workshop at ISWC, 2003.

[19] H. Sun, S. Li, W. Li, Z. Ming, and S. Cai, "Semantic-Based Retrieval of Remote Sensing Images in a Grid Environment", IEEE geo science and remote sensing letters, vol. 2, no. 4, pages 440- 444, 2005

[20] A. Hunter and R. Summerton. "Fusion rules for context-dependent aggregation of structured news reports". Journal of Applied Non- Classical Logics, pp. 329-366,