An Approach To Cooperating Organizational Memories Based On Semantic Negotiation and Unification

Martin Schaaf[1], Ludger van Elst[2]

[1]University of Kaiserslautern
Department of Computer Science
PO Box 3049, D-67653 Kaiserslautern, Germany

[2]German Research Center for Artificial Intelligence (DFKI)
Knowledge Management Department
PO Box 2080, D-67608 Kaiserslautern, Germany

[1]schaaf@informatik.uni-kl.de
[2]elst@dfki.uni-kl.de

Abstract

The term *"Organizational Memory Information System"* (OMIS or OM) has been assigned to systems that support the management of explicit knowledge in an organization. In a single OM-scenario a set of agents dedicated to particular management tasks can communicate and collaborate on a semantic level by the presence of a domain ontology acting as a semantic index to the stored information items. In order to support communication and collaboration across OM boundaries, a common understanding of domain specific terms must be established e.g. by developing a shared ontology. In this paper we sketch an evolutionary approach toward a shared ontology based on similarities of local concepts gained by negotiation. We identify three semantic levels of Inter-OM communication and present a generic communication pattern that incrementally moves communication to higher levels.

Introduction

The term *"Organizational Memory Information System"* (OMIS or OM) has been assigned to systems that support a variety of activities like storing, retrieval, or sharing of explicit knowledge in an organization. Explicit knowledge here means information items that can be accessed on a semantic layer on top of an explicitly specified conceptualization that is often called domain ontology. While the KnowMore approach (see [Abecker A., Bernardi A., Hinkelmann K., Kühn O., and Sintek M. 1998]) focused on the systematical aspects when building a single OMIS, the successor project FRODO extends this to a distributed, multi-OM scenario with an arbitrary number of autonomous, but cooperating OMs ([Elst van L., and Abecker A. 2001a], [Elst van L., and Abecker A. 2001b]). In contrast to a single KnowMore OM, where a domain ontology acts as a semantic index providing knowledge-based access to stored information items, in the multi-OM scenario, we have to cope with an ontology society and a common understanding of domain specific terms must be found. In the literature (e.g. [Bachmann B. 1997]), the term semantic unification has been assigned to this. Hence, an ontology society must be semantically unified before agents can communicate and collaborate across OM boundaries. Semantic unification can be established by a shared ontology that either replaces the domain ontology society or acts as super-ontology representing common concepts defined "on-top" of the local concepts. In the latter case, inter-OM communication among agents will be restricted to the common concepts.

Unfortunately, developing a shared ontology is a complex task that cannot be performed in an ad-hoc manner because significant knowledge about many concepts defined within the ontology society is required (see [Bachmann B. 1997]). Furthermore, a shared ontology typically reflects a long-term contract that should be based on stable knowledge. Hence, we propose an evolutionary approach toward a shared conceptualization distinguishing three different levels for Inter-OM communication:

1. **„No shared conceptualization"-Level:** Communication between Domain Ontology Agents (DOA) does not rely on a shared ontology but on a more or less coincidental matching of concepts defined within the ontology society.
2. **„Concept Similarity"-Level:** Communication between DOAs is based on concept-similarities e.g. based on evidence measures gained through negotiation. In contrast to a shared ontology, ad-hoc creation of concept-similarities is possible.
3. **„Shared Ontology "-Level:** Communication is based on a shared conceptualization.

While the overall goal, the development of a shared ontology, remains, we propose that a basic Inter-OM-communication is possible on the other levels, too. Therefore, we present a communication pattern, which incrementally migrates inter-OM communication from level 1 to level 2 by negotiation. Furthermore, we sketch a reasoning strategy for a mediator named Distributed Domain Ontology Agent (D^2OA) that enables DOAs to communicate and collaborate intelligently by semantic unification approximation on level 2. Because the underlying reasoning strategy utilizes case-based-reasoning (CBR), we will provide a very brief introduction to newer CBR-approaches relevant here. We conclude this paper by a short summary. Hints to future work are pointed out explicitly within the text.

An Example-Multi-OM Scenario

We start explaining our ideas by an example scenario shown in Figure 1. Here, two Organizational Memories (OM1 and OM2) get managed by two *Domain Ontology Agents*, namely *DOA Cornell* and *DOA Kaiserslautern*. Both agents interpret the *Knowledge Items* of the organizational memories according to a domain ontology shown as a concept graph in Figure 1. Without loss of generality, *Knowledge Items* are expected to be text documents being classified accordingly, that is, they are instances of the concepts defined by the domain ontology.

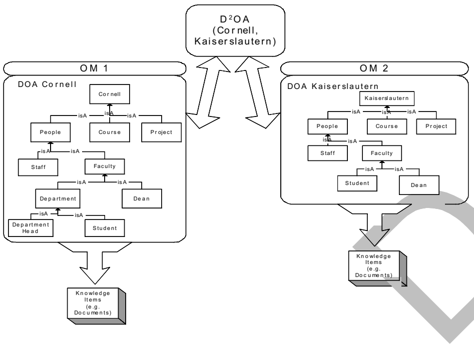

Figure 1: Example Scenario for Inter-OM Cooperation

Let us now assume that DOA Cornell requests all documents related to the concept *Department* from DOA Kaiserslautern. Because this concept is unknown for DOA Kaiserslautern, the request fails and both agents agree to establish a D^2OA as mediator for further negotiation. In our scenario, the D^2OA causes the DOA Cornell to transfer example documents for concept *Department* to DOA Kaiserslautern for classification. We expect this to result in a high evidence for concept *"DOA Cornell: Department"* being equal to the concept *"DOA Kaiserslautern: Faculty"*, which will be registered at the D^2OA by DOA Kaiserslautern. DOA Cornell can now re-request the documents by causing the D^2OA to translate the question and would receive all documents related to the concept *"DOA Kaiserslautern: Faculty"*. While this sounds easy and straightforward, there are some pitfalls. For example, from a "student perspective", the *"DOA Cornell: Department"* concept maps very well to *"DOA Kaiserslautern: Faculty"* including a mapping from *"DOA Cornell: Department Head"* to *"DOA Kaiserslautern: Dean"*. From an "administrative perspective", the dean in Kaiserslautern is more related to a dean of a faculty in Cornell. Consequently, DOA Cornell would have received documents in the request above that do not match the *"DOA Cornell: Department"* concept but, for example, the *"DOA Cornell: Faculty Staff"* concept. However, the results are more precise than by applying the strategy to weaken the request to the first concept both agents share by traversing the hierarchy toward the root (*People* in our example).

The exact mappings from and to the concept *"DOA Kaiserslautern: Faculty"* in the example above are:

$$DOA\ Kaiserslautern : Faculty \rightarrow\ DOA\ Cornell : Faculty$$
$$DOA\ Cornell : (Faculty \setminus Department \cup Student) \rightarrow\ DOA\ Kaiserslautern$$

In one direction it says that all documents classified as *Faculty* in Kaiserslautern can also be classified as *Faculty* in Cornell. In the other direction it is more complicated because *Department* and *Department Head* have no equivalent concept in Kaiserslautern. Documents belonging to these concepts might be of interest, too, but with lower similarity. We conclude our scenario by defining a generic communication pattern that ensures communication on the "Concept-Similarity"-level:

1. **Request:** A DOA requests *Knowledge Items* from the other DOA classified by the particular concept. The request is routed to a D^2OA acting as a mediator by approximating semantic unification.
2. **Negotiate:** If the D^2OA has no evidence mapping for particular DOA concepts involved in the request, it starts a negotiation by choosing one of the following operations (for further details see [Dieng R., and Hug S. 1998], [McGuinness D.L., Fikes R., Rice J., and Wilder S. 2000], and [Lacher M., and Groh G. 2001]):
    a. *Term-based evidence* considering the textual description (i.e., the "name") of a concept.
    b. *Topology-based evidence* considering the structure of the concept graph.
    c. *Instance-based evidence* that can be applied when ontology concepts are used for indexing and retrieving documents.

   In our approach, the concept mapping is stored at the D^2OA as a triple $(c_1, c_2, e) \in C \times C \times [0,1]$ reflecting the evidence gained between two concepts of the domain society. As we will see later, the *Term-based evidence* and *Topology-based evidence* operations can be deferred to semantic unification because they do not require additional communication between DOAs.

3. **Mediate:** Depending on the stored concept similarities, the D²OA mediates the knowledge exchange between two DOAs for the actual and further requests.

Facilitating Inter-OM Communication by Distributed Domain Ontology Agents

A D²OA is responsible for mediating between different DOAs by answering questions like "Which OM contains concepts like A and B?" or "What does A mean in OMy?". The key factor to an answer is the semantic unification, which is, traditionally, a yes or no criteria. In order to process requests like above, it is often not necessary to have a deeper understanding of the relationships between different concepts. Usually, it might be sufficient to have a basic understanding of concept similarity resulting in the notion of a weaker, fuzzy-like, semantic unification. However, such a semantic unification should still ensure high utility for the given answers that can only be measured a-posteriori. Therefore, our strategy for an approximation of semantic unification is based on a "useful" assessment of concept similarity. The relationship between similarity and utility is currently also a "hot topic" in the research of newer approaches to Case-Based-Reasoning that seems to fit very well to our problem domain, too. Figure 2 shows the extended utility-oriented view on CBR (summarized in [Bergmann R., Richter M. M., Schmitt S., Stahl A., and Vollrath I. 2001]). Unlike in early CBR approaches, it is now established that similarity is usually not just an arbitrary distance-like measure but also a function that approximately measures utility. Hence, traditional properties that have been demanded for similarity measures in earlier days (such as symmetry, reflexivity, or triangle inequality) are not required any more. Furthermore, similarity is not necessar-ily assessed between two problem descriptions but between two utility descriptions[1].

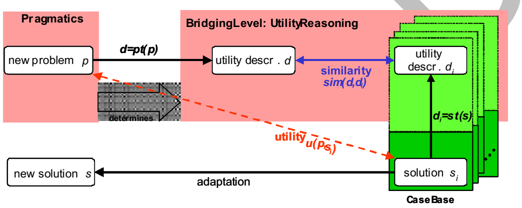

Figure 2: Extended View On Utility-Oriented CBR (taken from [Bergmann R., Richter M. M., Schmitt S., Stahl A., and Vollrath I. 2001])

[1] For a general introduction to CBR, we suggest consulting the literature, particularly the books [Bergmann, R 2001] or [Kolodner J. L. 1993].

Applying the extended utility-oriented view, the questions above can be reformulated to queries like "Give me the OM that defines the most similar concepts to my concepts A and B" or "Give me the concept of OMy most similar to concept A". In our approach the semantic unification approximation can be seen as a case-based-reasoning strategy selecting the most similar concepts s_i from a given case base that is, potentially, the set of all concepts defined within an ontology society. Hence, weak semantic unification has been reduced to retrieving similar concepts according to a utility description that is meta-knowledge about the ontology society. Please note that out approach is not intended to find or create a highly similar but the most similar concept from the given ones.

The future challenge is now to develop an appropriate utility description and a similarity model (see Figure 2). So far, we have identified the following aspects being relevant:

1. The evidence measure gained during a meaning negotiation between two DOAs: One can also imagine that such an evidence measure can be anticipated through other evidence measures.
2. The topology of the graph defined by the domain ontology corresponding to a concept: In [Bergmann R., and Stahl A. 1998] it is shown, how a similarity function $sim : C \times C \rightarrow [0,1]$ can be defined that uses a concept graph directly as a similarity model. By doing so, the topology of the concept graph of the corresponding domain ontology will be considered during each similarity assessment $sim(d, d_i)$. That replaces the *Topology-based evidence* mentioned.
3. The textual description of (e.g. the name) of a concept: This is a substitute for the *Term-based evidence*.
4. Experiences from previous, more or less successful semantic unifications: Storing these experiences as additional cases offers an interesting approach to a continuous learning-cycle for semantic unification.

Other contextual information (remember the "student"- and the "administrative" perspective from our scenario) may be relevant, too, and have to be further elaborated.

Summary

In this paper we proposed three different semantic levels of Inter-OM communication. We focused on the "Concept-Similarity"-Level and presented an approach for Inter-OM communication based on a weak semantic unification. Furthermore we showed, how this level could be established by an agent negotiation that determines evidence measures. Unlike traditional approaches to semantic unification, we only require an approximation by similarity partially based on the determined evidence measures. By utilizing CBR we mapped the problem to a stable and mature technology, which is supported by a variety of tools.

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