$\mathcal{K}$-$\mathcal{MORPH}$: Knowledge Morphing via Reconciliation of Contextualized Sub-ontologies

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Abstract. A knowledge-intensive problem is often not solved by an individual knowledge source; rather the solution needs to draw upon multiple, and even heterogeneous, knowledge sources. The synthesis of multiple knowledge sources to derive a 'comprehensive' knowledge source is a non-trivial problem. We discuss the need of knowledge morphing, and propose a Semantic Web based framework $\mathcal{K}$-$\mathcal{MORPH}$ for deriving a context-driven integration of multiple knowledge sources. We demonstrate the working of $\mathcal{K}$-$\mathcal{MORPH}$ by merging contextualized sub-ontologies from three different prostate cancer pathway ontologies for the problem-context *therapeutic decision support*.

1 Introduction

Knowledge-driven problem-solving demands 'complete' knowledge about the domain and its interpretation under different contexts. Since the availability of 'complete' knowledge is always challenging, therefore problem-solvers tend to manually integrate knowledge from multiple sources to formulate a comprehensive knowledge object that satisfies the problem's context. Knowledge morphing aims to formulate a comprehensive knowledge object, specific to a given context, through "the intelligent and autonomous fusion/integration of contextually, conceptually and functionally related knowledge objects that may exist in different representation modalities and formalisms, in order to establish a comprehensive, multi-faceted and networked view of all knowledge pertaining to a domain-specific problem"–Abidi 2005 [1]. The knowledge morphing approach extends the traditional notion of knowledge integration by providing the ability to 'reason' over the morphed knowledge to (a) infer new knowledge, (b) test hypotheses, (c) suggest recommendations and actions, and (d) query rules to prove problem-specific assertions or theorems.

2 $\mathcal{K}$-$\mathcal{MORPH}$: Solution Approach

The need for knowledge morphing is motivated by the realization that integration of knowledge sources should be driven by the *problem-context*–i.e. select and integrate only those knowledge fragments (within a knowledge source) that are relevant to the problem-context, as opposed to integrating the entire knowledge source. A well-defined problem-context, therefore, determines the scope of knowledge that is pertinent to the problem. For instance, in the domain of healthcare, clinical guidelines incorporate broad knowledge about the diagnosis, treatment, prognosis and follow-up care for a particular disease. For the context of *therapeutic decision support* one needs only therapeutic knowledge, which should be selected from multiple guidelines to formulate comprehensive therapeutic knowledge. We argue that the integration of the entire knowledge source exacerbates complexity of establishing knowledge interoperability between multiple knowledge sources. Therefore, in our approach, we define a Semantic Web based Knowledge Morphing Framework $\mathcal{K}$-$\mathcal{MORPH}$ to pursue knowledge morphing through reconciliation of ontology-encoded knowledge sources via following main tasks:

- *Task # 1*: Extracting contextualized sub-ontologies based on a given *problem-context*.
- *Task # 2*: Merging contextualized sub-ontologies based on identified/context-specific alignments to generate a morphed ontology.
- *Task # 3*: Detecting and resolving inconsistencies in the morphed ontology.

3 Related Work

By modeling knowledge sources as ontologies, semantic interoperability among knowledge sources can be achieved via *ontology reconciliation*. However, ontology reconciliation under different contexts is still an undertaking challenge [2]. The literature suggests other approaches for knowledge integration problem from different perspectives. For instance, the ECOIN framework performs semantic reconciliation of independent data sources, under a defined context, by defining *conversion functions* between contexts as a network [3]. ECOIN exploits the *modifiers* and *conversion functions*, to enable context mediation between data sources, and reconcile and integrate source schemas with respect to their conceptual specializations. Another initiative towards knowledge integration is reported in Mao et. al. [4] that use a Semantic Web framework, and propose an agent-oriented architecture that adopts a local sub-ontology evolution mechanism for dynamic self-organization of domain knowledge to support intelligent and efficient planning for problem solving in a distributed environment. Further more, Kang et. al. [5] also propose a Semantic Web based framework for (i) extracting sub-ontologies based on the user demands (i.e. problem-context in $\mathcal{K}$-$\mathcal{MORPH}$); and (ii) integrating extracted sub-ontologies into the ontology of the user demand (i.e. morphed ontology in $\mathcal{K}$-$\mathcal{MORPH}$). Their approach is similar to $\mathcal{K}$-$\mathcal{MORPH}$. However it is still a proposal, and no concrete results have been presented by them. A comparison of the above mentioned approaches in terms of the proposed tasks of $\mathcal{K}$-$\mathcal{MORPH}$ is shown as follows:

Table 3.1: $\mathcal{K}$-$\mathcal{MORPH}$: Comparison with the State-of-Art

$\mathcal{K}$-$\mathcal{MORPH}$ Tasks	ECOIN [3]	Mao et. al. [4]	Kang et. al. [5]
Task #1	N	Y	Y
Task #2	Y	Y	Y
Task #3	N	N	N

4 $\mathcal{K}$-$\mathcal{MORPH}$ Framework

We adopt a Semantic Web (SW) architecture to address the problem of knowledge morphing by (a) extracting contextualized sub-ontologies for the problem-context at hand; (b) merging contextualized sub-ontologies; and (c) detecting and resolving inconsistencies in the morphed ontology. Main tasks of $\mathcal{K}$-$\mathcal{MORPH}$ framework are briefly described in the following sub-sections.

Task # 1: Extracting Contextualized Sub-ontologies

Ontologies and contexts are used to model a domain with different views. Ontologies define a shared model that provides a global perspective, whereas contexts are used to realize a local aspect of a domain. A contextualized ontology deals with an adaptation of its ontology model to support a local view, and provides (i) a specific interpretation of its ontology concepts; and (ii) an implementation of its procedural knowledge that can be applied in a particular context [6]. In $\mathcal{K}$-$\mathcal{MORPH}$, from the given ontologies, the user identifies a set of concepts (and roles) that can be pertinent to the problem-context at hand. Based on those user-selected concepts (and roles), we apply our rule-based extraction method to extract a contextualized sub-ontology (i.e. a RDF-Sub-Graph) comprised of triples that correspond to the axioms and assertions for (i) the user-selected concept C (ii) individuals for C; (iii) roles in C; (iv) range-concepts for the roles in C; (v) sub-concepts of C; (vi) equivalent-concepts for C; (vii) restrictions on C; (viii) complex concepts that are composed of C; (ix) only the roles of the super-concepts that are also associated with C, and (x) super-concepts of C as an RDF Blank-Nodes. Our approach for extracting contextualized sub-ontologies is described in details in [7].

Task # 2: Merging Contextualized Sub-ontologies

Matching and alignment of ontologies have been carried out based on their lexical, conceptual and structural similarities [2]. When dealing with structural similarities, similarity scores between ontology-entities can be further improved based on the similarities between their structurally connected entities [2]. We believe such alignments can became more 'trustworthy' by finding similarities among entities that are driven from the underlying ontology axioms or assertions. Therefore we propose an ontology matching approach *proof-level ontology matching* (POM). Let two source ontologies $\mathcal{O}_1, \mathcal{O}_2$ and a similarity matrix $\mathcal{M}$ such that $\mathcal{M}_{ij} = \langle e_i, e_j, s \rangle$, where s is a similarity score between entities e_i and e_j from $\mathcal{O}_1$ and $\mathcal{O}_2$ respectively. Given two ontology-entities e, e', we write $e \vdash e'$, if there exists an axiom or assertion of e that derives an axiom or assertion of e'. Given similarity matrix $\mathcal{M}$, we calculate a similarity score between entities f_i and f_j, based on the similarity score $\forall \mathcal{M}_{ij} = \langle e_i, e_j, s \rangle$ such that $e_i \vdash f_i, e_j \vdash f_j$. Therefore, POM finds alignments not only based on structural similarities but also takes into account (similarities between) other deductively connected entities. we are currently working on our POM method, and will report further in up-coming publications.

Task # 3: Detecting and Resolving Inconsistencies

Inconsistencies–whether they occur during the process of ontology evolution or being produced during the ontology reconciliation process–result a potential harm to an ontology structure, and decrease credibility in representing a consistent and shared vocabulary of an underlying domain. When an inconsistency occurs, there are mainly two ways to deal with it: either resolve it, or reason with the inconsistent ontology [8]. We propose an approach for detecting and resolving inconsistencies. Our inconsistency detection deals with defined Integrity Constraint Rules $\mathcal{R}_I$ of the form $C_1 \wedge C_2 \wedge \cdots \wedge C_n \Rightarrow \bot$. An *inconsistent derivation* consists of derivation steps that lead to $\bot$ under $\mathcal{R}_I$. Our approach checks whether a given ontology $\mathcal{O}$ is inconsistent or not; by finding inconsistent derivations. For resolving inconsistencies, we generate sets of asserted ancestors $\mathcal{A}_1, \ldots, \mathcal{A}_n$, where removal of any $\mathcal{A}_i$ (and all derived triples of $\mathcal{A}_i$) resolves detected inconsistencies and results in a maximal consistent sub-ontology. We have implemented our approach in Euler [9].

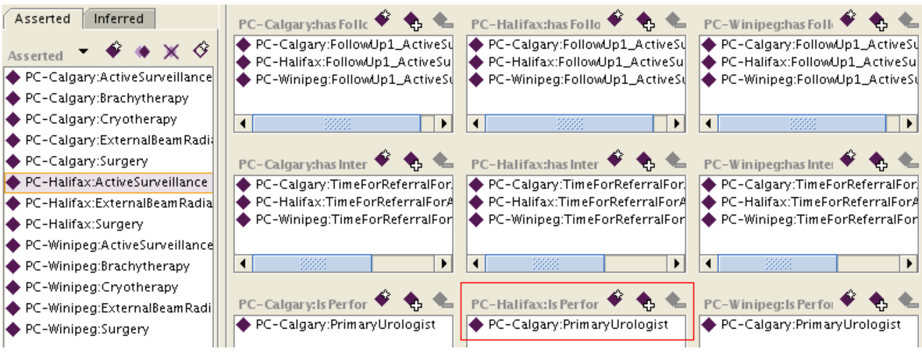

Fig. 1. Morphed Knowledge about PC-Halifax:ActiveSurveillance

5 Experiment and Results

In order to demonstrate the working of $\mathcal{K}$-$\mathcal{MORPH}$, we have developed a *PC Test-case* that uses three medical ontologies that describe the PC pathways for three different locations (Halifax, Calgary, and Winnipeg) [10]. Based on the problem-context *therapeutic decision support*, two concepts *Treatment* and *Clinician* were selected by the user. Based on the context-specific selected concepts, three contextualized sub-ontologies were extracted from the PC pathway ontologies. Using the pre-defined (context-specific) correspondences, alignments were found between classes–including their properties and instances. Based on the identified alignments, *therapeutic decision support* context-axioms and PC domain-axioms, extracted contextualized sub-ontologies were then merged to generate possible 'knowledge-links' between the aligned PC treatments. During the morphing process no inconsistencies were found, and finally the morphed ontology was generated. Figure 1 shows some of the exemplar results. In figure 1, the merged knowledge has determined that the treatment *Active Surveillance* in Halifax (represented by the instance `PC-Halifax:ActiveSurveillance`) can be conducted by a *Primary Urologist*. In the actual pathway, this information was not available for Halifax; but due to the ontology alignments this task was found similar to one in Calgary, and the actor performing this task in Calgary was extended to Halifax.

6 Conclusion

Optimal and complete decision support needs a comprehensive knowledge-base. Developing such a self-contained knowledge-base as an independent entity is a challenging undertaking. In this paper, we presented our knowledge morphing approach that performs a context-driven integration of knowledge sources to generate a comprehensive knowledge-base for the problem-context at hand. We demonstrated the working $\mathcal{K}$-$\mathcal{MORPH}$ by generating a comprehensive knowledge-base from three different clinical pathways for prostate cancer, pertaining to a problem-context *therapeutic decision support*.

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