I.J. Modern Education and Computer Science, **2015, 11, 67-78**
Published Online November 2015 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijmecs.2015.11.08

Ontology-Alignment Techniques: Survey and Analysis

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***Abstract*—**The ontology alignment consists in generating a set of correspondences between entities. These entities can be concepts, properties or instances. The ontology alignment is an important task because it allows the joint consideration of resources described by different ontologies. This paper aims at counting all works of the ontology alignment field and analyzing the approaches according to different techniques (terminological, structural, extensional and semantic). This can clear the way and help researchers to choose the appropriate solution to their issue. They can see the insufficiency, so that they can propose new approaches for stronger alignment. They can also adapt or reuse alignment techniques for specific research issues, such as semantic annotation, maintenance of links between entities, etc.

***Index Terms*—**Ontology Alignment, Terminological Method, Structural Method, Extensional Method, Semantic Method.

I. Introduction

The rapid development of Internet technology generated a growing interest in research on the sharing and integrating dispersed resources in a distributed environment. The Semantic Web offers the possibility for software agents to understand resources semantically linked in a decentralized architecture. Ontologies have been recognized as an essential component for sharing knowledge and realizing this vision. By defining concepts associated with particular areas, ontologies allow both to describe the content of the resources to be integrated, and to clarify the vocabulary used in queries of users. However, it is unlikely that a global ontology covering all distributed systems can be developed. In practice, ontologies of different systems have been developed independently of each other by different communities. Thus, if knowledge and data have to be shared, it is essential to establish semantic correspondences between the concerned ontologies. The ontology alignment task is important because it allows the joint consideration of resources described by different ontologies.

The Ontology Alignment is a complex task based on similarity measures. Many studies have been performed, but most of time only one measure is revealing insufficient to detect a similarity. Different approaches combining several measures sequentially were proposed: this combination is performed a priori, and it is not modified. The approaches should be more promising.

Our objective is to study, analyze and examine deferent alignment techniques and approaches that employ these techniques.

The rest of the paper is organized as follows: Section 2 describes techniques and methods used in the literature to address the research issue of similarity and dissimilarity, or correspondence between two entities in general. The deferent approaches that employ these techniques will be presented in Section 3. Section 4 presents statistics describing the rate of use of alignment techniques (terminological, structural, semantic and extensional) by different approaches. Finally, we conclude our work and mention some perspectives.

II. Alignment Techniques

The Ontology Alignment is performed according to a strategy or a combination of techniques for calculating similarity measures, and it uses a set of parameters (e.g., weighting parameters, thresholds, etc.) and a set of external resources (e.g., thesaurus, dictionary, etc.). At the end, we obtain a set of semantic links between the entities that compose the ontologies. There are several methods for calculating similarity between entities of several ontologies. Classifications of Alignment techniques are given in [94], [95] and [96].

A. Terminological methods

These methods are based on the comparison of terms, strings or texts. They are used to calculate the value of similarity between units of text, such as names, labels, comments, descriptions, etc. These methods can be further divided into two sub-categories: methods that compare the terms based on characters in these terms, and methods using some linguistic knowledge.

B. Structural methods

These methods calculate the similarity between two entities by exploiting structural information, when the concerned entities are connected to the others by semantic or syntactic links, forming a hierarchy or a graph of entities.

We call:

- Internal structural methods, methods that only exploit information about entity attributes,
- External structural methods, methods that consider relations between entities.

C. Extensional methods

These methods infer the similarity between two entities, especially concepts or classes, by analyzing their extensions, i.e. their instances.

D. Semantic methods

Techniques based on the external ontologies: When two ontologies have to be aligned, it is preferable that the comparisons are done according to a common knowledge. Thus, these techniques use an intermediate formal ontology to meet that need. This ontology will define a common context [35] for the two ontologies to be aligned.

Deductive techniques: Semantic methods are based on logical models, such as propositional satisfiability (SAT), SAT modal or description logics. They are also based on deduction methods to deduce the similarity between two entities. Techniques of description logics, such as the subsumption test, can be used to verify the semantic relations between entities, such as equivalence (similarity is equal to 1), the subsumption (similarity is between 0 and 1) or the exclusion (similarity is equal to 0), and therefore used to deduce the similarity between the entities.

These alignment techniques are integrated into approaches for mapping ontologies. We find approaches that combine multiple alignment techniques. Much work has been developed in the area of Ontology and focus on the alignment techniques.

III. Alignment Approaches

The literature counts a wide range of methods [31]. These are from various communities, such as information retrieval, databases, learning, knowledge engineering, automatic natural language processing, etc.

In [19] the authors consider a context where experts can use their own ontologies, called personal ontologies. Ontology is then represented by a support in the conceptual graph formalism. This support comprises a grid concept types, a hierarchy of relations types and a set of markers for the identification of instances.

The objective is to build a common knowledge model (common ontology) from different knowledge models of experts (personal ontology). This is realized, in a system called MULTIKAT, by comparing personal ontologies using techniques based on operations of the conceptual graph formalism or the structure of graphs.

Anchor-PROMPT [68] constructed a labeled oriented graph representing the ontology from the hierarchy of concepts (called classes in the algorithm) and the hierarchy of relations (called slots in the algorithm), where nodes in the graph are concepts and the arcs denote relations between concepts (labels of arcs are the names of relations). An initial list of anchor pairs (pairs of similar concepts) defined by the user or automatically identified by the lexicological mapping serves as input to the algorithm. Anchor-PROMPT then analysis paths in the sub-graphs limited by anchors, and determines which concepts appear frequently in similar positions on the similar paths.

GLUE [21] is the advanced version of LSD [20] which aims to find semi-automatic mappings between schemas for data integration. Like LSD, GLUE uses the learning technique (such as the naive Bayes learning technique) to find matches between two ontologies. GLUE includes several learning modules (Learners), which are entrained by instances of ontologies.

S-Match [34] is an algorithm and a system for semantically searching for correspondences based on the idea of using the engine of propositional satisfiability (SAT) [35] for the mapping schema issue. It takes as input two graphs of concepts (schemas), and generates as outputs relations between concepts, such as equivalence, overlapping, difference (mismatch), more general or more specific. The principal idea of this approach is to use logic to encode the concept of a node in the graph and applying SAT for reports.

COMA [22] is a system to match schemas (of databases, XML or ontologies) automatically or manually. The system provides a library of basic mapping algorithms (called matchers) and some mechanisms for combining results of the basic algorithms to get a final similarity value of two elements in two schemas.

OLA [30] is an algorithm to align ontologies represented in OWL. He tries to calculate the similarity of two entities in two ontologies based on their characteristics (their types: class, relations or instance; their reports with other entities: subclass, domain, co-domain ...) and combine the similarity values calculated for each pair of entities homogeneously.

It is further noted that:

- The approaches, coma and COMA ++, S-Match, manage many types of ontologies.
- The approaches, DCM, HSM, IceQ, their inputs have multiple ontologies.
- The approaches, coma and COMA++ and GeRoMeSuite, their internal presentations are oriented acyclic graphs.
- Most of systems focus on the discovery of simple

correspondences one-to-one. Although only a few systems have attempted to solve the problem of discovering more complex correspondences, such as IMAP, DCM, HSM, AOA, PORSCHE Optima Optima+.
- The approaches S-Match, DSSim and TaxoMap calculate the similarity measures between different entities of the ontology, as disjunction and subsumption. However, the other approaches only calculate the equivalence relations.
- Several approaches have introduced new ways for encoding the alignment process. For example, iMatch and CODI use the Markov networks. Others, like PARIS, propose interesting imbrications between the data links and the alignment schema. Other approaches, as VSBM and GBM, analyze also the image data.
- Many recent approaches (eg. Scarlet, OMviaUO BLOOMS & BLOOMS++) use, beside WordNet, other knowledge base sources, such as Wikipedia and ontologies.
- Several recent approaches have introduced the alignment check in the matching process, like Lily, YAM++ and LogMap.
- The approaches, Falcon, Anchor-Flood, Lily, AgreementMaker, LogMap FSM and effectively manage large-scale ontologies.
- The approaches, COMA++, S-Match, AgreementMaker, DSSim, Sambo and YAM++, are equipped with a graphical user interface.

Table.1. summarizes the schema and ontology alignment approaches. In fact, many approaches use the same techniques based on strings. We note also that some approaches use WordNet as an external resource.

In turn, the semantic measures are used only in some approaches, for example, CtxMatch, S-Match and LogMap.

The *Input* column represents the inputs of the systems.

The *Needs* column represents the resources to be available to star the system. This covers the manual aspect, referenced by "USER" in the table, when the user's back is required; "SEMI" when the system can take advantage of the user feedback; but can be "AUTOMATIC" when the system operates without the user intervention. The "INSTANCES" value indicates that the system requires data instances.

The columns, *Terminological Measures*, *Structural Measures*, *Extensional Measures* and *Semantic Measures*, specify the alignment techniques adopted by the approach in question.

Table 1. Summary of alignment approaches

Approach	Input	Needs	Terminological Measures	Structural Measures	Extensional Measures	Semantic Measures	Observation
T-tree [29]	Ontologies	AUTO, INSTANCES		Correlation			
SEMINT [52]	Relational schema	AUTO, INSTANCES	Neural network, Data types		Constraint-based		
DELTA [9]	Relational schema, EER	USER	String-based				
Hovy [41]	Ontologies	SEMI	String-based, Language-based	Taxonomic			
Cupid [58]	XML schema, Relational schema	AUTO	String-based, Language-based, Data types, Auxiliary thesaurus	Tree matching weighted by leaves			
LSD [17]	XML schema, Relational schema	AUTO, INSTANCES	Naive Bayes,	Hierarchical structure	Constraint-based		
COMA/ COMA++ [16]	XML schema, Relational schema OWL	USER	String-based, Language-based, Data types, Auxiliary thesaurus	DAG (tree) matching with a bias towards various structures, e.g., leaves, Repository of structures			
Similarity flooding [63]	XML schema, Relational schema	USER	String-based, Data types	Iterative fixed point computation			
XClust [50]	DTD	AUTO	Cardinality, WordNet	Paths, Children, Leaves, Clustering	Constraint-based		
Automatch [4]	Relational schema	AUTO, INSTANCES	Naive Bayes,	Internal structure, Statistics			

[92]	XML schema, Taxonomy	AUTO, INSTANCES	String-based, Language-based, WordNet				
IF-Map [53]	KIF, RDF	AUTO, INSTANCES	String-based	Formal concept analysis			
SBI&NB [42]	Classification	AUTO, INSTANCES	Statistics, Naive Bayes,	Pachinko Machine, Naive Bayes			
[54]	Relational schema	INSTANCES	Language-based	Mutual information, Dependency graph matching			
S-Match [33]	Classification, XML schema, OWL	AUTO	String-based, Language-based, WordNet			Propositional SAT	
GLUE [18]	XML schema, Relational schema, Taxonomic	AUTO, INSTANCES	Naive Bayes,	Hierarchical structure	Instances-Based, Constraint-based		
iMAP [13]	Relational schema	AUTO, INSTANCES	Naive Bayes,	Hierarchical structure	Constraint-based		
ASCO [3]	RDFS, OWL	AUTO	String-based, Language-based, WordNet	Iterative similarity propagation			
[89]	Web form	INSTANCES	Language-based	Mutual information			Data Integration
NOM [26]	RDF, OWL	AUTO, INSTANCES	String-based	Matching of neighbours, Taxonomic structure			
QOM [27]	RDF, OWL	AUTO, INSTANCES	String-based, Domain, Application, Vocabulary	Matching of neighbours, Taxonomic structure			
IceQ [91]	Web form	AUTO, SEMI	String-based	Clustering	Constraint-based		
OLA [30]	RDF, OWL	AUTO, INSTANCES	String-based, Language-based, Data type, WordNet	Iterative fixed point computation, Matching of neighbours, Taxonomic structure			
[79]	WSDL	AUTO	String-based, Language-based, WordNet	Structure comparison			
MWSDI [69]	WSDL, OWL	AUTO	String-based, Language-based, WordNet	Structure comparison			
BayesOWL [70]	Classification, OWL	AUTO	Text classifier, Google	Bayesian inference			
OMEN [64]	OWL	AUTO, ALIGNEMENT		Bayesian inference, Meta-rules			
DCM [8]	Web form	AUTO		Correlation, Statistics			Data integration
Dumas [5]	Relational schema	INSTANCES	String-based	Instance identification			
oMap [78]	OWL	AUTO, INSTANCES	Naive Bayes,, String-based	Similarity propagation			Query answering
eTuner [76]	Relational schema, Taxonomy	AUTO					
SAMBO [51]	OWL	AUTO, DOCUMENTS	String-based, Naive Bayes,, WordNet	Iterative structural similarity based on *is-a*, *part-of* hierarchies			Ontology merging
AROMA [12]	Classification, OWL	AUTO, INSTANCES	String-based	Association rules			

RiMOM [83]	OWL	AUTO, INSTANCES	String-based, Naive Bayes,, WordNet	Taxonomic structure, Similarity propagation			
LCS [46]	RDF, OWL	AUTO					
HSM [80]	Ontologies	AUTO		Co-occurrence patterns, Statistics			
CtxMatch/ CtxMatch2 [7]	Classification, OWL	USER	String-based, Language-based, WordNet			Based on description logics	
CBW [37]	OWL	AUTO	String-based	Coincidence-based weighting			
GeRoMeSuite [55]	SQL DDL, XML, OWL	AUTO, SEMI	String-based	Similarity flooding, Children			Merging, Composing
AOAS [93]	OWL	AUTO	String-based, Language-based	Compatible *is-a*, *part-of* paths		Rule-based inference	
ILIADS [87]	OWL	AUTO, INSTANCES	String-based, Language-based, WordNet	Matching neighbors, Clustering		Rule-based inference	Ontology merging
Scarlet [74]	OWL	AUTO	String-based			Ad hoc rule-based inference	
BeMatch [10]	BPEL, WCSL	AUTO, SEMI	String-based, Language-based, WordNet	Graph isomorphism			Service transformation
PORSCHE [75]	XSD	AUTO	String-based, Language-based, Thesaurus	Clustering, Tree mining			Mediation schema
Match-Planner [24]	XML	AUTO,	Second String, Language-based, WordNet				
Falcon-AO [40]	RDF, OWL	AUTO, INSTANCES	String-based, WordNet	Structural affinity			
SMB [61]	Web form, XML schema, OWL	AUTO					
FSM [45]	Relational schema	AUTO, INSTANCES	String-based				
Anchor-Flood [39]	RDFS, OWL	AUTO	String-based, Language-based, WordNet	Internal, external similarities, Iterative anchor-based similarity propagation			
[88]	OWL	AUTO, SEMI	String-based	Variations of similarity flooding			
AgreementMaker [11]	XML, RDFS, OWL, N3	AUTO, SEMI	String-based, Language-based, WordNet	Descendant, sibling similarities			
HAMSTER [66]	XML	AUTO, SEMI, INSTANCES	String-based, Language-based, Naive Bayes,, Click logs	Structure comparison			

Smart Matcher [90]	UML	AUTO, USER , INSTANCES	COMA++, FOAM	Structure comparison	Instances-based		Instance transformation
GEM/Optima/ Optima+ [23][86][87]	RDF, OWL, N3	AUTO, INSTANCES	String-based, Language-based, WordNet	Expectation-Maximization, Matching of neighbors			
YAM/YAM++ [25]	XML, OWL	AUTO, SEMI	WordNet	Structure profiles, Similarity flooding			
GOALS [59]	OWL	AUTO					
ContentMap [47]	OWL	AUTO, SEMI					Integrated ontology
SeqDisc [2]	WSDL	AUTO	String-based, Language-based	Leafs, Children, Ancestor comparison			
OMviaUO [62]	RDFS, OWL	AUTO	String-based, Language-based	Taxonomic		Rule-based inference	
BLOOMS/ BLOOMS+ [43]	RDFS, OWL	AUTO	Language-based, API alignment	Taxonomic structure		Rule-based inference	
Homolonto [71]	OBO	AUTO, SEMI	Language-based,	Children similarity			Homologous groups
DSSim [65]	OWL, SKOS	AUTO	String-based, Language-based, WordNet		Instances-based		Question answering
TaxoMap [38]	OWL	AUTO, SEMI	String-based, Language-based	Structure comparison via *is-a* hierarchies			
VSBM&GBM [44]	Ontologies	AUTO, INSTANCES	Statistics, SVM	Correlations in graph			
CSR [82]	OWL	AUTO, INSTANCES	String-based	Feature-based similarity, Machine learning			
Prior+ [60]	OWL	AUTO, INSTANCES	String-based, Language-based	Feature-based similarity, Neural network			
MoTo [28]	OWL	AUTO, INSTANCES	Naive Bayes, *k*-Nearest neighbor	Structural validation: Taxonomy, Other relations			Neural network
CODI [67]	OWL	AUTO, INSTANCES	SimMetrics	Structure comparison		Markov net inference	
CIDER [36]	OWL	AUTO	String-based, Language-based				
MapPSO [6]	OWL	AUTO	String-based, Language-based, WordNet	Population-based optimization			
ProbaMap [84]	Taxonomy	AUTO, INSTANCES,	Statistics, Naive Bayes, C4.5, SVM				
LogMap [48]	OWL	AUTO, SEMI	String-based, Language-based, WordNet	Structure comparison		Propositional Horn satisfiability	
AMC [72]	Relational schema, XML, OWL	AUTO, SEMI, INSTANCES					
iMatch [1]	OWL	AUTO, SEMI	String-based				
PARIS [81]	RDFS	AUTO, INSTANCES	String-based	Probabilistic estimates via iterative fixed point computation			
AMS [73]	Relational schema, XML, OWL	AUTO, SEMI, INSTANCES					

LogMap2 [49]	OWL	AUTO, SEMI	String-based, Language-based, WordNet	Structure comparison		Propositional Horn satisfiability	
XMapSiG/ XMapGen [14]	Ontology	SEMI	WordNet, String-based	Based on information about the presence of the properties and their cardinality constraints			
XMAP ++ [15]	Ontology OWL-DL	SEMI	WordNet, String-based, Aggregated similarities	Based on information about the presence of the properties and their cardinality constraints	Based on linguistic measures		RNA is used to calculate the best match between pairs of entities, to maximize the discovery of many similar couples and reduce the number of those who are dissimilar. The final alignment is obtained after filtering based on a threshold
RiMOM-IM [77]	Ontologies	SEMI	Tokens-based (TF/IDF), Aggregated similarities		Instances-based, cosines traditional similarity, maxpooling+ similarity		
MaasMatch [32]	Ontologies	AUTO	Language-based		Based on linguistic measures		
InsMT [56]	Ontologies	AUTO, SEMI	String-based (levenshtein, Jaro, SLIM-Winkler), Aggregated similarities		Instances-based		
InsMTL [57]	Ontologies	AUTO, SEMI	String-based (levenshtein distance, Jaro, SLIM-Winkler) , Aggregated similarities, WordNet		Instances-based, Based on linguistic measures		The system applies a local filter
AOT [56]	Ontologies	AUTO, SEMI	String-based (distance of levenshtein, Jaro, SLIM-Winkler, Jaro-Winkler, Smith-Waterman and Needleman-Wunsch), Aggregated similarities				The system applies a local filter, The system applies a second filter to identify global alignment
InstML [57]	Ontologies	AUTO, SEMI	String-based (distance of levenshtein, Jaro, SLIM-Winkler, Jaro-Winkler, Smith-Waterman and Needleman-Wunsch), Aggregated similarities, WordNet		Based on linguistic measures		

IV. STATISTICS

The approaches we have previously cited, their main difference reside in the strategy used to discover the similarity between two entities. In most cases, are used terminological and/or structural and/or extensional similarity measures. Semantic measures are operated in some approaches, for example, CtxMatch, S-Match and LogMap.

A combination strategy allows to find the final similarity. This, generally, represents an equivalence or subsumption relationship between two entities from two different ontologies. The use of multiple similarity measures gives often better results. On the other side, these tools do not always specify which matchers were used or how the similarities were aggregated. Moreover, it should be noted that frameworks are more suitable for reuse as well as the combination of existing similarity measures according to preset criteria. These systems also differ in functioning and interaction offered to their users.

The intervention of a domain expert in the ontology alignment process is often necessary to avoid inconsistencies. By more interactive tools, such as PROMPT or FOAM, suggesting alignment results to the user often gives better results. On the other side, they do not allow reusing the alignment results to deduce other correspondence relations.

Fig.1. shows that researches in the ontology alignment field started with the nineties. From 2000 to 2009, the number of works in this domain is becoming increasingly important with the appearance of the Semantic Web notion. This number reaches its maximum in 2010. Researches continue to this day.

From Fig. 2, it is clear that the terminological method intervenes in a large number of approaches. The structural method also marks its importance among other techniques. This can be explained by the fact that the methods based on terms or structure are often manageable and easy to be implemented. Unlike semantic methods which require the availability of semantic sources, difficult to be constructed. They also require complex reasoning engines to infer semantic relations.

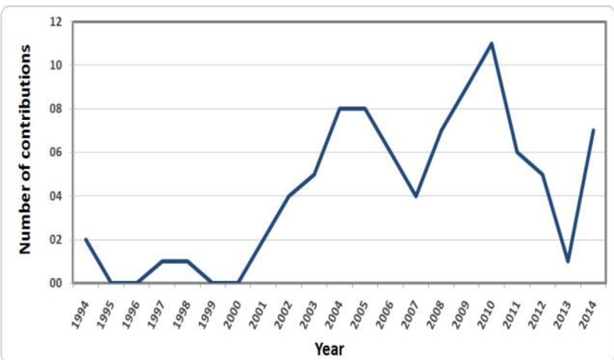

Fig.1. Evolution of the number of works in the ontology alignment field.

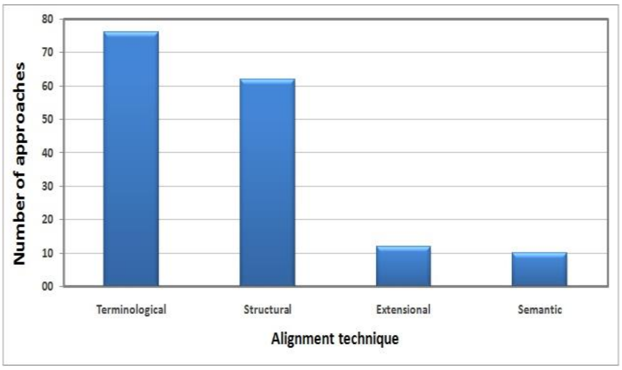

Fig.2. Rate of using alignment techniques (terminological, structural, extensional and semantic)

V. CONCLUSION AND PERSPECTIVES

The Alignment Process Consists In Producing A Set Of Mappings (Correspondences) Between Entities. However, The Automatic Generation Of Correspondences Between Two Ontologies Is Extremely Difficult, Due To The Differences (Conceptual, Habits, Etc.) Between Different Communities Concerned By These Ontologies. Furthermore, The Alignment Issue Is Particularly Acute When The Number And Volume Of Data Schemas Are Important. Indeed, In The Real Applications, Where Ontologies Are Voluminous And Complex, Requirements Of Execution Time And Memory Space Are Two Significant Factors That Directly Influence The Performance Of An Alignment Algorithm.

The Purpose Of This Paper Is To Identify And Cite Works In The Ontology Alignment Field. This Can Clear The Way For Researchers In This Domain. They Can Choose The Appropriate Approach To Their Problem. They Can Also See The Shortcomings And Correct Them, Or Propose New Alignment Approaches. As For Us, We Expect To Offer A Maintenance Approach Of Existing Alignments. This Problem Can Be Caused By The Development And Evolution Of Ontologies Making Parts Of An Existing Alignment.

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How to cite this paper: Fatima Ardjani, Djelloul Bouchiha, Mimoun Malki,"Ontology-Alignment Techniques: Survey and Analysis", IJMECS, vol.7, no.11, pp.67-78, 2015.DOI: 10.5815/ijmecs.2015.11.08