A new Ranking Technique for Integration among Higher-Level and Lower-Level Domain Ontologies and its Application to the Electromagnetic Domain

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***Abstract* – Nowadays ontologies represent a largely adopted information codification technique in many knowledge domains. Complex ontological frameworks have been developed in diverse areas, presenting the association of different levels of logic and semantic abstraction. These structures gather general contents (*Domain Ontologies*) and integrate them with more specific concepts (*Subdomain* and *Application Ontologies*). However, integration procedures may bring about complex issues such as semantic overlaps and knowledge base modifications. In order to minimize the occurrence of such events, an accurate selection and evaluation phase is advisable. In this paper we propose a methodology to evaluate higher-level domain ontologies in order to determine which candidate ontology would perform better if integrated with lower-level ones. The methodology is based on the computation of a set of multi-purpose ad-hoc metrics that are used as evaluation criteria in a multi-decisional ranking process. The methodology is applied to a real-life integration case study in the Electromagnetic knowledge domain. Two well-known scientific ontology frameworks are selected and evaluated in order to determine their suitability to provide a mid-level to proprietary Electromagnetic ontologies.**

Keywords – ontology, metric, ranking technique, integration .

I. INTRODUCTION

Recent years have seen a constant increase in ontology usage among heterogeneous scientific domains. Such rigorous formalizations [1] provide a globally accepted way of codifying knowledge and promoting information sharing and reuse across different research organizations. From Astronomy [2] to Healthcare [3], ontologies find a great variety of applications. On the contrary, the Electromagnetic (EM) scientific area did not benefit from robust ontological codifications so far.

The authors paved this way by proposing OntoCEM (Ontological Codification of ElectroMagnetism) [4]. The semantic description and integration of different branches of Electromagnetism is at the basis of OntoCEM. However, such ambitious goal hides many of the issues related to ontology merging procedures. Indeed, joining diverse ontologies may collide with potentially severe semantic heterogeneity of data, causing content overlaps or requiring knowledge base adjustments. At the same time, the need of an ontological superstructure made up of general scientific concepts (i.e., *scientific domain ontologies*) from which EM concepts (i.e., *EM application ontologies*) can inherit properties is perceived as well. This leads to the adoption of a hierarchical architecture [5], based on different layers of semantic abstraction and on the reuse of available ontologies. As a consequence, a deep integration activity is required.

In order to reduce typical issues that weigh down integration procedures, specific techniques for examining the ontologies that should be merged together are needed. Semantic completeness, domain adequacy and reusable contents availability are just a small example of the requirements that should be satisfied.

Evaluation metrics represent a common method to numerically establish the "goodness" of an ontology, as they take into account many of its aspects. A great amount of these metrics is nowadays available in literature, which consider ontology structure [6] and contents [7].

In this paper, rather than focusing on single metrics we propose a thorough methodology based on the computation of heterogeneous metrics and on their synthetical evaluation through a multi-decisional scoring process. The methodology is adopted to determine the best candidate for the integration with the EM ontologies defined in OntoCEM.

OntoCEM is briefly described in Section II. Section III introduces the proposed analysis technique. Sections IV to VI detail such technique, providing a tangible evaluation use case in the EM domain.

II. RELATED WORK

Ontological evaluation techniques based on the analysis of the design choices [8] have been proposed since late '90s. These methods evaluate ontologies without considering how ontology contents affect integration procedures. Kalfoglu et al. [7], instead, focus on this aspect by proposing distance measurements among different entities belonging to the same ontology or among entities codifying the same concept in different ontologies. Hu et al. [9] present a lattice-based similarity metric. Yunjiao et al. [10] extend classical tree similarity measurements towards content examination by considering domain expert contribution in evaluating the similarity between concept meanings. Other works measure semantic similarity by adopting lexical databases (i.e., WordNet) and by analyzing synonyms and hierarchical relationships. Among them, we recall GLUE [11], COMA++ [12] and SeCoOn [13].

 ISBN: 978-1-61208-155-7

Our proposal differs from previous works as we suggest an integrated approach based on the computation of heterogeneous metrics, which examine different ontological issues and on their aggregation by means of a consolidated ranking procedure. Finally, the entire evaluation process adopts a real-life scenario as benchmark case: i.e., the choice of the best-suited ontology for providing a scientific mid-level to an ontological framework describing the electromagnetism knowledge domain.

III. OntoCEM Architecture

As depicted in Fig. 1, OntoCEM [14] is organized into three semantic layers codified in OWL2-DL [15] language. The top level comprises publicly reusable scientific domain ontologies, collecting general concepts that belong to Math and Physics knowledge domains. The mid level gathers EM domain ontologies: these proprietary modules describe several EM branches and topics such as antennas, EM fields, EM propagation mechanisms, EM measurement units, etc. At the bottom there are ontologies describing specific EM applications, such as: shielding techniques, specific microwave devices, CAD processes, etc. Moving upward along the stack, contents become more and more abstract.

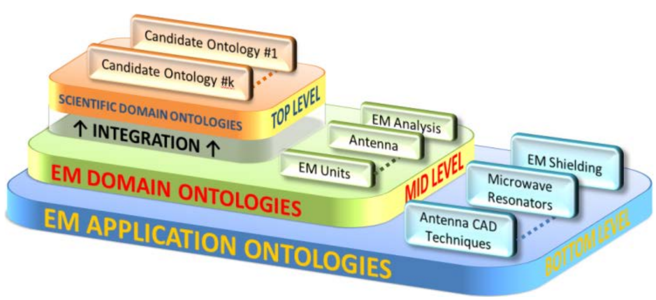

Figure 1. OntoCEM architecture.

IV. Ontology Evaluation Technique

Choosing the scientific domain ontology that would perform better if integrated with EM proprietary ontologies requires the application of a rigorous methodology. We propose a three-step technique, as described in Fig. 2.

Firstly, candidate scientific domain ontologies are selected by considering the following requirements: OWL-DL codification language, public availability and modularity.

Secondly, multi-purpose metrics are computed in order to analyze candidates in terms of size, structure, content, integration effort and reusability.

Thirdly, the candidates are ranked by using those metrics as performance criteria in a well-known multi-decisional process. This results in a rigorous, unambiguous classification.

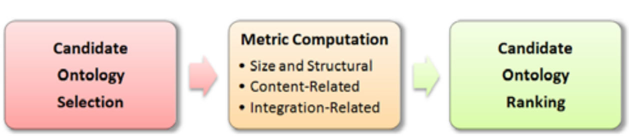

Figure 2. Proposed evaluation methodology.

V. Selecting the Candidate Ontologies

We selected candidate ontologies by identifying scientific semantic frameworks that mainly deal with Math and Physics domains. We searched for openly available, highly modular and wide ontology sets codified in OWL-DL in order to fulfill reusability and selective import requirements.

From such bases, two corpora of ontologies were chosen: the ontologies published by the Astronomical Department of the University of Maryland (UMD) [16] and the Semantic Web for Earth and Environmental Terminology (SWEET) Ontologies [17].

VI. Computing the Metrics

Three sets of metrics have been defined, each taking into account a different ontological aspect: 1) size and structure; 2) contents; 3) suitability to integration. In the following, the metrics are first described and then computed against the selected candidate ontologies.

A. *Overall considerations*

Although the proposed metrics refer to heterogeneous features of an ontology, they are designed to share common characteristics in order to make their behavior as uniform as possible.

- Metrics are closed-ended, i.e., defined in a closed numerical range. More in detail, the range is [0;1].
- Metrics producing out-of-bounds values require a linear scaling transformation (1) in order to be normalized to the definition range given above.

$$x_{norm} = \frac{x_a - \min_i\{x_i\}}{\max_i\{x_i\} - \min_i\{x_i\}} \quad (1)$$

  Where x_a is the actual value of the metric, x_{norm} its normalization and x_i all its possible values.
- Metrics must produce a maximization problem. Metrics behaving differently are suitably converted by complementing them.

B. *Size and Structure-related Metrics*

The first set of metrics monitors typical design aspects related to OWL language and do not consider any domain-related issue. Although they are relatively simple, structural metrics reveal themselves as an important source of information, especially for wide ontologies.

Class to Entity ratio (CtEr) measures the ratio between the total number of classes (*nCl*) and the total number of entities (*nEnt*).

$$CtEr = \frac{nCl}{nEnt} \quad (2)$$

Property to Entity ratio (PtEr) and **Instance to Entity ratio (ItEr)** quantify property and instance presence, as it is recognized to enrich the ontology [18]. Indeed, the less properties and instances there are, the more the ontology

 ISBN: 978-1-61208-155-7

resembles a mere taxonomy made up only of “is-A” relationships.

$$PtEr = \frac{nOP + nDP}{nEnt} \quad (3)$$

$$ItEr = \frac{nInst}{nEnt} \quad (4)$$

where *nOP*, *nDP* and *nInst* represent the number of Object Properties, Datatype Properties and Instances respectively.

Entities per Module ratio (EpMr) is the ratio between the number of entities (*nEnt*) and the number of available modules (*nM*) in the ontology.

$$EpMr = \frac{nEnt}{nM} \quad (5)$$

This is a non-normalized, bounded quantity. Its lower bound is the case of one entity per module, $EpMr_{min}=1$ and its upper bound is represented by all the entities defined in only one module, that gives: $EpMr_{MAX}=nEnt$. Therefore, recalling (1), the normalized ratio ($EpMr_{norm}$) is:

$$EpMr_{norm} = \frac{\left(\frac{nEnt}{nM}\right) - 1}{nEnt - 1} \quad (6)$$

In order to avoid modules huge in size and problems in finding contents, the value of this metrics should be as low as possible. Therefore, the complemented metrics (7) is considered:

$$EpMr = 1 - EpMr_{norm} \quad (7)$$

Table I presents size metric computation results with respect to the candidates. UMD ontologies showed a better performance in terms of *CtEr* whilst SWEET are preferable in terms of the other metrics. Better values for each metric have been highlighted.

TABLE I. SIZE METRIC COMPUTATION RESULTS

Metric	UMD	SWEET
CtEr	0.88	0.63
PtEr	0.06	0.08
ItEr	0.05	0.28
EpMr	0.923	0.995

C. *Content-related Metrics*

These metrics examine domain-related information. Entities defined in candidate ontologies are partitioned into three subsets and must be identified by a domain expert.

- ***Scientific (S) entities***: scientific concepts capable of acting as valid superclasses or useful reusable properties for EM concepts defined in OntoCEM ontologies. Their number is indicated as *nS*.
- ***Electromagnetic (E) entities***: concepts concerning EM. As EM concepts are located in OntoCEM modules as well, *E* entities may generate semantic conflicts during the integration procedure. Therefore it is preferable to have only a small quantity (*nE*) of them in candidate ontologies.
- ***Unusable (U) entities*** are entities that belong neither to *S* nor to *E* set. The number *nU* of *U* entities should be as low as possible, in order to reduce ontology loading times.

Additionally, we indicated as *ES* modules the modules comprising at least one *S* or *E* entity.

Table II enlists some *S* and *E* entities.

TABLE II. EXAMPLES OF *S* AND *E* ENTITES

Scientific (*S*) Entities	Electromagnetic (*E*) Entities
Classes	
Physical Property; Energy; Function; Scientific Model; Vector; Integral; Transmitter; Orientation;; Algorithm...	*Remote Sensing; Electric Dipole; Diffraction; EM Spectrum; Antenna; Wavelength; Microwave…*
Object Properties	
has Effect; has Component; has Unit; has Force…	*Radiate; has Frequency; has Spectral Band…*
Datatype Properties	
has Probability; has Scale; has Numeric Value…	*has Scattering Coefficient; has Resonant Frequency...*
Instances	
Sn; X Axis; Meter; per Second; dB; Joule; FFT...	*SNR; Ohm; Refractive Index; MHz; Siemens; Volt per meter…*

Domain Scientific Richness (DSR) weights the presence of *S* concepts.

$$DSR = \frac{nS}{nS + nE + nU} \quad (8)$$

Domain EM Richness (DER) quantifies the presence of *E* concepts.

$$DER = 1 - \frac{nE}{nS + nE + nU} \quad (9)$$

Loading Overhead (LO) assess the presence of *U* concepts.

$$LO = 1 - \frac{nU}{nS + nE + nU} \quad (10)$$

Table III shows computation results for the candidates. Better values for each metric have been highlighted. As UMD and SWEET content metrics have discordant values, a unifying methodology is needed. This technique will be described in Section VI.

TABLE III. CONTENT METRIC COMPUTATION RESULTS

Metric	UMD	SWEET
DSR	0.44	0.59
DER	0.94	0.93
LO	0.5	0.66

D. Integration-related Metrics

In order to evaluate how suitable a candidate ontology is to be integrated with available lower-level ontologies, we propose an approach based on the simulation of integration tasks.

First of all, a set of concepts (named *benchmark entities*, *BE*) codified in the lower-level ontology has to be identified on the basis of "structural" and/or "semantic" considerations. Indeed, we selected classes that subsume a great number of concepts and/or that are relevant from a domain expert point of view. Table IV enlists the chosen entities and provides a brief description for each of them. They are taken from each of the ten EM domain modules defined in OntoCEM mid-level (see Fig. 1).

TABLE IV. LIST OF BENCHMARK ENTITIES (*BE*)

EM Concept / *OntoCEM module*	Role in OntoCEM
Antenna / *Antenna*	Root concept subsuming all antenna typologies
Radio Propagation Model / *EM Propagation*	Root concept describing scientific models that estimate signal attenuation due to Path Loss in wireless communication systems
Uniform Plane Wave / *EM Waves*	Particular solution of Maxwell's equations with electric field assuming the same magnitude and phase in all planes perpendicular to the direction of propagation
MilliVolt per meter / *EM Units*	A common unit of measurement for electric field strength values
Dielectric Medium / *EM Medium*	Root concept extended by all other insulator media
Method of Moments / *EM Analysis*	It is a general numerical technique for solving EM problems stated in terms of an inhomogeneous equation
RF Measurement / *EM Measurements*	Root concept subsuming all kinds of measurements performed at RF frequencies
Plane Wave Shielding / *EM Compatibility*	It is the process that determines a total or partial block of EM radiation (propagating as a plane wave) in a far field region
Spectrum Analyzer / *EM Instruments*	Fundamental EM instrument for measuring the frequencies present in a complex signal or resulting from modulation on a carrier
Passive Microwave Device / *Microwave Devices*	Root concept subsuming all passive components operating at microwave frequencies

We designed three metrics adapting metrics proposed from Zhang in [6]. Such metrics must be computed with respect to each *BE*, then they are mediated over the total number of *BE* (*nBE*).

Ancestor Domain Pertinence (ADP). This metric was constructed starting from the so-called Depth of Inheritance metric (*DoI*) [6]. DoI quantifies the distance of the class identified as the best ancestor for the current *BE* from the root class of the candidate ontology. This distance represents the overall set of superclasses for the *BE*. However, *DoI* does not provide any information about the validity of those classes from a domain expert point of view. This additional feature is provided by *ADP* metric. It computes the ratio between the total number of "appropriate ancestors" (*nSA*) and *DoI*, according to the following formula:

$$ADP = \frac{\sum_{i=1}^{nBE} ADP_i}{nBE}, \quad ADP_i = \frac{nSA_i}{DoI_i} \qquad (11)$$

ADP_i refers to the *i-th* *BE* and *ADP* is the arithmetic mean over the *nBE*. The closer to zero *ADP* is, the more unfitting the superclasses are.

DoI Deviation (DoID). This metric is derived from *DoI* as well. It takes into account the maintenance issues, which could occur when the distance from the root class is too long (i.e., *DoI* is high). In this case, a modification in higher-level scientific domain concepts can involve relevant modifications in lower-level EM ontologies [6]. Therefore we set a reference value (DoI_{REF}) and measure the deviation of DoI_i from it. $DoID_i$ is normalized to the range [0;1] and converted to a maximization metric. *DoID* is its arithmetic mean.

$$DoID = \frac{\sum_{i=1}^{nBE} DoID_i}{nBE}, \quad DoID_i = 1 - \frac{|DoI_{REF} - DoI_i|}{max\{DoI_i, DoI_{REF}\}} \qquad (12)$$

The closer to one *DoID* is, the closer to the reference the actual *DoI* value is. We selected $DoI_{REF}=3$ as a proper reference.

Domain Property Reusability (DPR). It analyzes how the descriptive statements for the benchmark entity can be rendered. *DPR* is the ratio between the reusable OWL properties belonging to higher-level ontologies (nRP_i) and the number of natural language restrictions ($nNLR_i \geq nRP_i$) needed to codify the descriptive statement for the *i-th* benchmark entity:

$$DPR = \frac{\sum_{i=1}^{nBE} DPR_i}{nBE}, \quad DPR_i = \frac{nRP_i}{nNLR_i} \qquad (12)$$

The closer to one the *DPR* is, the more preferable the ontology is. Indeed, by counting the number of reusable properties, we measure how the higher-level ontology facilitates the integration enhancement. On the contrary, a *DPR* close to zero denotes a small reusability.

 ISBN: 978-1-61208-155-7

Considering all the *BE* detailed in Table IV, the candidate ontologies feature the following mean values in terms of *ADP*, *DoID* and *DPR* metrics (Table V). SWEET ontologies performed better with respect to all the integration metrics. Better values for each metric have been highlighted.

TABLE V. INTEGRATION METRIC COMPUTATION RESULTS

Metric	UMD	SWEET
ADP	0.667	0.91
DoID	0.398	0.659
DPR	0.386	0.711

VII. RANKING THE CANDIDATE ONTOLOGIES

In previous sections, metric computation produced discordant results. In order to assess which candidate is the best suited for the integration procedure in a rigorous and unambiguous way, we adopted a multi-decisional scoring technique. We selected the ELECTRE-I method [19]. It is the simpler version of the ELECTRE methods (*ELimination Et choix Traduisant la REalité*, that stands for *Elimination and Choice Expressing the Reality*). Such methodologies are widely used for their ability to cope with criteria giving contrasting evaluations.

A. Overall Considerations

Our metrics, called evaluation criteria ($\boldsymbol{C}=\{C_i\}$, $i=1,...,m$) according to ELECTRE terminology, are weighted by using subjective quantities ($\boldsymbol{W}=\{w_i\}$, $i=1,...,m$). A decision table (Table VI) is populated by the scores a_{ij}, expressing the performance of the A_i alternative against the C_j criterion. The alternatives are compared, in pair, by calculating concordance (c_{jk}) or discordance (d_{jk}) indices [19] according to (13) formulas.

$$c_{jk} = \frac{\sum_{i\in\left(\boldsymbol{C}^{+}_{jk}\cup\boldsymbol{C}^{=}_{jk}\right)} w_i}{\sum_{i\in\boldsymbol{C}_{jk}} w_i} = \sum_{i\in\left(\boldsymbol{C}^{+}_{jk}\cup\boldsymbol{C}^{=}_{jk}\right)} w_i \quad ,$$

$$d_{jk} = \frac{\max_{i\in\boldsymbol{C}^{-}_{jk}}\{w_i|a_{ij}-a_{ik}|\}}{\max_{i\in\boldsymbol{C}}\{w_i|a_{ij}-a_{ik}|\}} \quad , \tag{13}$$

$$\boldsymbol{C}_{jk} = \boldsymbol{C}^{+}_{jk} \cup \boldsymbol{C}^{=}_{jk} \cup \boldsymbol{C}^{-}_{jk}$$

where $\boldsymbol{C}^{+}_{jk}$, $\boldsymbol{C}^{=}_{jk}$ and $\boldsymbol{C}^{-}_{jk}$ represent respectively the subset of criteria against which alternative A_j is better, equivalent and worst than A_k.

TABLE VI. ELECTRE-I TYPICAL DECISION TABLE

Criteria	Weights	Alternatives				
		A_1	.	.	A_n	
C_1	W_1	a_{11}	.	.	a_{1n}	A_1
.	.	.	.	.	.	.
.	.	.	.	.	.	.
C_m	w_m	a_{m1}	.	.	a_{mn}	A_n

In order to assert that the alternative A_j *outranks* A_k, the concordance index should be at the same time above a concordance threshold c_{th} and the discordance index should be below a discordance threshold d_{th} (14), where c_{th} and d_{th} are the mean values of the indices calculated over the n alternatives [19].

$$\begin{cases} c_{jk} \geq c_{th} = \dfrac{1}{n(n-1)}\displaystyle\sum_{j=1}^{n}\sum_{\substack{k=1,\\k\neq j}}^{n} c_{jk} \\ d_{jk} \leq d_{th} = \dfrac{1}{n(n-1)}\displaystyle\sum_{j=1}^{n}\sum_{\substack{k=1,\\k\neq j}}^{n} c_{jk} \end{cases} \tag{14}$$

B. Candidates ranking

First of all, criterion weights were defined. We assumed [19] that the sum of the weights of all criteria equals to 1. Then, we distributed the weights amongst the three sets of metrics. We assigned heavier weights to sets better complying with our major objective, i.e., integration between our EM ontologies. Therefore, content and integration sets were both given a weight of 0.4. The set containing size metrics, which are general-purpose, was instead given a weight equal to 0.2. The same criterium was adopted to distribute weights among the single metrics belonging to each set.

Therefore, size metrics (i.e., *CtEr*, *PtEr*, *ItEr* and *EpMr*) share the same weight.

Among content-related metrics (i.e., *DSR*, *DER* and *LO*), the first one is the most relevant in our opinion. Indeed, the more S entities there are, the more suitable to integration the scientific candidate ontology could be. In addition, E entities introduce semantic overlaps, which may render the integration task onerous, therefore the *DER* metric has the second heaviest weight.

As to integration metrics, we assigned the heaviest weight to *ADP*, as it expresses the scientific suitability of higher-level concepts.

Table VII resumes the final decision table. The highest scores for each criteria have been highlighted.

TABLE VII. CANDIDATE ONTOLOGIES DECISION TABLE

C_i	w_i	A_1 (UMD)	A_2 (SWEET)
CtEr	0.05	0.88	0.63
PtEr	0.05	0.06	0.08
ItEr	0.05	0.05	0.28
EpMr	0.05	0.923	0.995
DSR	0.2	0.44	0.59
DER	0.15	0.94	0.93
LO	0.05	0.5	0.66
ADP	0.2	0.667	0.91
DoID	0.1	0.398	0.659
DPR	0.15	0.386	0.711

The following matrices report the concordance and discordance indices of the alternatives.

 ISBN: 978-1-61208-155-7

$$C = \begin{bmatrix} \cdot & c_{12} \\ c_{21} & \cdot \end{bmatrix} = \begin{bmatrix} \cdot & 0.2 \\ 0.8 & \cdot \end{bmatrix} \tag{15}$$

$$D = \begin{bmatrix} \cdot & d_{12} \\ d_{21} & \cdot \end{bmatrix} = \begin{bmatrix} \cdot & 1 \\ 0.256 & \cdot \end{bmatrix} \tag{16}$$

According to (14), we have the following concordance and discordance conditions against respective thresholds:

$$\begin{cases} (c_{12} = 0.2) < (c_{th} = 0.5) \\ (d_{12} = 1) > (d_{th} = 0.628) \end{cases} \tag{17}$$

$$\begin{cases} (c_{21} = 0.8) > (c_{th} = 0.5) \\ (d_{21} = 0.256) < (d_{th} = 0.628) \end{cases} \tag{18}$$

Since (18) satisfies both the conditions, the alternative A_2 (i.e., SWEET ontologies) shows a better integration behavior rather than A_1 (i.e., the UMD ontologies).

These results confirmed the assessments given by independent electromagnetic knowledge domain experts who, based on a preliminary overview of their content and on the evaluation of their “electromagnetic soundness”, accounted SWEET ontologies as the most profitable choice among candidates.

VIII. CONCLUSIONS

In this paper, a proposal for a ranking methodology dealing with scientific domain ontologies has been proposed. The aim of this evaluation technique is to assess, in a possibly rigorous way, how suitable to be integrated with EM ontologies a scientific domain ontology could be. In order to do that, a set of multi-purpose ontological metrics has been defined. They consider different aspects such as size and structure, contents and integration worthiness for a given candidate ontology. Moreover, these metrics take into account both ontology designer and domain expert point of view. The metrics have been used as evaluation criteria in a widely adopted multi-decisional scoring process belonging to the ELECTRE method family. Two well known scientific ontological framework have been compared and ranked, showing the validity of the proposed methodology.

REFERENCES

[1] G.T. Gruber, “Towards Principles for the Design of Ontologies Used for Knowledge Sharing,” Int. Journal of Human-Computer Studies, vol. 43, issue 5-6, pp. 907-928, 1995.

[2] S. Lesteven et al., “Ontologies For Astronomy,” Library and Information Services in Astronomy V: Common Challenges, Uncommon Solutions. (Astronomical Society of the Pacific) ASP Conference Series, vol. 377, p. 193-196, 2006.

[3] OpenClinical Ontologies homepage. Available at: http://www.openclinical.org/ontologies.html, (last accessed: May 2011)

[4] A. Esposito, L. Tarricone, L. Vallone and M. Zappatore, “A Proposal for an Electromagnetic Ontology Framework,” Int. Journal of Web and Grid Services, Vol. 4, No. 3, pp. 284-302, 2008.

[5] N. Guarino, “Formal ontology and information systems,” Proc. of the 1st Int. Conf. on Formal Ontologies in Information Systems, FOIS98, IOS Press, pp. 3-15, 1998.

[6] H. Zhang, Y.-F. Li and H. B .K. Tan, “Measuring Design Complexity of Semantic Web Ontologies,” The Journal of Systems and Software, Science Direct, vol. 83, pp. 803-814, 2010.

[7] Y. Kalfoglou et al., "Semantic Metrics," Proc. of 5th Int. Conf. on Knowledge Engineering and Knowledge Management (EKAW06), pp. 166-181, 2006.

[8] T. Lethbridge, “Metrics for Concept-Oriented Knowledge Bases”, in: International Journal of Software Engineering and Knowledge Engineering, vol. 8(2), pp. 161-188, 1998.

[9] H. Hu and X.-Y. Du, “A Lattice Metric for Evaluating Ontology Hierarchies,” Proc. of International Conference on Machine Learning and Cibernetics, 2007, vol. 7, pp. 3880-3883, 2007.

[10] X. Yunjiao, W. Chun, H. H. Ghenniwa and S. Weiming, “A New Tree Similarity measuring method and its application to ontology comparison,” Proc. of CSCWD’08, pp. 258-263, 2008.

[11] A. Doan, J. Madhavan, P. Domingos and A. Halevy, “Learning to Map Between Ontologies on the Semantic Web,” Proc. of the WWW Conference, Hawaii, USA, pp. 662-673, ACM Press, 2002.

[12] D. Aumuller, H. H. Do, S. Massmann and E. Rahm, “Schema and ontology matching with COMA++,” Proc. of SIGMOD, Software Demonstration, pp. 906-908, ACM Press, 2005.

[13] E. Sosa, A. Lozano-Tello and A. E. Prieto, “Semantic Comparison of Ontologies Based on WordNet,” Proc. of Complex Intelligent and Software Intensive Systems (CISIS08), pp. 899-904, 2008.

[14] W3C OWL Working Group, “OWL2 Web Ontology Language Document Overview”, W3C Recomm., 27th October 2009. Available at: http://www.w3.org/TR/owl2-overview/ (last accessed: May 2011).

[15] Ontological Codification of ElectroMagnetism v.2.1 (OntoCEM), University of Salento, Electromagnetic Lab Lecce (EML2). http://www.electromagnetics.unisalento.it/ /ontologies/OntoCEM/2.1/ (progressively available).

[16] "Astronomy/Science Ontology", Department of Astronomy, University of Maryland, USA. Available at: http://www.astro.umd.edu/~eshaya (last accessed: May 2011).

[17] Semantic Web for Earth and Environmental Terminology (SWEET) Ontologies, NASA JPL, CA, USA Available at: http://sweet.jpl.nasa.gov/ (last accessed: May 2011).

[18] S. Tartir, I. B. Arpinar, M. Moore, A. P. Sheth and B. Aleman-Meza, "OntoQA: Metric-Based Ontology Quality Analysis," Proc. of IEEE Workshop on Knowledge Acquisition from Distributed, Autonomous, Semantically Heterogeneous Data and Knowledge Sources (KADASH), Houston, Texas, USA, pp. 45-53, 2005.

[19] J. Figueira, S. Greco and M. Ehrgott (Eds.), Multiple Criteria Decision Analysis: The State of the Art Surveys, Springer Science and Business Media, Inc., New York, 2005.