Journal of Network Intelligence ©2020 ISSN 2414-8105 (Online)
Taiwan Ubiquitous Information Volume **5**, Number **4**, November **2020**

Multi-view Ontology Alignment Visualization (MOAV): A Human-Cognition Based Ontology Alignment Visualization Technique

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Received June 2020; revised July 2020

Abstract. *To further improve the quality of ontology alignment, it is necessary for an ontology matcher to introduce a user's knowledge into its automatic matching process, which yields the development of interactive ontology matching techniques. Since validating problematic entity correspondences is a difficult cognition task, user interaction based on Ontology Alignment Visualization (OAV) has become the critical component of an interactive ontology matcher, which directly affects the quality of validating result and the efficiency of validating process. The existing OAV tools are mainly developed based on their designers' subjective feelings and experiences, which do not take into consideration the law of human cognition. To improve the efficiency of the ontology alignment validating process, in this paper, a Multi-view OAV (MOAV) is proposed, which synthetically utilizes the human cognitive theory-information visualization and human-computer interaction. The experiment utilizes the Ontology Alignment Evaluation Initiative (OAEI)'s benchmark to test the performance of our proposal, and the experimental results show that MOAV can effectively improve a user's validating efficiency.*

Keywords: Multi-view Ontology Alignment Visualization; Human-cognition theory; OAEI

1. **Introduction.** Ontology matching [1]aims at determining the identical entities in two different ontologies, which is regarded as an effective technique to fill the semantic gap between two ontologies. The obtained ontology alignment, a set of entity correspondences, can be further used to integrate knowledge in two ontologies and support the co-operations among systems based on them. For an ontology matching system, similarity measure [2] plays an important role, which takes two ontology entities as inputs and a real number representing their similarity as an output. Since none of the similarity measure can distinguish all the heterogeneous entities in any context [3], the existing automatic ontology matchers encounter the performance bottleneck in terms of both effectiveness and efficiency. To improve the quality of obtained ontology alignment and the efficiency of ontology matching process, the alignment generated by an automatic ontology matcher needs to be verified by one or more users [4]. During the validating process, they need to proof the correct correspondences and filter the erroneous ones. Validating problematic entity correspondences is a cognition-intensive task since the users need to understand the meaning of an entity through scanning its content and context [5]. When the scale of the alignment to be validated is large and the semantic of some entity is obscure, validating the entity correspondences is an error-prone task. Ontology Alignment Visualization (OAV) can intuitively provide an user with the information that needs to be checked in an ontology alignment, which is an effective technique to improve the working efficiency and reduce the error rate.

The definition on view differs in various practical domains. For example, in mechanical drawing, the projection of objects in different directions is called a view. In a database, a view views the data in the database from a specific point of view. The content of the view is defined by the query. The view acts like a filter to see the data of interest. In this study, the role of view is similar to filtering, where humans acquire the information of interest through what they see. The existing OAVs are mostly single-view based, i.e., either indent list based or graph-based, which fail to efficiently exhibit the details of an entity in terms of human cognitive. When humans are faced with a visualization task, a single view that satisfies many requirements may be a view with the lowest common denominator, which is not optimal for any requirement. Such a view requires users to understand and absorb a good deal of different data in the meantime, some of which may be irrelevant to their needs. And then it creates a burden. Additionally, with a single view, users may need to extract and remember in their heads what they want to compare. As a consequence, maintaining and switching between these requires cognitive abilities. To overcome these problems, we synthetically consider the human cognitive theory [6] [7], information visualization [8] and human-computer interaction [4] [5]. In particular, as the term implies, "multi-view" makes use of multiple views to describe the object from different angles. First, from the perspective of human cognitive theory, human cognition is the result of the combined effect of whole processing and partial processing [9]. In terms of this, the views should consist of a whole and a part in the visualization task. This is the first framework principle (**FP.1**). Moreover, according to the principle of information visualization, as long as the information studied is semantically rich and can be visualized through various classification levels, multi-views can be used to present them. Finally, from the perspective of human-computer interaction, as long as the information under study requires humans to understand from the whole and part, it is necessary to use multi-views. Based on the above arguments, a Multi-view OAV (MOAV) is proposed to improve the efficiency of the ontology alignment validating process. This tool can effectively combine indenting list, node connection and other single view visualization methods according to users' cognitive load, thus effectively improving the efficiency of user inspection process.

The paper is organized as follows. First, the classification of existing OAV tools is introduced. Then the knowledge of cognition theory and ontology mapping respectively are introduced. Next, the design framework of MOAV is established. This framework describes a concept of ontology mapping visualization that is consistent with human cognition. Then, this paper compared MOAV with the existing representative OAV tools. Finally, the conclusion and future work are drawn.

2. **Related work.** Usually, OAV needs to first visualize two individual ontologies' entities and their relationships, and then display the correspondences among them. Recently, several tools for visualizing the ontology alignment have been developed, which can be classified into two types, i.e., indent list based OAV and graph-based OAV [10].

2.1. **Indent List based Ontology Alignment Visualization.** Indent list based OAV shows the alignment with the topology structure of a tree in the graph theory. Indentation list is the most commonly based OAV (see also Figure 1), where a line drawn from each source entity (node) connects the corresponding target entity (node). Ontology matching systems that utilize the indented list are COMA++ [11], YAM ++ [12], PROMPT [13], COGZ [14, 15], VisTA [16], SAMBO [17]and AgreementMaker [18]. Particularly, COMA++, introduces extra approaches to supplement the indented list, e.g., it depicts different connection lines with various colors, display the attributes of the relationship on the connection lines to avoid additional queries by the end user. PROMPT is a plug-in for Protégé, an ontology editor. It takes a view and displays the matching pairs that need to be modified by the user between two indented lists. COGZ is designed as a visual tool according to human cognitive processes. It is an extension of PROMPT. COGZ uses the same visual metaphor as COMA++. On this basis, the fish-eye zooming function is also used to support navigation of large ontologies. Although indent list based OAV is visually intuitive and clearly show the local hierarchy, its drawbacks are also obvious. When a large number of concept correspondences are under processing, their connecting lines will unavoidably overlap. As a result, only a part of an entity's context is not enough for a user to validate a correspondence. When the user clicks on a multi-level sub-tree, only part of the content is displayed due to the size limitation of the view. Moreover, the user cannot know which part of the ontology is displayed. In other words, the deep-nested tree may lose the original context.

2.2. **Graph-based Ontology Alignment Visualization.** Different from indent list based OAV, graph-based OAV describes the alignment with the topology structure of graph. The OPTIMA [19] (see Figure 2) uses a node-link technique to depict the alignment, which displays two ontologies separately and highlights the nodes that contain corresponding colors. AlViz [20] is also a plugin for Protégé. It applies multiple views through synchronous navigation of cluster diagrams and standard tree controls. The tool provides an overview of the ontology by clustering. In addition, clusters are colored based on their potential conceptual similarity to other ontologies. Besides, on the negative hand, it does not provide the ability for users to modify the alignment. On the positive side, compared to the indented list representation, the tool shows advantages by providing a more global overview, listing out the whole context of an entity. But since two ontologies are displayed separately, a user cannot see the links between mapped elements and select any mappings for editing.

In addition, Alignment Cubes [21] used 3D graphics representation. It compares the matching results from different algorithms. Alignment Cubes allow interactive rotation

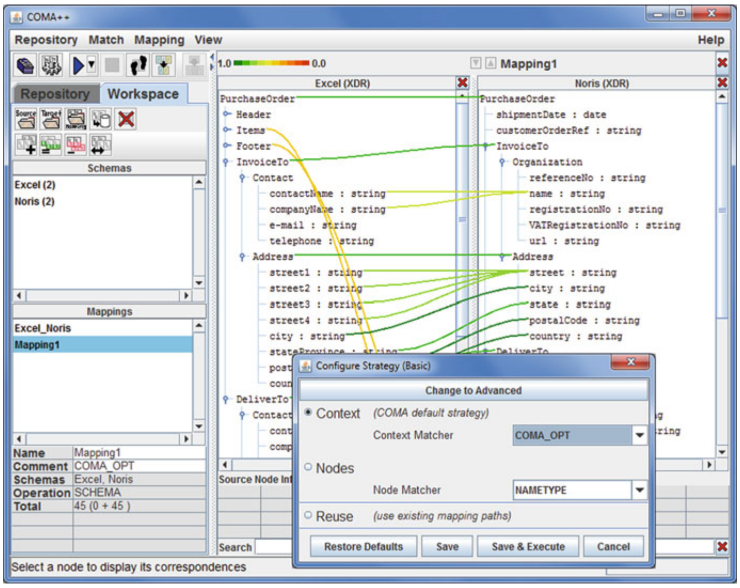

FIGURE 1. Indent list based visualization tool (COMA++'s Interface)

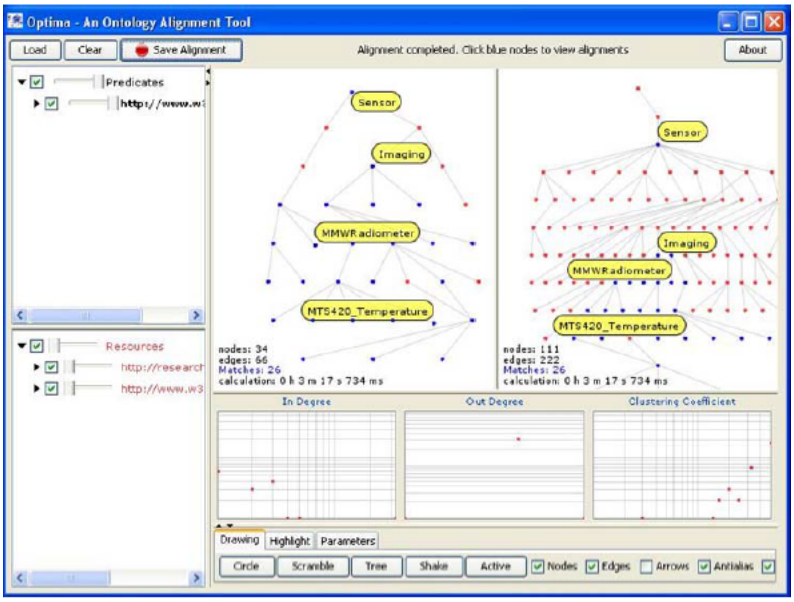

FIGURE 2. Graph-based visualization tool (OPTIMA's Interface)

and scaling to compensate for the visualization deficiencies of 3D graphics representation, including occlusion and distortion. But it does not allow the user to modify the mappings.

The two kinds of OAV mentioned above can both be used to help a user validate an entity correspondence, but the simple use of only one could be inefficient [10]. On the one hand, indent list based OAV can only provide local information for a user, and when he penetrates deeply into an ontology's hierarchy, it is easy to get lost. On the other hand, the graph-based OAV provides a user with a global overview, but it has deficiencies in local information display, which yields such problems as information occlusion and view confusion. More importantly, none of these tools take into account the cognitive laws of the user, except for COGZ.

3. **Human Cognition and Ontology Alignment Visualization.**

3.1. **Human Cognition and Cognition Load.** Human cognition refers to the process by which people acquire knowledge or apply knowledge, which is people's most basic psychological process. In the cognition procedure, human brain receives information input from the outside world, processes it through the brain, and converts it into internal psychological activities, which in turn governs human behavior [22].

The term cognitive load is derived from cognitive load theory [23, 24, 25], which was first proposed by cognitive psychologist J. Sweller in 1988. It is a theory that determines instructional design based on the interaction between human cognitive structure and external information structure. In the theory of cognitive load, J. Sweller extracts related concepts from cognitive psychology, and believes that human cognitive construction is related to long-term memory and working memory. Cognitive psychology [26] divides memory into transient memory, short-term memory, and long-term memory according to the length of time that information is kept and the way information is encoded, stored, and processed. Transient memory refers to the moment when sensory information enters the sensory region of the brain and there is no conscious memory activity. Short-term memory is the memory in which information enters consciousness and remains within 1 minute. Long-term memory refers to memory with a storage time of more than 1 minute, which can generally be maintained for many years or even a lifetime. Long-term memory mainly comes from the restatement of the short-term memory stage, and it is also formed by the impression at one time. The capacity of long-term memory is considered to be infinite, and information is stored therein in a graphical. A graphical is an information unit standardized or classified according to the function of the information and its purpose, and can be any knowledge structure that has been learned. An illustration can be either an unordered piece of information or a complex interaction or an ordered knowledge group. Regardless of the size, each graphical is treated as an entity and can be completely extracted and processed from long-term memory. Thereafter, when the individual is performing cognitive activities here, the information graphical associated with it in long-term memory is aroused and is in an active state. Information in this state of activity is called working memory [27]. The capacity of working memory is limited. It can only store 5-9 basic information at a time, and because working memory generally can only process 2-3 pieces of information at the same time, the information processing process creates a load on individual cognition [28]. That is, the cognitive load is the total amount of information to be processed that is applied to working memory. Therefore, effective processing of long-term memory and working memory is the key method to satisfy human cognitive construction.

3.2. **Ontology Alignment Visualization.** Ontology is an explicit specification of a conceptualization [29], which defines a common vocabulary for the knowledge domain. In the field of knowledge domain, ontology supports shared information structure, reuse of domain knowledge, and clarifies domain assumptions. Ontologies include classes, attributes, and relationships that formally describe a domain. Each class represents an entity in the domain, and contains attributes that describe the characteristics of the class. However, ontology has been widely used in many fields. Meanwhile, different tasks or different perspectives have led to the heterogeneity definition of the same concepts in the same domain by ontology designers. Therefore, the subjectivity of ontology modeling leads to heterogeneous ontology, which is characterized by differences in synonyms, hyponyms and hypernyms[30]. In more detail, heterogeneous problems include terminological heterogeneity (lexical or semantic), structural heterogeneity (number of subclasses, heterogeneity of attributes, heterogeneity of class ancestors and descendants), and heterogeneity between instances. In view of the heterogeneity of ontology, a variety of solutions are proposed. And the technology generally accepted in the industry is the ontology matching technique, which is to find the corresponding relationship between semantically related entities, i.e., ontology alignment. Ontology matching usually means the interoperation between two ontologies based on semantic relationships such as synonyms, hyponyms and hypernyms[31]. This paper focuses on the problem of conceptual heterogeneity. An ontology alignment is a set of communications between entities of two ontologies. Given two ontologies, a correspondence is a 5-uple ¡*id*, e_1, e_2, *r*, *n*¿ [32], where:

- *id* is an identifier for the given mapping;
- e_1 and e_2 are entities, e.g., properties and classes of the source and target ontology;
- r is the semantic relation between e_1 and e_2;
- n is the number of confidence measure in the range [0, 1], which indicates the degree to which the author or algorithm believes that the relationship exists.

Ontology matching is competent for building the semantic relationship between two heterogeneous entities, and the obtained mapping is the basis for achieving ontology interoperability. Manual matching is impractical on the part of efficiency and effectiveness when the ontology is large in size. Therefore, in order to match two heterogeneous ontologies, many ontology matching systems have been developed. However, due to the bottleneck caused by the similarity measure [33], the performance of the automatic matcher (in terms of accuracy and recall rate) is limited. Therefore, automatic generation of mappings should only be considered as the first step in the final match, and verification made by one or more users is critical to ensure the quality of the match. Interactive ontology matching is to enable users and automatic matchers to collaborate in a reasonable amount of time to generate high quality ontology alignment. User interface (UI) is one of the key components to achieve effective interaction ontology matching.

UI is an integral part of the human-computer interaction system. Since the ontology is a complex knowledge base, verifying ontology alignment pairs is a task involving high memory load task. In order to verify each alignment, the user needs to consider many aspects, including terminological similarity (lexical or semantic), structural similarity (number of subclasses, correspondence between attributes, position in hierarchy depth, degree of matching between classes ancestors or descendants), as well as extension-based similarity (degree of similarity between instances), and these aspects must be kept in mind. This is not possible without the support of visualization tools such as UI. The purpose of ontology visualization is to help users understand the details inside the ontology. Considering the complexity of ontology and matching, one of the key aspects of visualizing them is that they do not make users feel particularly stressed [34]. People use working memory to understand things, but working memory is limited. When there is too much information, people are easily overwhelmed. In addition, another important aspect of ontology visualization is to provide users with enough information to verify the correctness of each mapping, including the vocabulary and structural information of the ontology. The existing visualization techniques of ontology alignment are all designed based on the designer's intuition or experience, without a theoretical support.

M. Card defines visualization as "visualization is the use of computer-supported, interactive data visualization representations to expand awareness" [35]. According to the theory of human cognition presented in Section 3.1, long-term memory is stored in human brain in the form of graphical, so we can simulate long-term memory and working memory of human through visualization. The whole visual content can be regarded as a person's long-term memory, while the visual content currently displayed is regarded as a person's working memory (**FP.2**).

4. **Multi-View Ontology Alignment Visualization.** In this section, the Multi-View Ontology Alignment Visualization (MOAV), an interactive ontology matching visualization prototype based on human cognition, is presented in details. In the following section, the interface of MOAV and each sub-view of it will be introduced one by one.

The software tooling requirements (REQ) for each framework principle (FP) are described below.

(#1) **FP**: From the perspective of human cognitive theory, human cognition is the result of the combined effect of whole processing and partial processing.

REQ: MOAV divides the user interface into 3 views, which respectively describe source ontology, target ontology, and mappings, and each of them has two sub-views to present the global and local information, respectively.

(#2) **FP**: Effective processing of long-term memory and working memory is the key method to satisfy human cognitive construction.

REQ: The whole visual content can be regarded as a person's long-term memory, while the visual content currently displayed is regarded as a person's working memory.

4.1. **General Interface.** Since the ontology alignment is rich in semantics, which includes two levels of ontology and matching results, user need to understand both the global information, i.e., the hierarchy structure of the ontologies, and the local information, i.e., the concept's inner and context information before validating an alignment. In the user's memory, the ontology alignment can be divided into three parts: source ontology, target ontology and alignment.

Accordingly, MOAV divides the user interface into 3 views, which respectively describe ontology1, ontology2, and alignment, and each of them has two sub-views to present the global and local information, respectively. Here, totally 6 views are utilized, which are respectively named as V1-V6. MOAV's interface is shown in Figure 3. As can be seen from the figure, V1 and V5, V2 and V6 display the information of the source ontology and the target ontology, respectively. During the cognitive procedure, first, a user needs to understand the requirements of the task, i.e., the correspondences that need to be judged, which is shown in V3. After some correspondence being selected by him, the local information of them will be displayed in V4, i.e., part of the parent-child relationship between two entities will be displayed. Since only V5, V6 can fully display all entities, and V4, as the main part, only shows the parent class and subclass of corresponding matching mapping, so the size of ontology is not limited.

4.2. **The Alignment View.** V3 displays all the potential problematic correspondences and V4 shows the direct ascendant and descendants for each concept in a correspondence, which represents the work being completed, i.e., working memory. As shown in figure 3, range B is people's long-term memory and range A is people's working memory (**REQ.1**). Because the user's working memory is limited, and to reduce the user's workload, we only show one match at a time. In V4, the points represent entities in the ontology, and lines represent the relationships between them. The middle point of the left half of V4 represents the source entity, and the middle point of the right half represents the target entity. The line connecting them represents the relationship of ?equivalence?, the top dot represents the parent class, and the bottom dot represents the subclass. When the mouse is over the node and remains still, the properties of the corresponding entity are displayed. In V4, users can determine the correctness of the mapping by the class name, the number

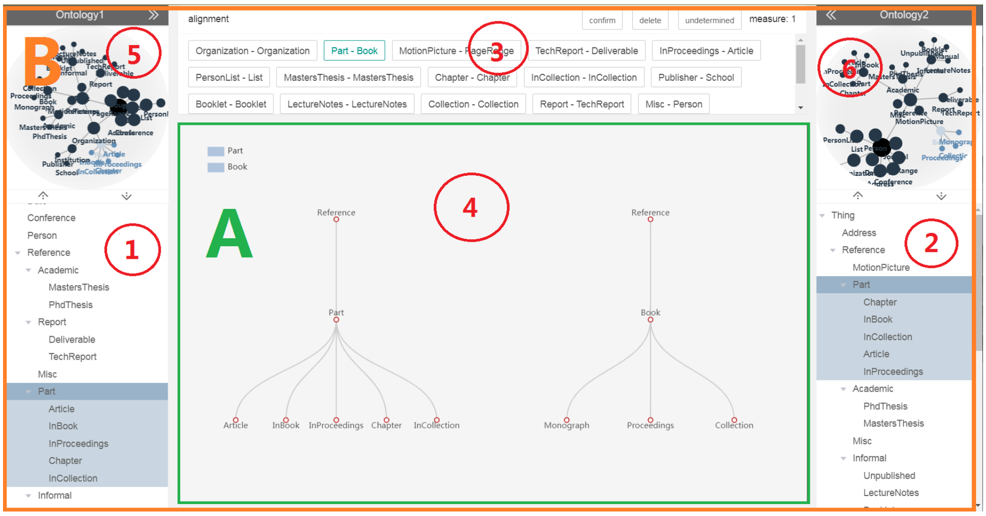

FIGURE 3. The interactive interface of MOAV

of subclasses, and the relationship between attributes. However, the V4 only shows two mapped concepts and their direct context, i.e., their direct ascendant descendant concepts. This work mainly focuses on the "is-a" relationship between two concepts, and we will improve our approach to deal with more complex relationships such as "part-of" in the future.

4.3. **The Ontology View.** V1 and V2 provide the local view of two ontologies. V5 and V6 provide the global view of two ontologies (**REQ.2**). V1 and V5, V2 and V6 respectively represent the source ontology and target ontology. In this work, V1 and V2 utilize the indented list, and V5 and V6 use the node connection diagram. This work mainly aims at visualizing the is-a relationship between concepts, and thus, V1 and V2 cannot show other DL rules. We need to explain that according to Bo Fu's [36] eye tracking experimental results on indented list and node connection diagram, indented list is conducive to information processing and node connection diagram is conducive to information search. Therefore, indent list based OAV and graph-based OAV must be combined to complement each other so that users can grasp the information they need more efficiently and quickly. When the local information in V4 is not enough for the user to validate the correspondence, these four views can provide him with the global and local information. Last, in these four views, various colors are used to display the entities displayed in V4, which is convenient for users to find the position of the matching pair in the ontology. In these four views, the user can verify the correctness of the mapping by the depth of the class in the hierarchy.

5. Experiment.

5.1. **Experimental Configuration.** In the experiment, to test the performance of MOAV, the well-known Ontology Alignment Evaluation Initiative (OAEI) benchmark[1] is used, and a brief description [37] on it is shown in Table 1. The latest benchmark is in 2017. The benchmark test data set has not been updated since 2011, so the 2011 benchmark is actually the latest version. Each testing case in the Benchmark consists of two ontologies to be mapped and a reference alignment for evaluating the alignment's quality. We randomly select 10 testing cases from Benchmark, and we further draw from each

[1]http://oaei.ontologymatching.org/2011/benchmarks/.

Table 1. The brief description on OAEI benchmark

Testing Case	Brief description
101-104	The to-be-matched ontology is exactly the same or both are only slightly different in the constraints of OWL.
201-210	The concept structure of the to-be-matched ontology is the same, but the language features are different.
221-247	The language features of the ontology to be matched are the same, but the conceptual structure is different.

Table 2. Statistics on Testing Cases

	Number of alignment	Number of correct	Number of errors	$f - measure(A)$
103	20	10	10	0.5
104	20	10	10	0.5
202	20	10	10	0.5
203	20	10	10	0.5
204	20	10	10	0.5
210	20	11	9	0.55
221	20	10	10	0.5
228	20	9	11	0.45
230	20	10	10	0.5
240	20	9	11	0.45

testing cases 20 mapping pairs from the reference alignment, and randomly modify about 10 mapping pairs as the disturbances. For details, please see also Table 2.

A total of 16 people were invited to participate in the experiment, who were divided into four groups according to their occupational background: ordinary computer professional(G1), the ontology expert(G2), the domain experts(G3) and the experts in both ontology and domain(G4), which show the varied degree of proficiency in the field of ontology alignment. Participants used MOAV, COMA++ and OPTIMA to edit the 10 modified cases. This experiment compares MOAV with COMA++ and OPTIMA. COMA++ and OPTIMA were chosen for the following reasons:

TABLE 3. Results validated by the ordinary computer professionals

	G1			G2			G3			G4		
	f(OPTIMA)	f(COMA++)	f(MOAV)	f(OPTIMA)	f(COMA++)	f(MOAV)	f(OPTIMA)	f(COMA++)	f(MOAV)	f(OPTIMA)	f(COMA++)	f(MOAV)
103	0.5	0.45	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
104	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
202	0.4	0.3	0.5	0.5	0.3	0.5	0.4	0.3	0.5	0.45	0.3	0.5
203	0.35	0.5	0.5	0.5	0.5	0.45	0.45	0.4	0.45	0.45	0.5	0.5
204	0.35	0.3	0.5	0.4	0.3	0.5	0.25	0.3	0.45	0.45	0.35	0.5
210	0.15	0.2	0.3	0.4	0.35	0.35	0.3	0.35	0.45	0.35	0.35	0.45
221	0.3	0.5	0.5	0.5	0.5	0.5	0.4	0.45	0.5	0.45	0.5	0.5
228	0.45	0.55	0.55	0.55	0.55	0.55	0.45	0.5	0.5	0.5	0.55	0.55
230	0.5	0.5	0.5	0.45	0.35	0.5	0.35	0.3	0.5	0.5	0.35	0.5
240	0.5	0.5	0.5	0.55	0.55	0.55	0.45	0.5	0.55	0.55	0.55	0.55

- COMA++ and OPTIMA are representational tools for tree and graph based visualization, respectively.
- AgreementMaker, COGZ and other tree-based tools are much the same in terms of visual effects, but COMA++ is much easier to use.
- The Alignment Cube tool mainly compares the matching results ob tained by using different algorithms, which is different from the problem to be solved in this paper. The AlViz tool, which is visualized by clustering, cannot display a single matching pair, which is not sufficient for the experiment in this article. There are fewer graph-based visualization tools, so OPTIMA was chosen.

The participants validated and invalidated the mapping pairs with different visualization tools. In order to evaluate the effectiveness of the tool more clearly, $f-measure(A)$ is introduced.

$$f-measure(A)=\frac{Correct}{N}$$
$$f(T)=f-measure(A)-f-measure(A')$$

Where A is the matching result of a group of alignment, and A' is the alignment after the tool T check. $F-measure(A)$ is the error rate of the matching result. N and $Correct$ are the total number of matching pairs and correct in A. $F(T)$ is the effectiveness of the visualization tool T.

5.2. **Results and analysis.** Table 3 shows the results obtained by the participants with MOAV, COMA++ and OPTIMA, respectively. The numerical values represent the statistical results.

As can be seen from the table, there are three testing case sets: the first testing case set (103, 104), the second testing case set (202, 203, 204, 210), and the third testing case set (221, 228, 230). In 240, f(MOAV) are both higher than those of f(COMA++) and f(OPTIMA), which indicates that MOAV can effectively improve the user's cognitive efficiency. In the second testing case set (202-2, 203, 204, 210), MOAV shows the global view of the ontologies through V5 and V6, which helps the participants quickly catch the context of the correspondences and understand the exact meaning of the concept, where COMA++ cannot show the parent and child classes to the users. However, in Table 3, the results of test set 210 are generally around 0.35, because the language used in this testing case is French, and neither of two competitors provided an electronic dictionary for the user. In summary, compare with the visualization tool with single view, MOAV can more effectively help the user obtain the information he need to validate the problematic correspondence.

6. **Conclusion and Future Work.** Interactive ontology matching visualization technology is the key to further improve the ontology alignment's quality. To implement an efficient human-machine interaction mechanism is an urgent need for the interactive ontology matching technique. To this end, this paper combines human cognitive theory to design an interactive ontology matching visualization framework based on multiple views. The comparison with indent-based lists and tree-based visualization tools shows that our proposal is effective.

The current MOAV is only a rough visualization framework. It currently displays only the inheritance relationships between classes. Future work will consider ways to improve MOAV, such as the relationship between attributes, the degree of similarity between instances, and so on.

Acknowledgment. This work is supported by the Guangxi Key Laboratory of Automatic Detecting Technology and Instruments (No. YQ20206), the Program for New Century Excellent Talents in Fujian Province University (No. GY-Z18155), the 2018 Program for Outstanding Young Scientific Researcher in Fujian Province University, the Fujian province undergraduate universities teaching reform research project (No. FBJG20190156), the Scientific Research Foundation of Fujian University of Technology (No. GY-Z17162).

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