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Integrating Sensor Ontologies with Global and Local Alignment Extractions

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In order to enhance the communication between sensor networks in the Internet of things (IoT), it is indispensable to establish the semantic connections between sensor ontologies in this field. For this purpose, this paper proposes an up-and-coming sensor ontology integrating technique, which uses debate mechanism (DM) to extract the sensor ontology alignment from various alignments determined by different matchers. In particular, we use the correctness factor of each matcher to determine a correspondence's global factor, and utilize the support strength and disprove strength in the debating process to calculate its local factor. Through comprehensively considering these two factors, the judgment factor of an entity mapping can be obtained, which is further applied in extracting the final sensor ontology alignment. This work makes use of the bibliographic track provided by the Ontology Alignment Evaluation Initiative (OAEI) and five real sensor ontologies in the experiment to assess the performance of our method. The comparing results with the most advanced ontology matching techniques show the robustness and effectiveness of our approach.

1. Introduction

With the wide range of applications and distribution of wireless communication systems, especially about the fifth-generation (5G) networks, the update speed technology in the Internet of things (IoT) is advancing by leaps and bounds [1, 2]. The popularity of IoT is increasing with artificial intelligence technology, which covers a wide range of applications [3–13]. As crucial components of IoT, sensor networks include connected sensors and associated devices, which deploy plenty of heterogeneous sensing nodes for capturing environmental data. On the one hand, due to their key features, i.e., autonomy, ease of deployment, and self-configurable and effective energy management, the sensor network has become a very active research field where an assortment of systems has been developed [14–17]. On the

other hand, it cannot be ignored that the scarcity of integration and communication among these networks always separates critical data streams and exacerbates the existing problem of too much data and lack of knowledge [18]. For the purpose of solving this problem, the Semantic Web (SW) technology is used to date sensor networks to annotate sensor data with spatial, temporal, and topic semantic metadata. The communication and fusion between Semantic Web technology and sensor network give birth to the Semantic Sensor Web (SSW), which is dedicated to providing semantics for sensor perception, enabling advanced applications such as situational awareness of transformers to have interoperability and advanced analysis capabilities. The sensor ontology is combined with semantic annotation to integrate and share conceptual models, enhance the semantics of sensor data, and use different sensor ontologies to annotate

sensor data. Thus, it is essential to set up strong links between semantically concerning sensor information, which is the so-called sensor ontology matching [19].

Sensor ontology matching is aimed at determining the correspondences between heterogeneous entities that exist in two sensor ontologies, and the output sensor mapping set is defined as sensor ontology alignment [20]. Many works of experts, scholars, and institutions have been done to enhance the quality of ontology alignment. One of the most authoritative organizations is the Ontology Alignment Evaluation Initiative (OAEI), which is aimed at comparing ontology matching systems on precisely defined test cases [21]. These test cases can be composed of ontologies of varying complexity (from simple thesauri to expressive OWL ontologies) and use different evaluation modalities (e.g., blind evaluation, open evaluation, or consensus). The results of the OAEI show that there are still challenges in improving the quality of the matching work. More precisely, one of the critical issues in ontology matching is obtaining high-quality ontology comparisons. Thus, the way to pick, combine, and adjust distinct ontology matchers containing a specific matching technique has become a significant challenge [22]. Although plenty of techniques about machine learning have been proposed to determine the optimal aggregating weights for the matchers [23–29], the catch is that they pay little attention to the effects engendered by each entity mapping's preferences on different matchers, which decreases the quality of ontology alignment [30]. To overcome this drawback, this work proposes a novel sensor ontology alignment extracting method based on debating mechanism (DM) [31]. In our proposal, a semantic sensor network integration technique is used with the ontology alignment extraction technology. For the purpose of improving alignment's quality, we introduce the correctness factor of each matcher to determine a correspondence's global factor, and utilize the support strength and disprove strength in the debating process to calculate its local factor. Through comprehensively considering these two factors, the confidence of the judgment factor of an entity mapping is improved.

The rest of the paper is arranged as follows: Section 2 introduces the related concepts of sensor ontology and ontology alignment extraction; Section 3 describes in details the DM-based ontology alignment extracting method with global and local factors; Section 4 externalizes the experimental results and makes the corresponding analysis; Section 5 draws the conclusion.

2. Sensor Ontology and Ontology Alignment Extraction

2.1. Sensor Ontology. An ontology is considered to be the solution to data heterogeneity on the web, which formally specifies the domain concepts and their relationships to give the definition of domain knowledge [29, 32]. With the sensor ontology becoming a powerful tool for integration and dealing with heterogeneous, more and more sensor ontologies have appeared. The Semantic Sensor Network (SSN) (https://www.w3.org/TR/vocab-ssn) ontology was proposed by the W3C Semantic Sensor Network Incubator group

(SSN-XG) as an OWL 2 ontology to shape sensors and observations, which describe sensors from various aspects, i.e., capabilities, measurement processes, and observations. OSSN (https://www.w3.org/2005/Incubator/ssn/wiki/SSN#Sensor) is an ontology developed by SSN-XG in 2005. The IoT-Lite ontology (http://www.w3.org/Submission/2015/SUBM-iot-lite-20151126) outlines the resources, entities, and services of the Internet of things (IoT), which is a lightweight ontology as well as an instance of the SSN ontology. The Sensor, Observation, Sample, and Actuator (SOSA) (http://www.w3.org/ns/sosa) ontology provides a lightweight kernel for SSN, which is designed to broad target audience and application areas which has access to ontologies. What is more, SOSA acts as a minimal interoperability fall-back level, i.e., it defines those common classes and properties for which data can be safely exchanged across all uses of SSN, its modules, and SOSA. SensorOntology2009 (https://www.w3.org/2005/Incubator/ssn/wiki/Sensor Ontology 2009) is an ontology developed by Michael Compton, Holger Neuhaus, and Nguyen Tran from CSIRO (Australia). It has been used as the initial version of the Semantic Sensor Network ontology.

A sensor ontology is defined as $O = (C, P, I)$, in which C, P, and I separately represent class set, property set, and instance set, respectively. A sensor ontology alignment A is an entity correspondence set where the entity correspondence inside is defined as a 4-tuples $\text{corr} = (e, e', n, \text{relation})$, e and e' are the entities of two ontologies, respectively, $n \in [0, 1]$ represents a similarity value between e and e', while relation is the equivalence relation. The process of determining the entity correspondence between sensor ontologies is called sensor ontology matching.

Figure 1 shows an example of two sensor ontologies and their alignment. As depicted in Figure 1, the symbol of a rectangle denotes the entity; the line with two arrows suggests the mapping between two entities. The ontology matcher takes two entities as input and outputs a real number that reflects the similarity in [0, 1]. The matching process cannot guarantee the comparative quality obtained by a single matcher, so multiple matchers usually need to work together to increase evidence of potential matches or discrepancies. All entity correspondences' similarity values obtained by an ontology matcher are restored in the corresponding similarity matrix, where the similarity values higher than the threshold are regarded as a correct mapping by this matcher.

2.2. Ontology Alignment Extraction. Various ontology matchers employ different information or features between two ontologies to measure the similarity values between two entities. Each ontology matcher has a particular similarity measure, divided into three categories, i.e., syntactic-based measures, linguistic-based measures, and structure-based measures [33]. To be specific, syntax-based similarity measures calculate two strings' similarity values according to their syntax information [34–36]. Linguistic-based similarity measure under the use of a background knowledge base, i.e., WordNet [37] and the work done by structure-based similarity measure is under the use of two concepts' parent-child concepts defined in their ontologies to do the work.
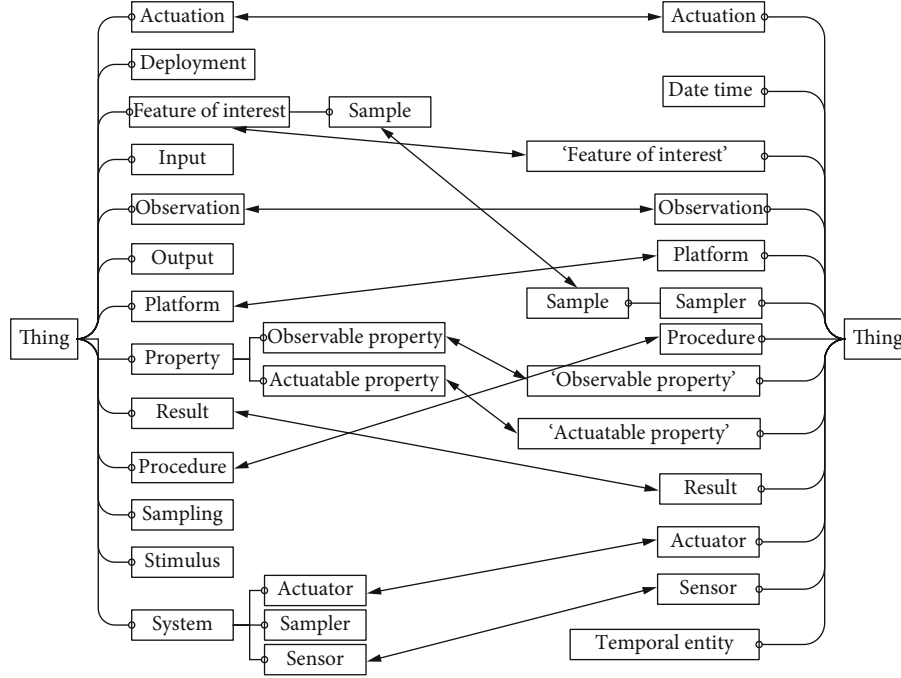
FIGURE 1: An example of sensor ontology matching.

Although these relevant methods have been extensively researched and taken into practice, it is still a challenge to satisfy the need for an effective ontology matcher on some specific matching task. With the emergence of various ontology matchers, ontology matching systems usually apply multiple matchers to enhance the alignment's quality [25, 38–40]. To better aggregate various ontology matchers, this work proposes a novel ontology alignment extracting method, whose framework is shown in Figure 2.

As shown in Figure 2, our approach is divided into two steps, i.e., various ontology alignment determination and DM-based alignment extraction. Preprocessing step generally includes ontology analysis and conversion ontology format. In this work, an argument ar is defined as follows:

$$ar = \{c, n, v, h\}, \tag{1}$$

where $c = (e, e')$ is a correspondence and v $(v \in N)$ represents the artificially preset matcher number, and h $(h \in \{0, 1\})$ is the measure factor of similarity value determined as follows:

$$h = \begin{cases} 1, & \text{if } n \geq \delta, \\ 0, & \text{if } n < \delta, \end{cases} \tag{2}$$

where δ $(\delta \in [0, 1])$ is the threshold of similarity value. In particular, when $h = 1$, the matcher accepts c, otherwise rejects. Supposing k is the number of matchers, c might belong to one of the five categories C_i, $i = 1, \cdots, 5$, which are, respectively, defined as follows:

(i) If c is accepted by k matchers, $c \in C_1$

(ii) If c is rejected by k matchers, $c \in C_5$

When $k \geq 2$ and k is an even number:

(iii) If c is accepted by more than half matchers, $c \in C_2$

(iv) If c is rejected by more than half matchers, $c \in C_4$

(v) Otherwise, $c \in C_3$

When $k \geq 3$ and k is an odd number:

(vi) If c is accepted by more than $(k + 1)/2$ matchers, $c \in C_2$

(vii) If c is rejected by more than $(k + 1)/2$ matchers, $c \in C_2$

(viii) Otherwise, $c \in C_3$

Since $c \in C_1$ is accepted by all the matchers as a correct correspondence, and $c \in C_5$ is rejected by all the matchers, the correspondences of types C_1 and C_5 are directly regarded as correct or wrong correspondences in the extraction process, which do not participate in the argumentation. Besides, correspondences belong to C_2, C_3, and C_4 should participate in the argumentation process.

Given two arguments be set as $a = \{c_1, n_1, v_1, h_1\}$ and $b = \{c_2, n_2, v_2, h_2\}$. There are four relationships between b and a, i.e., unite, attack, supporting, and disproval. Among them, union relationship is marked as $U(b, a)$, attack relationship is $A(b, a)$, and support and disprove are $S(b, a)$ and $D(b, a)$, respectively. To be specific, the four relationships are defined as the following descriptions:

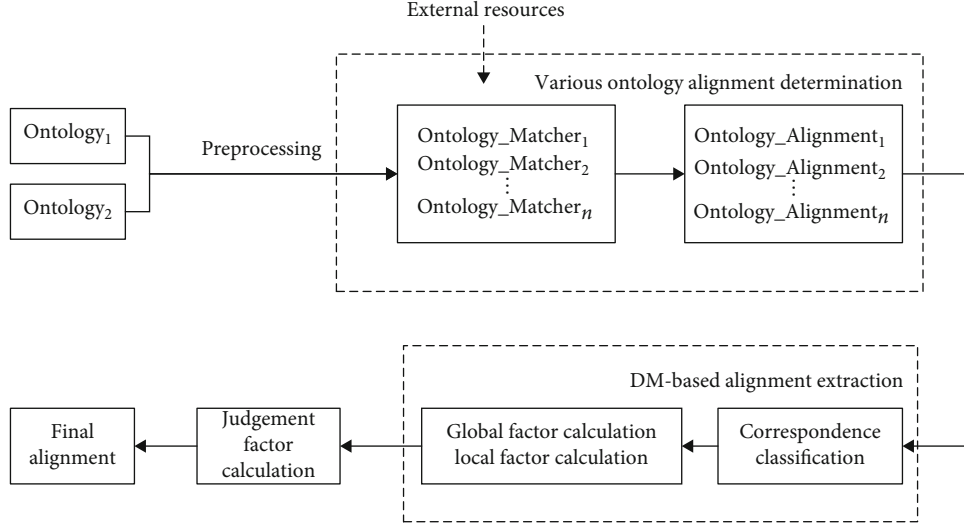(i) When $c_1 = c_2$, $v_1 \neq v_2$, $h_1 = h_2$, b is united with a, which is denoted as $U(b, a)$

FIGURE 2: The framework of sensor ontology alignment extraction.

(ii) When $c_1 = c_2$, $v_1 \neq v_2$, $h_1 \neq h_2$, b attacks a, which is denoted as $A(b, a)$

(iii) When $c_2 = C_2$ or $c_2 = C_3$, $v_1 = v_2$, $n_1 > n_2$, $h_1 = h_2 = 1$, or when $c_2 = C_4$ or C_3, $n_1 < n_2$, $h_1 = h_2 = 0$, b supports a, which is denoted as $S(b, a)$

(iv) When $v_1 = v_2$, $c_1 = C_i$, $c_2 = C_j$, $i > j(i, j \in (2, 3, 4))$, $n_1 > n_2$, $h_1 = 1$, $h_2 = 0$, or when $v_1 = v_2$, $c_1 = C_i$, $c_2 = C_j$, $i < j(i, j \in (2, 3, 4))$, $n_1 < n_2$, $h_1 = 0$, $h_2 = 1$, b disproves a, which is denoted as $D(b, a)$

3. Debate Mechanism-Based Ontology Alignment Extraction

DM's argumentation is defined as a 7-tuple: $\{ar, \text{strength}, U, A, S, D, M\}$, where U, A, S, and D are the relationships mentioned above, $M = \{m_1, m_2, \cdots, m_n\}$ is the set of matchers which include n matchers, ar is the argument attached to correspondence c, and strength stands for the strength value with respect to c in terms of a matcher m_i, which is defined as follows:

$$\text{Strength}_c^{m_i} = \frac{\sum_{ar \in AR} |\{x \mid x \in AR \wedge S(x, ar)\}| - \sum_{ar \in AR} |\{x \mid x \in AR \wedge D(x, ar)\}|}{\sum_{ar \in AR} |\{x \mid x \in AR \wedge S(x, ar)\}| + \sum_{ar \in AR} |\{x \mid x \in AR \wedge D(x, ar)\}|}.$$
(3)

In order to extract the sensor ontology alignment from various alignments determined by different matchers, we define a correspondence's global factor as the correctness factor of each matcher to consider their similarity from different aspects, and local factor as the support strength and disprove strength in the debating process to consider the possibility of being a correct mapping from the perspective of other correspondences. In this work, a sensor entity correspondence c in each matcher is regarded as an argument made by it, and we need to calculate its judgment factor to determine whether it can be extracted into the final alignment. Therefore, it is critical to enhance the confidence of an entity mapping's judg-

ment factor. To this end, we use the correctness factor of each matcher to determine a correspondence's global factor and utilize the support strength and disprove strength in the debating process to calculate its local factor. After that, the judgment factor of an entity mapping can be obtained by comprehensively considering these two factors.

To be specific, assuming $r_c \in \{0, 1\}$ is the judgment factor of c. The following debating process determines its value:

Step 1. It is obvious that r_c is 1 (or 0) when c belongs to C_1 (or C_5), and we can delete similarity values in the corresponding row and column of c from the similarity matrices.

Step 2. Calculate the correctness factor of the matcher m_i as follows:

$$\sigma_{m_i} = \frac{\sum_{m_i} |\{c \mid c \in (C_1, C_5)\}|}{\sum_{m_i} |c|},$$
(4)

whose molecular calculates the number of correspondences belong to C_1 (or C_5) and denominator of the number of correspondences in total.

Step 3. In each matcher, the debating process is launched according to the relationships "support" and "disprove":

(1) For the C_2 type of argument, the matchers that support it account for the majority, so it is calculated whether the supporting party could defeat the disproving party successfully. Below we explain the situation above. Assuming that for c, the three matchers m_1, m_2, and m_3 support it but m_4 disprove it, the support strength Ss of matcher m_i is defined as follows:

$$Ss_t^{m_i} = \frac{\sum_{x \in AR} n_x - \sum_{y \in AR} n_y}{\sum_{x \in AR} n_x + \sum_{y \in AR} n_y},$$
(5)

where argument $x = \{c, n_x, v_x, h_x\}$, argument $y = \{c, n_y, v_y, h_y\}$, $S(x, t)$, $D(y, t)$, $v_x = v_y$, and where $\sum_{x \in AR} n_x$ calculates the sum of similarity value of the arguments supporting argument $t = \{c, n_x, v_x, h_x\}$ and the same to $\sum_{y \in AR} n_y$.

It is determined that the mapping can be established between e and e' when $Ss_t^{m_1} > Ss_t^{m_4}$, $Ss_t^{m_2} > Ss_t^{m_4}$, and $Ss_t^{m_3} > Ss_t^{m_4}$, and r_c is set to 1. Otherwise, c is transformed into C_3, performing Step 4.

(2) For the C_4 type of argument, the matchers that disprove it account for the majority, so it is calculated whether the attack from the disproving party to the supporting party is successful. Below we explain the situation above. Assuming that for c, the three matchers m_1, m_2, and m_3 disprove it but m_4 support, the disprove strength Ds of matcher m_i is defined as follows:

$$Ds_t^{m_i} = \frac{\sum_{x \in AR} n_x - \sum_{y \in AR} n_y}{\sum_{x \in AR} n_x + \sum_{y \in AR} n_y}, \tag{6}$$

where argument $x = \{c, n_x, v_x, h_x\}$, argument $y = \{c, n_y, v_y, h_y\}$, $D(x, t)$, $S(y, t)$, $v_x = v_y$, and where $\sum_{x \in AR} n_x$ calculates the sum of similarity value of the arguments disproving argument $t = \{c, n_x, v_x, h_x\}$ and the same to $\sum_{y \in AR} n_y$. It is determined that the mapping cannot be established between e_i and e_j' when $Ds_t^{m_1} > Ds_t^{m_4}$, $Ds_t^{m_2} > Ds_t^{m_4}$, and $Ds_t^{m_3} > Ds_t^{m_4}$, and $r_c = 0$. Otherwise, c is transformed into C_3, performing Step 4.

Step 4. For the C_3 type of argument, the matchers with opposite opinions are almost evenly matched. It is necessary to calculate which of the two parties attacked each other successfully and calculate the strength value of each matcher. The attack with the higher the strength value is successful. Assuming that for c, the two matchers m_1 and m_2 disprove it but m_3 and m_4 support it. $r_c = 0$ if $\delta_{m_1} \bullet \text{Strength}_c^{m_1} + \delta_{m_2} \bullet \text{Strength}_c^{m_2} > \delta_{m_3} \bullet \text{Strength}_c^{m_3} + \delta_{m_4} \bullet \text{Strength}_c^{m_4}$. Otherwise, $r_c = 1$.

Step 5. Select c with $r_c = 1$ and determine the correspondence set based on them.

4. Experiment

4.1. Experimental Configuration. In the experiment, we use the bibliographic track from Ontology Alignment Evaluation Initiative (OAEI) to test the robustness of our approach through statistical comparison with the most advanced ontology matching techniques, as well as five sensor ontologies to validate the effectiveness of our proposal. We use four popular ontology matchers, which are, respectively, based on Levenshtein distance [41], Jaro-Winkler distance [42], similarity flooding (SF) [43], and WordNet similarity [44]. In particular, Levenshtein distance and Jaro-Winkler distance are terminology-based measures, WordNet is a

TABLE 1: Brief description on OAEI's bibliographic track.

Testing case	Description
101	Identical ontologies
201–202	Ontologies varying in terminology and semantic characteristics
221–237	Ontologies varying in structure characteristics
248–261	Ontologies varying in terminology, semantics, and structure characteristics

semantic-based measure, and SF uses a versatile graph matching algorithm. The similarity threshold is empirically set as 0.85, which can ensure the average highest quality of alignment in all testing cases. Typically, the alignment is assessed in terms of two measures, commonly known as precision and recall [45], which are, respectively, defined as follows:

$$\begin{aligned} \text{Recall} &= \frac{|R \bigcap A|}{|R|}, \\ \text{Precision} &= \frac{|R \bigcap A|}{|A|}, \end{aligned} \tag{7}$$

where A is the obtained alignment and R is the reference alignment. recall and precision are designed to examine the validity of the proposal. They use a set of standard answers as a reference to calculate the relative ratio as shown in the formula, which is about the result of the proposal and the reference. In our application, recall is used to measure the ability of the proposal to find the correct matching pair, and precision is used to measure the correct rate of the proposal to find the matching pair. In particular, recall = 1 means that all correct matching pairs have been found, and precision = 1 means that all matching pairs found are correct matching pairs. To trade off these two metrics, we further use the f-measure, which is the harmonic mean of recall and precision [46]:

$$f\text{-measure} = \frac{2\,\text{precision} - \text{recall}}{\text{recall} + \text{precision}}. \tag{8}$$

The bibliographic track (http://oaei.ontologymatching.org/2016/results/benchmarks) provided by the Ontology Alignment Evaluation Initiative (OAEI) is applied to test the robustness of our approach, and five real sensor ontologies are used to test our approach's effectiveness. Table 1 provides an abstract of OAEI's bibliographic track, where each testing case comprises of two to-be-mapped ontologies and one reference alignment for assessing the effectiveness of the ontology matcher. Figures 3(a)–3(d), respectively, compare our approach with four single similarity measures in terms of recall, precision, and f-measure. And relevant data is given by the Ontology Alignment Evaluation Initiative (OAEI) (http://oaei.ontologymatching.org/2016/). Figure 4, respectively, compares our approach with OAEI's participants [21], i.e., AML, edna, and LogMapLt in terms of f-measure. Table 2 describes our proposal's results on five sets of real

(a) Comparison on recall precision and f-measure on testing case 101

(b) Comparison on recall precision and f-measure on testing case 201-210

(c) Comparison on recall precision and f-measure on testing case 221-237

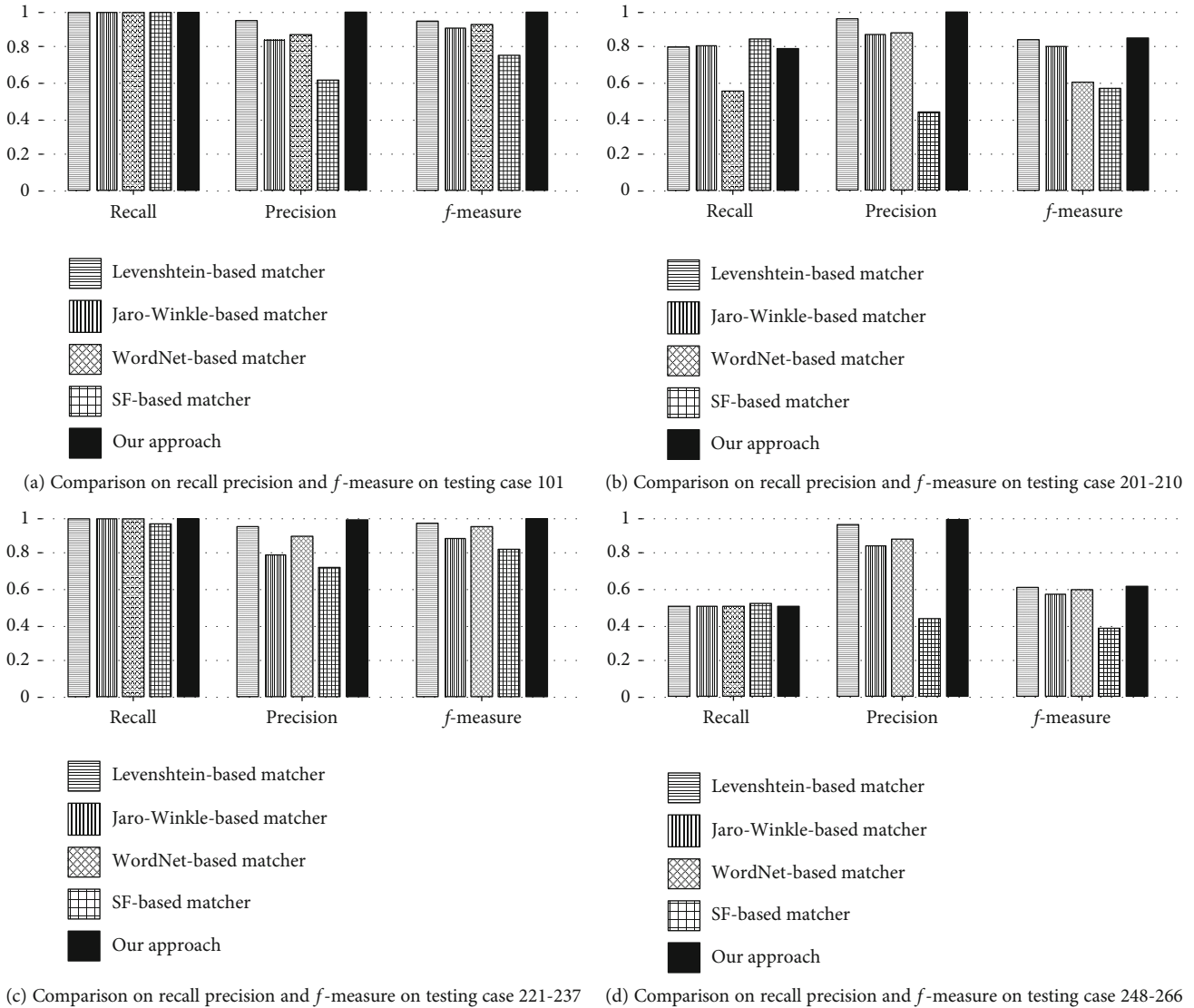(d) Comparison on recall precision and f-measure on testing case 248-266

FIGURE 3: Comparison with four single similarity measures in terms of recall, precision, and f-measure.

sensor ontology matching tasks and compares them with other OAEI competitors in SOSA and SN matching tasks.

As shown in Figure 3, comparing with four single similarity measures, our approach's f-measure is highest in all testing cases presented. We pick testing case 101, which contains strictly identical ontologies as a representative one of the testing cases about two identical ontologies in OAEI's benchmark. As Figure 3(a) indicates that our proposal achieves good results, which proves the superiority of it, therefore, our proposal has perfect accuracy in establishing the correct matching pair. DM adopts local factors on matchers in order to fully consider the contexts of the entities and external resources, aiming to improve the recall value. Besides, the mechanism fully considers the use of global factors for the alignment of different matchers to improve the precision value. In more detail, in testing cases 201-210 presented in Figure 3(b), which describe two ontologies with different terminology and semantic characteristics in each case, case 201 contains ontologies without entity names and 202 without entity. In these cases, our proposal's performance is signifi-

cantly better than the other methods, indicating that we have done a good job due to the consideration of support and disprove strength. In Figure 3(c), testing cases 221-247 are about ontologies with different structural characteristics. And results illustrate the effectiveness of our proposals and edna. In addition, our proposal is superior to edna in testing cases 221-223, which are about the ontologies with no specialization, with a flattened hierarchy, and the ontology with an expended hierarchy. A similar situation is shown in Figure 3(d), which compares the performance on testing cases about ontologies with different terminology, semantics, and structure characteristics. Our method considers the contextual information based on the ontology concept structure in calculating the strength value of the correspondence so that it can effectively overcome the problems of literal heterogeneity and information asymmetry when dealing with testing cases 201-261. In particular, our proposal has a certain competence with the most OAEI competitors in the aspect of recall, i.e., in case 101-247, where our approach can reach a level of 1.0 in recall value, indicating that the ability to find reference alignments is strong. To
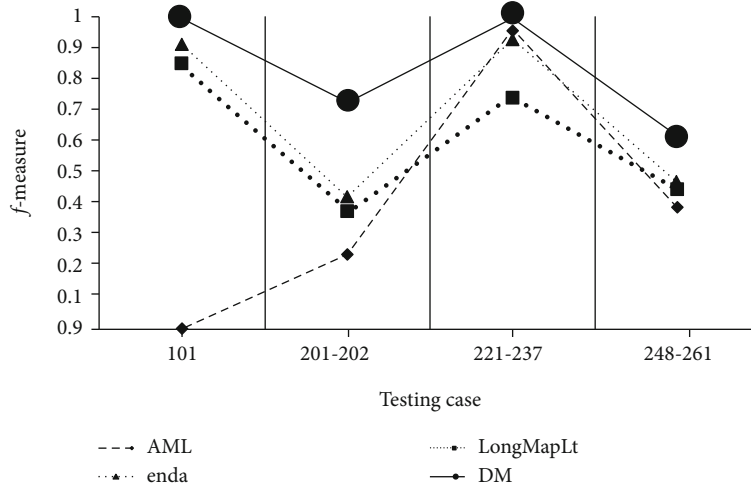
FIGURE 4: Comparison with OAEI's participants in terms of f-measure.

TABLE 2: Comparison on two pairs of real sensor ontologies with four matchers.

Matching task	Ontology quality measure	SF-based matcher	Jaro-Winkler-based matcher	WordNet-based matcher	Levenshtein-based matcher	Our approach
SOSA-OSSN	Recall	0.50	1.00	1.00	1.00	1.00
	Precision	0.20	1.00	0.67	1.00	1.00
	f-measure	0.29	1.00	0.80	1.00	1.00
SOSA-SN	Recall	1.00	1.00	1.00	1.00	1.00
	Precision	0.07	0.75	0.33	0.75	1.00
	f-measure	0.13	0.86	0.50	0.86	1.00
SSN-IoT	Recall	1.00	1.00	1.0	1.00	1.00
	Precision	0.01	1.00	0.33	1.00	1.00
	f-measure	0.03	1.00	0.50	1.00	1.00
SSN-OSSN	Recall	0.35	1.00	0.97	1.00	0.97
	Precision	0.06	0.94	0.80	1.00	1.00
	f-measure	0.11	0.97	0.88	1.00	0.98
SSN-SN	Recall	0.56	1.00	1.00	1.00	1.00
	Precision	0.02	0.90	0.52	1.00	1.00
	f-measure	0.04	0.95	0.70	1.00	1.00

improve the recall value and precision value, we introduce different ontology matching techniques to mine more potential correspondences and excavate the relationship between different arguments by support strength and disprove strength to explore more correct correspondences. It is worth learning that since the hypothetical goal of SF is to accurately obtain a matching element for each element in the source ontology, this method can get a higher recall rate.

Since our proposal takes into account each entity mapping's preference on different matchers, the alignment quality is relatively high. Figure 4 shows the result of the comparison with OAEI's participants in terms of f-measure, which indicates the certain comparability of our proposal in the field of ontology matching system. To be specific, the f-measure value generated by our proposal is

better than these OAEI's participants owing to the fact that we integrate the advantages of different basic similarity measures through DM so as to comprehensively consider the matching problem from different perspectives in the ontology matching process. To conclude, our proposal is able to improve the result's precision value significantly and, meanwhile, ensure a high recall value, which makes it outperforms other competitors on various matching tasks.

4.2. Real Sensor Ontology. The five sensor ontologies used are SSN, SOSA, IoT, SN, and OSSN, which are described in Table 3, and more details on them are presented in Section 2.1.

When matching the real sensor ontology, it can be seen from Table 2 that our method can obtain almost the same result as golden alignment. When matching the new SSN

TABLE 3: Main features of sensor ontologies.

Ontology	Number of entities	Website
Semantic Sensor Network (SSN) ontology	55	https://www.w3.org/ns/ssn/
Sensor, Observation, Sample, and Actuator (SOSA) ontology	42	http://www.w3.org/ns/sosa/
IoT-Lite (IoT) ontology	40	https://www.w3.org/Submission/2015/SUBM-iot-lite-20151126
SensorOntology2009 (SN) ontology	152	https://www.w3.org/2005/Incubator/ssn/wiki/SensorOntology2009
Original Semantic Sensor Network (OSSN) ontology	107	https://www.w3.org/2005/Incubator/ssn/wiki/SSN#Sensor

and OSSN, our method gets a recall rate of 0.97. This is because we assume that the alignment base is one-to-one. That is to say, a concept in an ontology can only be mapped to another one in another ontology, and vice versa. However, in some practical tasks, the cardinality may be one-to-many. For example, the concept "stimultium" in the new SSN is mapped to the concept "stimultium" in OSSN, which is the same as another assertion, "Sensor Input." In our method, it will no longer participate in the filtering process if the "Stimulus" in the new SSN is first mapped to the "Stimulus" in the original SSN in terms of ID (although the "Stimulus" annotation in the new SSN is the same as the "Sensor Input" annotation in the OSSN), which reduces the recall value of our method. In our proposal, we make the three metrics to reach the level of perfection.

5. Conclusion

Since artificial intelligence has greatly changed the data link form, IoT technologies are making significant progress these years, where ontology matching plays an advance role [47–51]. As far as the quality of the ontology alignment is concerned, the final alignment is composed of mappings. Therefore, it is particularly important to extract correct mappings from the alignments produced by different matchers and to filter out incorrect mappings. Different from the previous ontology meta-matching technology used by Xue et al. [52, 53], the ontology alignment extraction technology using DM considers the matching opinions of each basic matcher to each mapping, so as to output the final alignment. The sensor ontology extracting approach is aimed at finding high-quality alignment from various sensor ontology alignments, which can be used to bridge the semantic gap between heterogeneous sensor ontologies and integrate the knowledge defined inside. To enhance the quality of alignment, we propose a novel sensor ontology extracting method, which uses the debating mechanism. During various ontology matcher's debating processes, we propose to calculate both entity correspondence's global factor and local factor to determine its judgment factor, which is able to enhance its confidence. Although the experimental results show that our approach is able to decide on high-quality sensor ontology alignments effectively, there is still room for improvement. In the next work, we will try to describe the similarity between matching pairs by applying a new method and improve the extraction

method to make it more suitable for the characteristics of the sensor ontology.

Data Availability

The data used to support this study can be found in http://oaei.ontologymatching.org.

Conflicts of Interest

The authors declare that they have no conflicts of interest in the work.

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