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Leveraging Cognitive Context Knowledge for Argumentation-Based Object Classification in Multi-Sensor Networks

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ABSTRACT It is a great challenge to achieve interpretable collaborative object classification in multi-sensor networks. In this situation, argumentation-based object classification has been considered a promising paradigm, due to its natural means of justifying and explaining complicated decision making within multiple agents. However, disagreements between sensor agents are often encountered because of various object category levels. To address this category of granularity inconsistent problem in multi-sensor collaborative object classification tasks, we propose a cognitive context knowledge-enriched method for classification conflict resolution. The cognitive context is concerned, in this paper, to investigate how rich contextual knowledge-equipped cognitive agents can facilitate semantic consensus in argumentation-based object classification. The empirical evaluation demonstrates the effectiveness of our method with improvement over state-of-the-art, especially in the presence of noisy sensor data, while giving argumentative explanations. Therefore, it is suggested that people who can benefit from the proposed method in this paper are the human user of multi-sensor object classification systems, in which explaining decision support is one of the important factors concerned.

INDEX TERMS Multi-sensor networks, argumentation, cognitive context, explainable artificial intelligence, object classification.

I. INTRODUCTION

As multi-sensor networks for object classification become increasingly complex, it has been one of the most important requirements to build explainable artificial intelligence (XAI) systems for human users [1], [2]. Since most of intelligent algorithms to classify objects are lack of transparency and interpretability (i.e. black box), it is urgently needed to give the reasons behind the decision support of multi-sensor systems, e.g. battlefield situational awareness scenarios. In particular, semantic explanations, rather than evidences, are expected to reveal the underlying reasoning process in human-interpretable terms. Hence, explaining the predictions of intelligent systems, as a basic component of XAI [3], [4], poses a serious challenge to researchers from academics and industry in multi-sensor networks.

One research area in which explanation is available is that performing classification tasks towards the use of agent argumentation [5], i.e. a popular approach to commonsense reasoning [6]. It is noted that argumentation provides a natural means of justifying agents' point views that greatly resemble the way, in which humans come to a well-founded consensus. Thus, multi-agent argumentation based object classification techniques are gaining increasingly interests in intelligent system research community, due to its interpretability [7], [8]. In addition, to give semantic explanations for classification, our previous research [9] has shown that argumentation-based multi-agent collaboration classification could be improved by semantic attribute-value tree guided rule learning.

However, in the current multi-sensor networks, multi-granularity often exists in categories of objects [10], which may confuse the object classification tasks at different abstract levels. Considering space object classification for example, its main tasks is to classify the objects

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(e.g. satellites, debris and missiles) with electromagnetic, optical and other sensors in complex space environments. Not only the attribute-values (e.g. critical earth orbit, highly elliptical orbit, tundra orbit) of objects are hierarchical, but also the categories (e.g. satellite, reconnaissance surveillance satellite, early warning satellite) of objects are various in granularity. In this circumstance, different sensor agents may have classification assertions at different abstract levels [11], thus lead to disagreement of categorizing in argumentation based object classification. This is the problem that how to cope with category granularity inconsistency in multi-sensor object classification systems.

In this work, we attempt to bridge the gap between argumentation based object classification and semantic knowledge guided machine learning. Our hypothesis is that cognitive context knowledge could be exploited to construct arguments for reaching semantic consensus dynamically, and further increase object classification performance based on argumentation. Thus we propose a cognitive context knowledge enriched argumentation method for object classification in multi-sensor networks, called CCEA. Cognitive context is concerned in our research, for the reason that not only the static semantic attribute-value tree, but also the dynamic cognition of object category granularity plays important roles in reaching agreements and giving semantic explanations. As an implementation of the proposed method, Prism algorisms [12], which learn human-interpretable modular classification rules, are used by each sensor agent to generate classification arguments. In general, two significant contributions are believed to be provided in this study. First, we bridge the gap between argumentation based object classification and semantic knowledge guided machine learning, with a cognitive context enriched method, which demonstrate the effectiveness with improved classification performance over state-of-the-art. Second, a justified and explainable object classification mechanism is established to reach semantic consensus of multi-sensor networks through argumentation in human-interpretable terms.

The rest of this paper is organized as follows. In next section, related studies are reviewed. Section III presents our cognitive context knowledge enriched method. The proposed method is evaluated in comparison with state-of-the-art alternatives in Section IV. Finally, this work is concluded in Section V.

II. RELATED WORK

Concerning explainable object classification, it is widely accepted that not only good system performance is required, but also the reasons behind decision support are quite important to human users. Generally, object classification in machine learning research communities is a basic topic on categorizing new observations with a classifier, which learned from lots of categorized examples. To provide easy assimilated object classification for decision making in multi-sensor sensor networks, in this paper, the areas of work related to our method are argumentation based object classification and machine learning classifiers enhanced with hierarchical semantic knowledge.

A. ARGUMENTATION BASED OBJECT CLASSIFICATION

Recently, multi-agent argumentation has been known as one of the effective techniques to multi-party decision making, for the reason that it can provide explanations with justified arguments when reaching consensus [5]. In general, according to different structures of object classification systems, there are two different argumentation approaches, including concentrated ones and distributed ones. On one hand, the basic idea of concentrated argumentation based approach is to construct arguments in favor of all possible categorization of the particular object to be classified, thus a ''valid'' classification can be suggested by the so-called argumentation framework [13]. In Carstens's study [14], they developed a classification method that combines reasoning through argumentation with supervised classifiers, thus the possibility of misclassification can be reduced. It is noted that an computational argumentation framework, which incorporates high level activity classification arguments with low level sensor classifiers, has been proposed by Fan *et al.* [15]. Their experiments showed that the CAA (Computational Abstract Argumentation) frameworks not only can give comparable classification results within reduced learning time, but also could provide argumentative explanations. Thus the explanatory power for object classification can be offered by argumentation [16]. On the other hand, in distributed argumentation based approaches object classification tasks are performed by reaching consensus among multiple classifier agents. In order to cope with the inconsistent problem transparently in multiple classifier system, Conţiu *et al.* [6] proposed a conflict resolution method based on multi-agent argumentation, instead of voting mechanism. Their experiments, evaluated on a remote sensing crop dataset, illustrated that the proposed method could outperform the voting alternatives significantly. Considering multi-agent learning, an argumentation based framework for multi-agent inductive learning [17] is proposed by introducing dialogue game, to improve the performance of classification systems, with the two agents scenario. Wardeh *et al.* [18] proposed the so-called PISA (Pooling Information from Several Agents) argumentation mechanism that allows each agent to hold only one fixed assertion, arguing about the categories of objects. Furthermore, Hao *et al.* [7] proposed Arguing Prism, a multi-agent argumentation based approach for collaborative classification, using the Prism modular classification rule learning algorithms. The empirical investigation on its tolerance of inconsistent data demonstrated the superior classification performance of Arguing Prism.

The proposed method in this paper adopts argumentation based object classification, for the reason that it is a similar approach to the behaviors that several persons making joint decisions in the networked environments. Corresponding to Contin et al.'s work [6], which exploited ensemble learning to categorize objects, we also perform object classification tasks with multiple classifiers, but focuses on leveraging cognitive context for improving the arguments generation. In addition, the method proposed in this paper could cope with the multi-class problem with more than two agents, and each agent could flexibly alter object classification assertion for multi-sensor networks, rather than the fixed mechanism in existing works.

B. MACHINE LEARNING CLASSIFIERS ENHANCED WITH HIERARCHICAL SEMANTIC KNOWLEDGE

It is well know that hierarchical classification is one of the main styles for categorizing objects [11]. Through the use of common semantic taxonomies, which defined in the "Is-A" subset relationship, hierarchical classifiers could discriminate objects at different abstract levels, rather than just make a "flat" classification. As a typical kind of semantic taxonomies, Ontology is developed for representing domain knowledge in cognitive computing. And Ontology based classifiers, which organize domain knowledge hierarchically for object classification, have received much research attention [19]–[21]. For instance, to investigate the typical object classification dataset "Animals with Attributes" [22], researchers have constructed a semantic taxonomy, called AwA-10 [23], by querying the WordNet Ontology [24]. Using this hierarchical semantic knowledge guided by Ontology, Liu et al. obtained Hierarchical Classification Rules (HCRs), and constructed classifiers for object classification at various abstract levels [25]. Our previous work [9] has demonstrated that semantic attribute-value trees (SAT), which based on the hierarchical relations in attribute values of objects to be classified, can be used to generate object classification rules at various abstract levels. Besides, Ontology reasoning in the SAT enriched approach can also be used to generate arguments for agents in argumentation based object classification tasks.

Here, we propose a cognitive context knowledge enriched method, by exploring the hierarchical semantic knowledge both in semantic attribute-values and object categories, for generating classification arguments dynamically. In previous works, only the semantic attribute-value hierarchy was used as a static knowledge source for argumentation based multi-agent classification, thus ignoring the problem of object category granularity inconsistent in object classification systems. Hence, in this paper, not only the SAT, but also the rich context knowledge of categories is concerned dynamically, aiming to discriminate the objects at various abstract levels.

III. THE COGNITIVE CONTEXT KNOWLEDGE ENRICHED METHOD

In this section, we show how to leverage cognitive context knowledge for argumentation based object classification, namely CCEA, in order to cope with the category granularity inconsistent problem in multi-sensor networks. In particular, we assume that each sensor agent applies not only domain Ontology guided Prism rule learning technique with semantic attribute-value trees, but also multi-granular classification rules, to generate arguments dynamically. An overview of the proposed method appears in Figure 1. The system, which provides object classification results with semantic explanations when given object instance to be classified, consists of three components, showing in three different colors respectively. The first component, indicated in purple box, is our collaborative argumentation model for multiparty classification, presented in subsection *A*. Then, Prism rule learning guided by semantic attribute-value context for each sensor agent, is detailed in subsection *B* within the blue box. Finally, in subsection *C*, we describe how to generate arguments guided by category context knowledge dynamically, for reaching agreements with argument game. It is indicated in the yellow box, to bridge the gap between the purple one and the blue one.

A. MULTIPARTY CLASSIFICATION BASED ON THE COLLABORATIVE ARGUMENTATION MODEL

As indicated previously, in multi-sensor object classification systems, multiple sensor agents try to reach semantic consensus about the category of a particular object. Here each sensor agent could learn from its own training datasets, and make the prediction of object categories. We focus on multi-sensor collaborative classification, which defined formally as follows.

Definition 1 (Multi-Sensor Collaborative Classification): Given a multi-sensor object classification system, where the set of sensor agents $\mathcal{A}g = \{Ag_1, \cdots, Ag_n\}$, the example space $\mathcal{X}$ and the shared object category concept space C, each sensor agent has its own training data, $\mathcal{T}_1, \cdots, \mathcal{T}_n$. For a new object instance $\boldsymbol{x}(\boldsymbol{x} \in \mathcal{X})$, the aim of multi-sensor collaborative classification is to predict the category of $\boldsymbol{x}$, such that it is compatible with each sensor agent's learned classifier.

Since computational argumentation has been recognized as a feasible technique for conflict resolution through multi-party argument game, we build a multiparty collaborative argumentation model for reaching agreements in object classification, via extending Yao et al.'s Arena [26] with different kinds of arguments. Generally, an argumentation framework consists of a finite set of arguments and corresponding attack relations among them. In this case, our argumentation model, described in purple box of Figure 1, uses different arguments from Dung's abstract framework [27], in that classifying arguments are generated for a given argumentation topic.

Definition 2 (Multiparty Collaborative Argumentation Model, MCAM): The multiparty collaborative argumentation model is formally defined as MCAM $=< \mathcal{T}c, \mathcal{P}ar, \mathcal{R}ef, \mathcal{O}, \mathcal{R}oles, ArRul, \mathcal{Q}, \mathcal{R} >$, where: (i) $\mathcal{T}c$ is the topic to be argued; (ii) $\mathcal{P}ar \subseteq \mathcal{A}g$, is the set of all participant agents in multiparty argumentation; (iii) $\mathcal{R}ef$ is the Referee agent, who manages to coordinate multiple arguing agents; (iv) $\mathcal{O}$ is the common context knowledge shared by agents in $\mathcal{P}ar-$; (v) $\mathcal{R}oles$ $=\{$*Master*, *Challenger*, *Spectator*$\}$, is the set of roles played by agents in $\mathcal{P}ar$, consisting of masters, challengers and spectators respectively; (vi) $\mathcal{A}r\mathcal{R}ul$ is the set of argumentative rules abided by

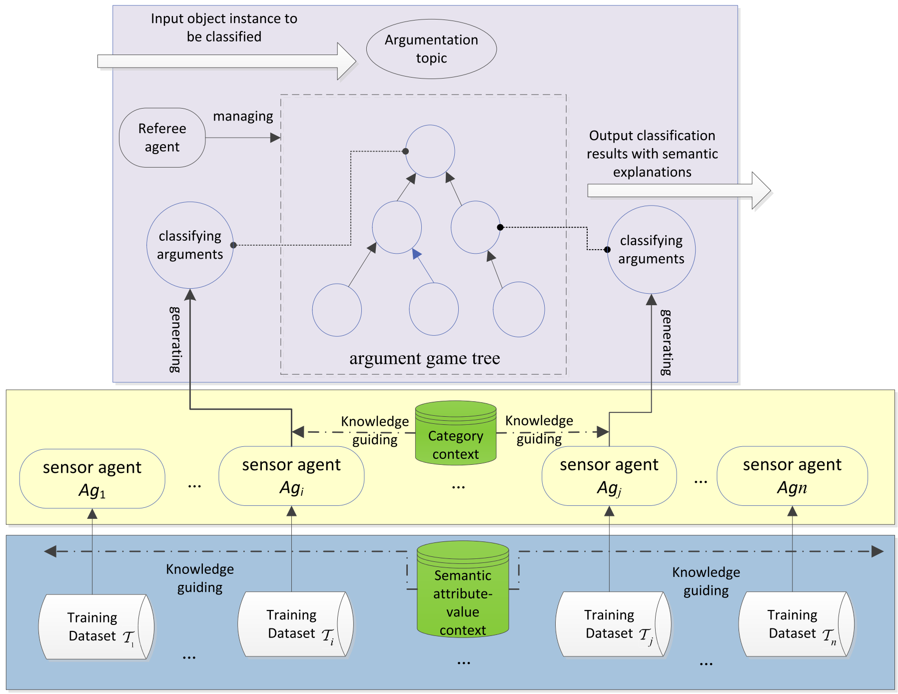

FIGURE 1. An overview of the proposed method.

agents in $\mathcal{P}ar$; (vii) $\mathcal{Q}$ is the set of classifying arguments; (viii) $\mathcal{R}$ is the set of attack relationships between arguments, namely $\mathcal{R} = Q \times Q$.

The MCAM is built here to allow multiple sensor agents to argue about the category of a new object instance collaboratively. Each sensor agent argues for its own assertion and against other conflicting ones. Classifying arguments for or against a particular category assertion are generated through learning from a sensor agent's own local training dataset. Specifically, it is defined formally as follows.

Definition 3 (classifying Argument): A classifying argument $\boldsymbol{Arg}$=$<Ag, \boldsymbol{x}, ca, \boldsymbol{s}, \vartheta \ >$, where: (i) $Ag \in \mathcal{P}ar$ is the proponent agent; (ii) $\boldsymbol{x} \in \mathcal{T}c$, is the object instance to be classified; (iii) $ca \in \mathcal{C}$, is the classification assertion; (iv) $\boldsymbol{s}$ is the supporting reason of ca, a.k.a. prerequisite; (v) $\vartheta \in (0, 1]$ is the strength of Ag' s classifying argument, noted as $stren^{Ag}(\boldsymbol{Arg})$.

It is noted that the strength of a classifying argument depends on the choice of machine learning algorithms. Without loss of generality, classifying arguments in our study are generated using Prism inductive rule learning algorithms, which will be described in the next subsection. In general, there are three different kinds of classifying arguments in MCAM, defined from **Definition 4** to **6**.

Definition 4 (Advocating Argument): An argument $\boldsymbol{Arg}$=$<Ag, \boldsymbol{x}, ca, \boldsymbol{s}, \vartheta \ >$ is an advocating argument for the given topic Tc in MCAM, iff: (i) $Ag = Master$; (ii) $\boldsymbol{x} \equiv \mathcal{T}c$; (iii) $ca \in \mathcal{C}$; (iv) $\boldsymbol{x}, \boldsymbol{s} \vdash ca$; (v) $\vartheta \geq Threshold$ ($0<Threshold\leq 1$).

Where "$\equiv$" represents a equivalent relation between the two vectors, and "$\vdash$" represents implication relation in Mathematical logic. The subsequent description in this paper follows the same convention.

Definition 5 (Rebutting Argument): Suppose Ag_i ($Ag_i \in \mathcal{P}ar$) and $Ag_k(Ag_k \in \mathcal{P}ar)$ are two participant agents in MCAM, $Arg =< Ag_i, \boldsymbol{x}, ca, \boldsymbol{s}, \vartheta \ >$ and $Arg' =< Ag_k, \boldsymbol{x}', ca', \boldsymbol{s'}, \vartheta' >$ are two classifying arguments proposed by them respectively. $\boldsymbol{Arg}$ is the rebutting argument of$\boldsymbol{Arg}'$, iff: (i) $Ag_i \neq Ag_k$, $Ag_i \in \{Mast, Challenger\}, Ag_k \in \{Master, Challenger\}$; (ii) $\boldsymbol{x} \equiv \boldsymbol{x'}$; (iii) $ca \neq ca'$, $ca \in \mathcal{C}$, $ca' \in \mathcal{C}$; (iv) $\boldsymbol{Arg} \succ^{[\![Ag_i, Ag_k]\!]} \boldsymbol{Arg'}$.

Where $\boldsymbol{Arg} \succ^{[\![Ag_i, Ag_k]\!]} \boldsymbol{Arg'}$ means that $\boldsymbol{Arg}$ is preferred to $\boldsymbol{Arg'}$ between $Ag_i and Ag_k$, considering the strength of these two classifying arguments.

Definition 6 (Undercutting Argument): Suppose Ag_i ($Ag_i \in \mathcal{P}ar$) and $Ag_k(Ag_k \in \mathcal{P}ar)$ are two participant agents in MCAM, $\boldsymbol{Arg} =< Ag_i, \boldsymbol{x}, ca, \boldsymbol{s}, \vartheta \ >$ and $\boldsymbol{Arg}' =< Ag_k, \boldsymbol{x}', ca', \boldsymbol{s}', \vartheta' \ >$ are two classifying arguments proposed by them respectively. $\boldsymbol{Arg}$ is the undercutting argument of$\boldsymbol{Arg}'$, iff: (i) $Ag_i \neq Ag_k$, $Ag_i \in \{Master\}, Challenger, Ag_k Master, Challenger$; (ii) $\boldsymbol{x} \equiv \boldsymbol{x'}$; (iii) $ca = \mathfrak{P}\left(ca'\right)$; (iv) $\boldsymbol{s'} \sqsubset \boldsymbol{s}$.

Where $ca = \mathfrak{P}\left(ca'\right)$ means that ca' is the negative concept of ca, namely $\mathfrak{P}\left(ca'\right) = \neg ca'$, and $\boldsymbol{s'} \sqsubset \boldsymbol{s}$ means that a more-general-than relation [17] exists between $\boldsymbol{s'}$ and $\boldsymbol{s}$, and $\boldsymbol{s'}$ is more general than $\boldsymbol{s}$.

The classifying arguments are communicated via the speech acts among multiple sensor agents, and the realization of these speech acts is detailed through the collaborative argumentation dialogue protocol in MCAM. Assuming that we have a new object instance to be classified, the collaborative argumentation dialogue protocol operates as follows:

(1) At the first round, the *master* proposes a new classifying argument $\boldsymbol{Arg}$, such that its $stren^{Ag}(\boldsymbol{Arg})$ is higher than a given threshold. The Referee agent establishes a new argument game tree, showed in Figure 1, whose root represents the *master*'s classification assertion;

(2) In the second round, the other participate agents attempt to defend or attack the proposing argument. If all the agents fail to perform any speech act, the dialogue terminates, and the object instance is classified according to the assertion prompted by the *master*. Otherwise, the argument game tree is updated with submitted speech acts;

(3) The argumentation process continues until the *master* is defeated, then another round of argumentation begins, the protocol moves to (1);

(4) If two subsequent rounds passed without any new speech acts being submitted to the argument game tree, or if a particular number of rounds have passed without reaching semantic consensus, the Referee agent $\mathcal{R}ef$ terminates the dialogue.

More details of the implementation of MCAM will no longer be described in this section due to the limited space. Once a collaborative argumentation dialogue has been terminated, the status of the argument game tree will indicate the object classification result and its underlying reasons in form of classifying arguments.

B. PRISM RULE LEARNING WITH SEMANTIC ATTRIBUTE-VALUE TREES

As already stated above, each sensor agent in MCAM has its own local training datasets of object examples for learning to generate classifying arguments. Here each object example consists of several attribute-value pairs and a single class label indicating its category. In this case, given a particular object instance to be classified, all the participant agents try to find arguments for or against certain classification assertion through machine learning algorithms. We choose a modular rule induction algorithm, namely Prism, rather than the "black box" algorithms (e.g. support vector machine, artificial neural network, etc.), for the reason that Prism can provide transparent classifiers, even can be more easily assimilated by human users than decision trees [28].

Although modular classification rules are readily acceptable, sensor agents still need to have access to background domain knowledge, in order to facilitate arguing with other agents and give semantic explanations to human users. Generally, domain knowledge can be represented by Ontology, which is a formal understanding of shared context knowledge. Thus domain Ontology could be employed by machine learning algorithms in reasoning and inducing. Considering the aforementioned space object classification tasks, the domain Ontology of space objects is a shared understanding within a community of domain experts, and can be used for reasoning about the categories of space objects.

Typically, the hierarchical structure in the datasets of a particular domain is represented by the class-subclass relations of domain Ontology. Thus, we can make generalization over the value of attributes while learning classification rules, in order to obtain compact and semantic explainable classifiers. By exploiting the domain Ontology of attributes, the Semantic Attribute-value Tree (SAT) is proposed to enhance context knowledge for classification rule learning. In what follows, we define SAT, and introduce the related notations of SAT.

Definition 7 (Semantic Attribute-value Tree, SAT): A SAT associated with a nominal attribute $\mathbb{A}$, noted as $SAT(\mathbb{A})$, is a tree with root node $\mathbb{A}$, and all the leaf nodes of it relate to its primitive attribute values. Besides, all the other non-leaf nodes relate to generalized values of the attribute $\mathbb{A}$. The edges of SAT indicate the "class-subclass" relations between attribute value nodes, from the most generalized root node to the most specified leaf nodes.

According to the definition of SAT, given a nominal attribute $\mathbb{A}$, the structure of $SAT(\mathbb{A})$ are described as follows: (i) the root node is noted as $Root\_SAT(\mathbb{A})$; (ii) All the primitive values of $\mathbb{A}$ are represented by the set of leaf nodes, noted as $Prim(\mathbb{A})$, also $Leaves\_SAT(\mathbb{A})$; (iii) All the child nodes of an arbitrary node v (except for the leaf nodes) are noted as $Children(\mathbb{A}, v)$; (iv) Given an arbitrary node v, the depth $Depth(\mathbb{A},v)$ in $SAT(\mathbb{A})$ is the total number of edges from the root node to v; (v) Given an arbitrary node v, let the $IsLeaf(\mathbb{A},v)$ to be the Boolean flag of v, that is, if $v \in Leaves\_SAT(\mathbb{A})$, then $IsLeaf(\mathbb{A},v) = T$, else $IsLeaf(\mathbb{A},v) = F$.

As described in the previous subsection, in MCAM, given a training dataset of object examples $\mathcal{T} = \{\boldsymbol{e}_i|\boldsymbol{e}_i = (\boldsymbol{x}_i, c_i), \boldsymbol{x}_i \in \mathcal{X}, c_i \in \mathcal{C}, i = 1, 2, \cdots\}$, suppose $\mathcal{A} = \{\mathbb{A}_1, \ldots \mathbb{A}_A\}$ is the set of all the referred attributes, $\mathcal{S}^* = \{SAT\ (\mathbb{A}), \cdots, SAT\ (\mathbb{A}_A)$ is the set of the corresponding SAT, $\mathcal{V}\_\mathbb{A} = \{v_1, \cdots, v_t\}$ is the set of attribute $\mathbb{A}$' s values, and $\mathcal{C}=\{c_1, \cdots, c_n\}$ is the set of all the categories. In this case, we have the following conventions: (i) $\Lambda(SAT\ (\mathbb{A}_k), v)$ is the set of node v's ancestors in $SAT\ (\mathbb{A}_k)$; (ii) $\lambda(SAT\ (\mathbb{A}_k), v)$ is the father node of v in $SAT\ (\mathbb{A}_k)$; (iii) $\sigma(c_i, \mathcal{T}(i = 1, \cdots n)$ is the accumulated count of the appearance of c_i in $\mathcal{T}$; (iv) $\sigma(\mathbb{A}_k, v, \mathcal{T})$ is the accumulated count of the appearance of attribute-value pair $\mathbb{A}_k = v$ in $\mathcal{T}$; (v) suppose $\{v_{k1}, , \cdots, v_{kV}\}$ is the set of attribute $\mathbb{A}_k$'s values, then $\mathcal{T} = \{\mathcal{T}_1, \cdots, \mathcal{T}_V$ means the V subsets of $\mathcal{T}$ divided by V values of the very attribute.

To illustrate the evaluation criterions for the generalization of attribute values in learning classification rules, we first give the definition of classification information entropy, and then the related classification information gain.

Definition 8 (Classification Information Entropy): Given a training dataset of object examples $\mathcal{T} = \{\boldsymbol{e}_i|\boldsymbol{e}_i = (\boldsymbol{x}_i, c_i), \boldsymbol{x}_i \in \mathcal{X}, c_i \in \mathcal{C}, i = 1, 2, \cdots\}$ with concept space of categories $\mathcal{C} = \{c_1, \cdots, c_n\}$, the classification information

TABLE 1. **Attribute value generalization algorithm based on classification information gain.**

Algorithm 1. Generalizing_attribute_value($\mathcal{T}$, $\mathcal{C}$, $\mathbb{A}_k$)	
input: a set of training *examples* $\mathcal{T}$ with concept space of categories $\mathcal{C}$ and attribute $\mathbb{A}_k$	
output: a set of generalized attribute $\mathbb{A}_k$' s values $\mathcal{V}_k$	
01	$cIG := CInfoGain_{\mathcal{T}}(\mathcal{C}, \mathbb{A}_k)$
02	$\mathcal{B}an := \emptyset$
03	$\mathcal{V}_k := getAttributeValues(\mathcal{T}, \mathbb{A}_k)$
04	**while TRUE do**
05	**if** $\exists v$ s.t. $v \in \mathcal{V}_k \wedge v \notin \mathcal{B}an$ **then**
06	$v' := \lambda(SAT(\mathbb{A}_i), v)$
07	$\mathcal{V}_k{}' := replaceWithMoreGeneralTerm(\mathcal{V}_k, v')$
08	$\mathcal{T}' := replaceWithMoreGeneralTerm(\mathcal{T}, \mathbb{A}_k, \mathcal{V}_k{}')$
09	**if** $CInfoGain_{\mathcal{T}'}(\mathcal{C}, \mathbb{A}_i) = cIG$ **then**
10	$\mathcal{T} := \mathcal{T}', \mathcal{V}_k := \mathcal{V}_k{}'$
11	**else**
12	$\mathcal{B}an := \mathcal{B}an \cup \{v\}$
13	**end if**
14	**else**
15	**break**
16	**end if**
17	**end while**
18	**return** $\mathcal{V}_k$

entropy of $\mathcal{C}$

$$CInfoEnt_{\mathcal{T}}(\mathcal{C}) = -\sum_{i=1}^{n} \frac{\sigma(c_i, \mathrm{T})}{m(\mathrm{T})} \cdot \log_2\left(\frac{\sigma(c_i, \mathrm{T})}{m(\mathrm{T})}\right) \tag{1}$$

where $m(\mathcal{T})$ is the total number of examples in $\mathcal{T}$.

Definition 9 (Classification Information Gain): Given a training dataset of object examples $\mathcal{T} = \{\boldsymbol{e}_i | \boldsymbol{e}_i = (\boldsymbol{x}_i, c_i), \boldsymbol{x}_i \in \mathcal{X}, c_i \in \mathcal{C}, i = 1, 2, \cdots\}$ with concept space of categories $\mathcal{C}$=$\{c_1, \cdots, c_n\}$ and the referred attribute set $\mathcal{A} = \{\mathbb{A}_1, \ldots \mathbb{A}_A\}$, the classification information gain of $\mathcal{C}$ and $\mathbb{A}_k (\mathbb{A}_k \in \mathcal{A}, k = 1, \cdots A,)$

$$\begin{aligned} CInfoGain_{\mathcal{T}}(\mathcal{C}, \mathcal{A}_k) = {} & CInfoEnt_{\mathcal{T}}(\mathcal{C}) \\ & - \sum_{l=1}^{V} \frac{m(\mathcal{T}_V)}{m(\mathcal{T})} \cdot CInfoEnt_{\mathcal{T}_V}(\mathcal{C}) \end{aligned} \tag{2}$$

where $CInfoEnt_{\mathcal{T}_V}(\mathcal{C})$ is classification information entropy of $\mathcal{C}$ in subset $\mathcal{T}_V$.

It is clearly that given a certain concept space $\mathcal{C}$, the larger the value of $CInfoGain_{\mathcal{T}}(\mathcal{C}, \mathbb{A}_k)$, the greater the contribution of attribute $\mathbb{A}_k$ to the classification task. Thus, we exploit classification information gain as a generalization criterion when performing rule learning guided by SAT. In what follows, our attribute value generalization algorithm based on classification information gain is presented in TABLE 1. The main idea of this generalization algorithm is to replace the nominal attribute values with their father node iteratively, during the bottom-up induction of Prism learning, until the value of classification information gain no longer grows.

In **Algorithm 1**, we first compute the initial value of classification information gain (line 01), and construct an empty set $\mathcal{B}an$ for preserving the attribute values that cannot be generalized (line 02). At the same time a set for preserving all the values of attribute $\mathbb{A}_k$ is constructed (line 03). Then when there is an attribute value $v \in \mathcal{V}_i$ that can be generalized (line 05 to 14), the generalized attribute value v' is obtained with SAT. In this case, a new set $\mathcal{V}_k{}'$ is created through replacing v with v', and the corresponding new training set $\mathcal{T}'$. Next, it is checked that if the value of classification information gain drops in this generalization process. If the value does not change, then replace $\mathcal{T}$ with $\mathcal{T}'$, and $\mathcal{V}_k$ with V_k' respectively, else put this attribute value v in the set $\mathcal{B}an$. The above execution is going on repeatedly, until there is no attribute value in $\mathcal{V}_k$, which can decrease the classification information gain.

After the set of generalized values for each attribute in $\mathcal{A}$, a new SAT guided algorithm is proposed for introducing the semantic attribute-value tree into Prism induction, to learn compact and human-interpretable classification rules. This algorithm is described in TABLE 2.

In **Algorithm 2**, an empty set $\mathcal{H}$ for preserving the learned classification rules is first constructed (line 01). Then for a

TABLE 2. SAT guided Prism induction for learning modular classification rules.

Algorithm 2. SATE-Prism_learning($\mathcal{T}$, $\mathcal{VG}$)	
input: a set of training *examples* $\mathcal{T}$, the set of generalized attribute value sets $\mathcal{VG} = \{\mathcal{V}_1, \cdots, \mathcal{V}_\varphi\}$	
output: a set of classification rules $\mathcal{H}$	
01	$\mathcal{H} := \emptyset$
02	**for each** $c_i \in \mathcal{C}$ <u>do</u>
03	**repeat**
04	$\mathcal{S} := \mathcal{T}$
05	$\wp := \perp$
06	$\hbar :=$ (IF $\wp$ THEN c_i)
07	**repeat**
08	**for each** $\mathcal{V}_l \in \mathcal{VG}$ **do**
09	**for each** $\mathbb{A}_k = v$ in $\mathcal{V}_l$ **do**
10	$\delta := \frac{\sum_{j=1}^{n} \lvert (examples \in \mathcal{S}\ with\ \mathbb{A}_k = w_j) \wedge w_j \in Children(\mathbb{A}_k, v) \wedge \wp \wedge (\in c_i) \rvert}{\sum_{j=1}^{n} (examples \in \mathcal{S}\ with\ \mathbb{A}_k = w_j) \wedge w_j \in Children(\mathbb{A}_k, v) \wedge \wp}$
11	**end for**
12	**end for**
13	find attribute-value pair *Ax=vx* that maximizes δ
14	$\wp := \wp \wedge (Ax, vx)$
15	$\mathcal{S} :=$ {examples in $\mathcal{S}$ that satisfy $Ax = vx$}
16	**until** all examples in $\mathcal{S}$ belong to c_i
17	$\mathcal{T} := \mathcal{T} - \mathcal{S}$
18	$\mathcal{H} := \mathcal{H} \cup \hbar$
19	**until** there are no tuples in $\mathcal{T}$ that belong to c_i
20	**end for**
21	**return** $\mathcal{H}$

particular object category $c_i (c_i \in \mathfrak{C})$, the attribute value hierarchy is introduced into Prism rule learning process, guided by SAT (line 02 to 16). While seeking for the attribute-value pair, which makes the maximum contribution to object classification information amount δ, two loops need to be executed. These two loops consist of the outer one for the set of generalized attribute value sets $\mathcal{VG}$ and the inner one for each set of attribute values $\mathcal{V}_l$ (line 08 to 12). It is noted that the bottom-up inductive reasoning is executed in both Prism learning and the hierarchical structure of SAT. Thus they can be combined seamlessly for learning modular classification rules. In the next subsection, we will demonstrate how to generate classifying arguments for MCAM.

C. GENERATING ARGUMENTS WITH MULTI-GRANULAR CLASSIFICATION RULES

Having presented the multiparty collaborative argumentation model and each sensor agent's classification rule learning enhanced with SAT context knowledge, this subsection describes the generation of classifying arguments used in argumentation for MACM. Although it is shown that Prism learning for classification rules can be enhanced by the context knowledge of semantic attribute values, the classifying arguments for collaborative argumentation in real time are still confronted with category granularity inconsistent difficulties. Thus, in what follows, we first present the proposed multi-granular classification rule learning algorithm, and then illustrate how to generate classifying arguments with the rules dynamically for collaborative argumentation.

In most current research of distributed machine learning communities, classification tasks are performed with the ''flat'' structure of object category set, without any consideration on various levels of class labels. In fact, many realistic object classification tasks themselves contain hierarchical structures of categories. Thus it is a big challenge for the sensor agents in MCAM to reach consensus about a particular category of a new object. In this circumstance, we propose to learn multi-granular classification rules for generating classifying arguments in a coordinated manner. Here, the definition of multi-granular classification rule is firstly described as follows.

Definition 10 (Multi-Granular Classification Rule): A multi-granular classification rule $mgcr$ is defined in the form:$IF\ \mathbb{A}_i rel_i v_{ix} \bigwedge \cdots \bigwedge \mathbb{A}_j rel_j v_{jx} \cdots \bigwedge class = c_k \quad THEN$ $class = sub_{c_k}$, where $\mathbb{A}_i, \ldots, \mathbb{A}_j \in A$ are attributes, $rel_i, \cdots, rel_j \in \{=, \neq, <, >, \leq, \geq\}$, are relational operators, $v_{ix}, \cdots, v_{jx}$ are attribute values, and sub_{c_k} is the direct subclass of c_k in the category taxonomy $\mathfrak{Ta}$.

Clearly, the prerequisite of a $mgcr$, noted as $prer(mgcr)$, is a logical conjunction of attribute-value pairs and a category discrimination. The consequent, noted as $cons(mgcr)$ is a subcategory classification. Here, an attribute-value pair typically has the form $\mathbb{A}_i = v_{ix}$ for nominal attributes, and other forms for numeric attributes. As indicated in the foregoing subsection, we focus on nominal attributes in this paper, which can be enhanced with SAT for Prism rule learning.

As seen from **Definition 10**, using the multi-granular classification rules top-down recursively, we can easily obtain the specific category of a new object. In this way, Given a series of multi-granular classification rules, $mgcr_1, mgcr_2, \cdots mgcr_\eta$, used for hierarchical classification, it is obvious that $cons(mgcr_i) \in prer(mgcr_{i+1})(1 < i \leq \eta + 1)$. Since the range of a given object category gradually becomes smaller with the use of multi-granular classification rules, such a learning process of subsequent rules converges quickly. Therefore, the various levels of a new object's categories required in MCAM can be obtained by using the multi-granular classification rules.

Following the description of subsection *B*, multi-granular classification rules can be learned hierarchically from the training datasets, referring to the category taxonomy $\mathfrak{Ta}$, which obtained from domain Ontology. Our proposed algorithm for learning multi-granular classification rules is described in TABLE 3.

In **Algorithm** 3, a set of multi-granular classification rules are learned from a training dataset $\mathfrak{T}$ and category taxonomy $\mathfrak{Ta}$, concerning target category c_k. First, a new training dataset $\mathfrak{T}'$ is created based on $\mathfrak{T}$, leaving the examples labeled by the subclass of c_k(line 04 to 11). Then, SATE-Prism classification rules (described in **Algorithm 2**) are derived from T′ with various attribute sets (line 14 to 17). It is noted that although several rules may have the same consequent, their prerequisites consist of different attribute-value pairs. Next, the given target category c_k is added to multi-granular classification rules that are transformed (line 18 to 21). This *mgcr*_Learning algorithm executes recursively until the rules for each subclass of c_k are learned (line 22 to 25).

As defined in subsection *A*, there are three different kinds of classification rules, namely advocating arguments, rebutting arguments and undercutting arguments. Since sensor agents in MCAM may have difficulties in reaching agreements about the object categories at various abstract levels, they need to exploit the cognitive context knowledge mentioned above for generating classifying arguments required dynamically. In what follows, we describe the process of generating these three kinds of arguments used by sensor agents, with the learned multi-granular classification rules.

1) ADVOCATING ARGUMENTS

Given an object instance $\boldsymbol{x}(\boldsymbol{x} \in \mathfrak{X})$ to be classified, a $mgcr$ based advocating argument $\boldsymbol{\alpha} =< Ag, \boldsymbol{x}, ca, \boldsymbol{h}, num, den, \vartheta >$, where Ag is the proponent agent, ca is the classification assertion, $\boldsymbol{h}$ is the corresponding rule giving the reasons for ca, num is the count of examples covered correctly by $\boldsymbol{h}$ in Ag's local data repository, den is the count of examples covered by $\boldsymbol{h}$ in Ag's local data repository, ϑ is the strength of $\boldsymbol{\alpha}$. Here, suppose the given object instance $\boldsymbol{x} = (v_1, \cdots, v_n)$, then the process of generating advocating arguments is performed by agent Ag in the following steps.

Step 1: Check that whether there are any $mgcr$ that covering the object instance $\boldsymbol{x}$. If it is true, then return the rule with maximum strength, as the supporting rule for the advocating argument, else, turn to the next step;

Step 2: Considering the category of $\boldsymbol{x}$, to find its father concept in the category taxonomy $\mathfrak{Ta}$. If it exists, then change the category of $\boldsymbol{x}$ to its father concept, and go back to **Step 1**, else turn to the next step;

Step 3: Iterative execute the **Step 2** until there is no father concept for the current category. If the $mgcr$ is find, then return the advocating argument based on that rule, else return false, indicating that agent Ag cannot generate any advocating argument for the object instance $\boldsymbol{x}$.

2) REBUTTING ARGUMENTS

Given an object instance $\boldsymbol{x}(\boldsymbol{x} \in \mathfrak{X})$ to be classified and its advocating argument $\boldsymbol{\alpha} =< Ag, \boldsymbol{x}, ca, \boldsymbol{h}, num, den, \vartheta >$, then its corresponding rebutting argument $\boldsymbol{\beta} =< Ag', \boldsymbol{x}, ca', \boldsymbol{h'}, num', den', \vartheta' >$, where: (i) $Ag' \neq Ag$, is rebutting agent; (ii) $ca' \neq ca$, means that Ag' holds a different classification assertion from ca; (iii) $\boldsymbol{h'}$ is another classification rule giving the reasons for ca'; (iv) num' is the count of examples covered correctly by $\boldsymbol{h'}$ in Ag''s local data repository; (v) den is the count of examples covered by $\boldsymbol{h'}$ in Ag''s local data repository; (vi) ϑ' is the strength of $\boldsymbol{\beta}$. In this circumstance, the process of generating rebutting arguments is performed by agent Ag', following the steps in (1), but requiring to satisfy the condition of strength, i.e. $\xi^{[\![Ag,Ag']\!]}(\boldsymbol{\beta}) > \xi^{[\![Ag,Ag']\!]}(\boldsymbol{\alpha})$.

3) UNDERCUTTING ARGUMENTS

Given an object instance $\boldsymbol{x}(\boldsymbol{x} \in \mathfrak{X})$ to be classified and its advocating argument $\boldsymbol{\alpha}{=}{<}Ag, \boldsymbol{x}, ca, \boldsymbol{h}, num, den, \vartheta >$, then its corresponding undercutting argument $\boldsymbol{\gamma} =< Ag'', \boldsymbol{x}, ca'', \boldsymbol{h}'', num'', den'', \vartheta'' >$, where: (i) $Ag'' \neq Ag$, is undercutting agent; (ii) $ca'' = \mathfrak{P}(ca)$, means that Ag'' holds the negation of classification assertion from ca; (iii) $\boldsymbol{h} \sqsubset \boldsymbol{h}''$, is a longer classification rule than $\boldsymbol{h}$, giving the reasons for ca''; (iv) num'' is the count of examples covered correctly by $\boldsymbol{h''}$ in Ag'''s local data repository; (v) den'' is the count of examples covered by $\boldsymbol{h''}$ in Ag'''s local data repository; (vi) ϑ'' is the strength of $\boldsymbol{\gamma}$. In this circumstance, the process of generating undercutting arguments is performed by agent Ag'', following the steps in (1), but requiring to satisfy the condition of

TABLE 3. Learning multi-granular classification rules for generating arguments.

Algorithm 3. $mgcr$_Learning $(\mathcal{T}, \mathfrak{Ta},\ c_k)$

input: a training dataset $\mathcal{T}$ with attribute set $\mathcal{A}$, category taxonomy $\mathfrak{Ta}$, target category c_k
output: a set of multi-granular classification rules $\mathcal{MR}$

$\mathcal{T}' := \mathcal{T}$
$\mathcal{MR} := \emptyset$
$sub\_c_k := \text{getSubClass}(c_k)$
for each $exa \in \mathcal{T}'$ **do**
  $cate\_set := sub\_c_k \cap \text{getSuperClass}(\mathcal{T}, \text{cateOf}(exa))$
  if $cate\_set \neq \emptyset$ **then**
    $exa\_cate := \text{getOneElement}(cate\_set)$
  else
    $\mathcal{T}' := \mathcal{T}' - \{exa\}$
  end if
end for
$attr\_set := \emptyset$
$rule\_set := \emptyset$
repeat
  $attr\_set := attr\_set \cup \text{attributeUsed}(rule\_set)$
  $rul\_set := \text{SATE-Prism\_Learning}(\mathcal{T}', \mathcal{A} - attr\_set)$
until $rule\_set == \emptyset$
for each $rule \in rule\_set$ **do**
  $mg\_rule := \text{generatedNewRule}(rule, c_k)$
  $\mathcal{MR} := \mathcal{MR} \cup \{mg\_rule\}$
end for
$\mathcal{T}'' := \mathcal{T}$
for each $sub\_cate \in sub\_c_k$ **do**
  $\mathcal{MR} := \mathcal{MR} \cup mgcr\_\text{Learning}\ (\mathcal{T}'', \mathfrak{Ta},\ c_k)$
end for
return $\mathcal{MR}$

more-general-than relation in **Step 1**, i.e. a more specific *mgcr* is needed for the undercutting argument.

IV. EMPIRICAL EVALUATION

In this section, the empirical evaluation of our proposed CCEA method is presented. We demonstrate that the cognitive context knowledge can facilitate argumentation based object classification in multi-sensor networks, and further improve its classification performance. Thus various experiments were performed using a practical Space Object Classification dataset, i.e. SOC dataset, and seven benchmark datasets from the UCI Machine Learning Repository [29]. In general, two aspects of experiments were designed to evaluate the effectiveness of CCEA method. On one hand, the hierarchical categorization performance in argumentation based object classification can be improved by leveraging cognitive context knowledge; On the other hand, does our cognitive context knowledge enriched method exhibit robustness to noisy sensor data?

For the practical SOC dataset, it was collected from NORAD_Catalog (North American Aerospace Defense Command)[1] and UCS_Satellite database (Union of Concerned Scientists).[2] The NORAD_Catalog contains 8071 space object examples, with 9 attributes (*cospar_id*, *nord_id*, *period*, *perigee*, *apogee*, *eccentricity*, *rcs*, *size*, *amr*) and 3 categories (*Debris*, *RocketBody* and *Satellite*). UCS_Satellite database contains 1346 satellite object examples, with 17 attributes (*cospar_id, nord_id, period, perigee,*

[1]http://www.norad.mil

[2]https://www.ucsusa.org/nuclear-weapons/space-weapons/satellite-database

TABLE 4. Datasets used for our empirical evaluation.

No	Datasets	#examples	#nominal attributes	#categories	#category levels
D1	*Lymphography*	148	6	5	3
D2	*Soybean*	307	35	19	4
D3	*Car*	1728	6	4	3
D4	*Poker hand*	1025010	10	10	3
D5	*Audiology*	226	69	24	5
D6	*Nursery*	12960	8	5	4
D7	*Dermatology*	366	33	6	4
D8	SOC	9099	6	23	4

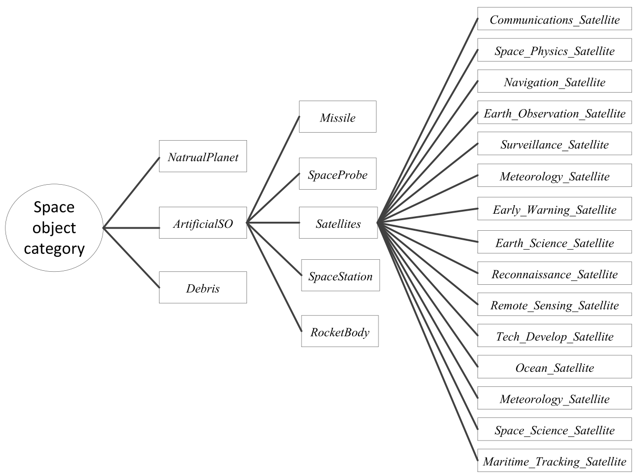

FIGURE 2. The illustration of multi-granular categories in SOC dataset.

apogee, eccentricity, orbit type, orbit class, longitude, power, dry mass, launch mass, launch vehicle, launch site, owner, contractor, users) and 15 categories (*Communications Satellite, Space Physics Satellite, Navigation Satellite, Earth Observation Satellite, Surveillance Satellite, Meteorology Satellite, Early Warning Satellite, Earth Science Satellite, Reconnaissance Satellite, Remote Sensing Satellite, Technology Development Satellite, Ocean Satellite, Meteorology Satellite, Space Science Satellite, Maritime Tracking Satellite*). For the purpose of our experiments, these two datasets were merged into the SOC dataset, through left join on the attribute *cospar_id*. Thus 9099 object examples are obtained in the SOC dataset. In general, three SATs were obtained, including *orbit type, payload* and*RadioWave*. Besides, the multi-granular categories of objects is illustrated in Figure 2.

The details of the chosen datasets for our experimental can be seen in TABLE 4. These datasets vary in their numbers of examples, nominal attributes, categories and category levels. Without loss of generality, the cognitive context knowledge, i.e. the semantic attribute-value and category hierarchies were obtained using the WordNet Ontology [21]. Thus all of these datasets are ready for learning by each sensor agent to perform argumentation based object classification tasks.

It is noted that all the experiment results presented in this section are estimated using Ten-fold Cross-Validation (TCV). That is to say, the given dataset was first partitioned into ten equal sized subsets, and then each subset was used for testing in turn, while the remaining nine subsets were used in the training phrase. Considering the CCEA method in this paper, let's assume each training dataset was randomly assigned to five sensor agents for generating classifying arguments. Then the argumentation based object classification tasks were executed on the remaining test datasets.

Briefly, our experimental platform has been implemented with Java Agent DEvelopment Framework (JADE)[3] and WEKA machine leaning workbench [30]. The experiments were conducted to compare the method of CCEA with Prism inductive learning algorithm, against two other argumentation based object classification methods, i.e. Arguing Prism [7] and Arguing SATE-Prism [9]. In what follows, we first present the evaluation of hierarchical categorization performance, and then investigate CCEA's tolerance to noisy sensor data.

A. HIERARCHICAL CATEGORIZATION PERFORMANCE

This subsection presents experiments conducted to compare the hierarchical categorization performance of CCEA, against Arguing Prism and Arguing SATE-Prism, using the datasets mentioned above. For each of the compared methods, three common hierarchical categorization metrics [11] were estimated. They are hierarchical precision (hP), hierarchical recall (hR) and hierarchical f-measure (hF). Supposing there are M object instances in the test dataset, then these hierarchical categorization metrics are defined as follows.

$$hP = \frac{\sum_{k=1}^{M} \left| \hat{P}_k \cap \hat{T}_k \right|}{\sum_{k=1}^{M} \left| \hat{P}_k \right|} \tag{3}$$

[3] http://jade.tilab.com/

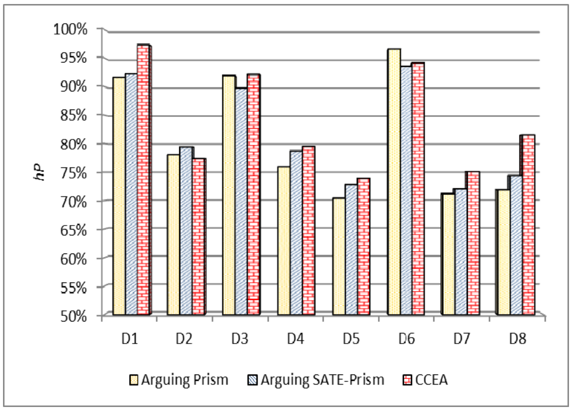

FIGURE 3. Hierarchical precision obtained using different methods.

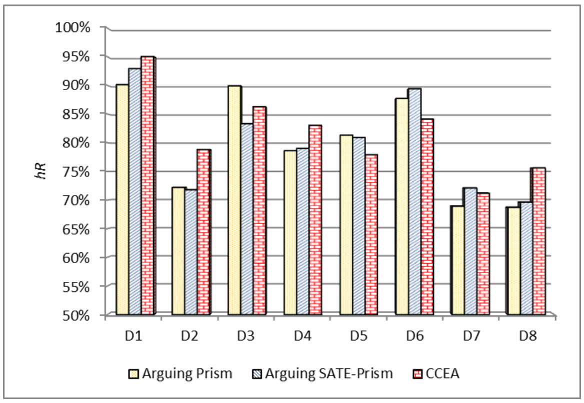

FIGURE 4. Hierarchical recall obtained using different methods.

$$hR = \frac{\sum_{k=1}^{M} \left|\hat{P}_k \cap \hat{T}_k\right|}{\sum_{k=1}^{M} \left|\hat{T}_k\right|} \tag{4}$$

$$hF = \frac{2 * hP * hR}{hP + hR} \tag{5}$$

where $\hat{P}_k$ is the set, consisting of the most specific categories predicted for the k th object instance, and all their ancestor categories; and $\hat{T}_k$ is the set, consisting of the true most specific categories for the k th object instance, and all their ancestor categories. In this circumstance, it is well known that hF is a synthesized indicator for the evaluation of hierarchical categorization performance.

The results of hierarchical categorization are described from Figure 3 to Figure 5, by comparing the operation of CCEA, according to hP, hR and hF, with respect to Arguing Prism and Arguing SATE-Prism. First, in Figure 3, it can be seen that, considering hP, CCEA produces the best results in 6 of 8 datasets tested, performing slightly worse than the other two methods only on two datasets (D2 and D6). Second, Figure 4 shows that, although CCEA performs worst on 2 datasets, it still obtain acceptable performance with 5 other test datasets. Finally, for the synthesized indicator hF, which is showed in Figure 5, it is noted that the proposed method in this paper performs best in all the 8 datasets compared

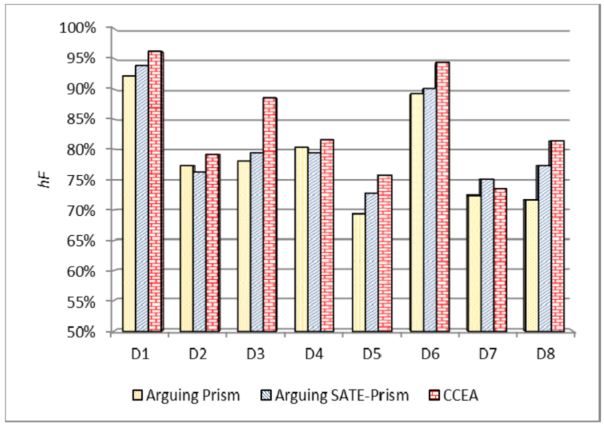

FIGURE 5. Hierarchical f-measure obtained using different methods.

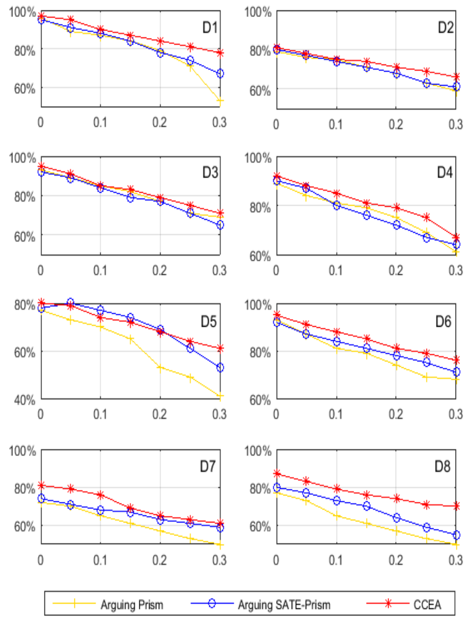

FIGURE 6. CCEA's classification accuracy with multiple noise rates.

to Arguing Prism and Arguing SATE-Prism. This is a strong evidence that indicating the superiority of CCEA.

B. NOISE TOLERANCE IN MULTI-SENSOR OBJECT CLASSIFICATION

To investigate CCEA's robustness to noise in argumentation based object classification, we explore to conduct experiments with noisy sensor data for learning. Here, seven version of the eight datasets used in the previous subsection were generated by introducing different noise rates. For example, if the noise rate is 0.15, then for each object example in a particular dataset, every category, is replaced by another value in its category taxonomy with a probability of 15%. For each noise rate (0.05, 0.1, 0.15, 0.2, 0.25, 0.3), the CCEA method, Arguing Prism and Arguing SATE-Prism were performed using the same setup to subsection A.

The experiment results are described in Figure 6, in which the horizontal axis represents the noise rate and the vertical one represents the object classification accuracy. It can easily be observed that, for all the three argumentation based object classification methods, the accuracy decreases with the increasing noise rate in the eight investigated datasets. However, it is noted that CCEA out-performs the other two methods with presence of noisy sensor data, in 7 out of 8 datasets. Considering the D5 dataset, on which the best performance is exhibited when the noise rate is more than 0.2. This robust object classification for noisy sensor data is due to the shared background knowledge advantages offered by the cognitive context enriched method in argumentation based object classification.

V. CONCLUSION

A cognitive context knowledge enriched method has been proposed for argumentation based object classification in multi-sensor networks. The method, namely CCEA, advances static domain-driven knowledge discovery via exploring cognitive context knowledge to generate classifying arguments dynamically. Thus the category granularity inconsistent problem of objects among different sensor agents can be addressed with rich contextual knowledge, not only consists in semantic attribute-value trees, but also in category taxonomies. The empirical study demonstrates that CCEA outperforms state-of-the-art methods, especially for noisy sensor data. The tolerance to noise in our method due to the transferred cognitive context knowledge among multiple sensor agents.

With respect to argumentation based object classification, our method offers the following advantages: (i) it allows sensor agents to give semantic explanations about object classification results collaboratively, with easy assimilated context knowledge in dialogue game process; (ii) it builds an effective disagreement resolution mechanism for multi-sensor object classification through dynamic cognitive context knowledge transfer.

In this paper, we focus on leveraging cognitive context knowledge for dealing with the category granularity inconsistent problem in argumentation based object classification. Future research will explore knowledge transfer among sensor agents further, to improve the multi-sensor object classification. We would like to harness the power of shared context knowledge for reaching semantic consensus. It is believed that this explainable artificial intelligence applications are very close to the thinking way of humans, who are good at classifying objects via understanding the context using rich cognitive knowledge.

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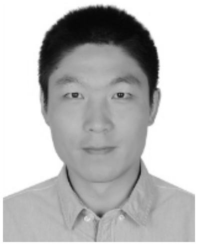

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