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Intelligent Ontology CBR System for Fault Diagnosis and Repair

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Abstract: Previous research in decision making has proposed the use of a case based reasoning approach to accumulate, organize, preserve, link and share diverse knowledge coming from past experiences. However, existing CBR systems lack semantic understanding, which is important for intelligent knowledge retrieval in decision support system. To develop an intelligent CBR system which can not only carry out data matching retrieval, but also perform semantic associated data access, and improve the traditional keyword-based search. .An effective case representation method as well as an appropriate case retrieval approach must be found. Ontology technology is an ideal selection for realizing our system because owing to the good semantic understanding offered by ontology. Thus, we adopt ontology approach as a means to acquire domain knowledge and construct a case-base and use ontological semantic retrieval as the case retrieval method. The resulting ontology based CBR tool is experimented in fault diagnosis and repairing domain, a semi-structured decision-making environment involving multiple attributes. The results showed the feasibility and the applicability of our approach, and the benefit of the ontology support.

Keywords: Decision Support System, Case Based Reasoning, Ontology, Owl, Diagnosis

1. Introduction

Several organizational decision problem solving situations are critical and recurring in nature. In this kind of activities, knowledge capitalization is of a considerable contribution during the problem solving; it would be easier for the decision maker to reuse the solution corresponding to a similar problem already solved than to solve it which would require a whole analysis of the problem. Therefore, mechanisms to capture the experiential knowledge of experts can be of significant value to the organization in general, and the decision makers in particular [1].

Previous research in decision making has proposed the use of a case based reasoning approach to accumulate, organize, preserve, link and share diverse knowledge coming from past experiences, and thus support such activities [2]. Moreover a shared meaning of the conflict resolution scheme that has worked in the past may get developed and used in the current situation [3]. The development of a shared repository that stores the knowledge of expert members and their experience invoked in prior solutions, retains the rules, policies and procedures of an organization and acquires relevant data and knowledge from the external environment using web technologies [4] can be useful for subsequent groups engaged in similar problem solving activities and will clearly assist them.

Case-based reasoning (CBR) often shows significant promise for improving the effectiveness of decision support. However, existing CBR systems lack semantic understanding, which is important for intelligent knowledge retrieval in decision support system [5]. While there has been substantial research in decision making and case-based reasoning systems, the explicit use of ontology based reasoning to support repetitive decision problem solving activities has received less attention. To develop a such effective system, two issues are critical: the first is how to find an effective method for case representation, which ensures domain knowledge can be acquired in an accurate easy manner, thus laying a good foundation for case retrieval; the next is how to find an appropriate method for case retrieval, which assures the right knowledge can be retrieved to solve a specific problem when a new task takes place.

The objective of this paper is to construct an intelligent CBR system with the support of semantics. The system can not only carry out data matching retrieval, but also perform semantic associated data access, and improve the traditional keyword-based search. In order to get it, an effective case representation method, as well as an appropriate case retrieval approach, must be found. So, among existing AI technology, ontology technology is an ideal selection for realizing our system because ontology has not only powerful ability of

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knowledge representation, but also good semantic understanding.

As a way to deal with these needs, we suggest that the integration of ontology within a CBR system is likely to provide additional information processing support. Ontology is used as a means to acquire domain knowledge and construct a case-base and use ontological semantic retrieval method as the case retrieval. Besides the case base, the system uses three ontologies: decision domain ontology, task ontology related to fault diagnosis of the given equipment, and domain ontology related to the industrial equipment. This system will allow a more efficient searching in the case base by exploiting the semantic relations which exist between the cases. The system uses the semantic relations (intra-ontology) existing between the concepts within each of the ontologies, as well as the relations (inter ontology) which existing between the concepts that belong to different ontologies. We experiment the resulting system in fault diagnosis and repair domain, a semi-structured decision-making environment involving multiple attributes. A case is executed to illustrate the use of the proposed CBR system.

The remaining part of the paper is organized as follows. First, we present a background consisting of case-based reasoning and ontology. Then, we outline the integration of ontology to CBR in literature. Next, we present our ontology approach to improve the CBR system. Finally, we present an example relating to fault diagnosis and repairing domain before concluding.

2. RELATED WORK

Knowledge management encompasses various practices of managing knowledge such as knowledge generation, capture, sharing, and application. Within these practices, effective sharing and use of knowledge depends – to a large extent – on the organization's ability to create and manage its knowledge. This knowledge can be described as the way organizations store it from the past to support present activities [6].

Knowledge management and Case-Based Reasoning (CBR) as an alternative reasoning paradigm and computational problem solving method are two intertwined topics that have increasingly attracted more and more attention and grown in importance for businesses and academics over the past few years. The main principle of CBR is: *similar problems have similar solutions.*

Case-based reasoning is a problem solving paradigm that in many respects is fundamentally different from other major AI approaches. Instead of relying solely on general knowledge of a problem domain, or making associations along generalized relationships between problem descriptors and conclusions, the case-based reasoning formalism was proposed as a way of storing human experiences and retrieving stored cases similar to the current item through a process of analogical search. It draws its knowledge from a reasonably large set of cases contained in the case library of past problems and by adapting their solutions solves new problems rather than only from a set of rules. Furthermore, case-based reasoning systems are claimed to "learn" through addition of further significant cases to the case-base and by forms of abstraction which may then be applied to this collection of cases [7].

Reasoning by re-using past cases is a powerful and frequently applied way to solve problems for humans. However, one of the drawbacks of CBR is the lack of flexibility of the knowledge representation. Indeed, the structure of the case is considered as constraining and strict which does not allow dealing with a carried out experiment in its semantic context, really limiting the performances of the system.

Among existing AI technology, ontology technology is an ideal selection for realizing this kind of system because ontology has not only powerful ability of knowledge representation, but also good semantic understanding. Ontologies provide a semantic based approach to explicitly represent information in a computable manner so that information can be automatically processed and integrated. Ontology also provides shared understanding of a domain to overcome differences in terminology from various sources [8].

The ontology-based model has its advantages in: (1) Facilitating knowledge sharing by providing a formal specification of the semantics for context information; (2) Supporting for logic reasoning, referring to the capability of inferring new context information based on the defined classes and properties; (3) Enabling knowledge reuse by use of existing and mature ontology libraries without starting from scratch; (4) Having the stronger ability for expressing complex context information. Several studies have given empirical evidence for the dominating role of ontologies integrated with specific, previously experienced situations (what we call cases) in human problem solving.

In [9] the authors present a method that uses semantic information to improve relevant case retrieval in case-based reasoning systems. The method overcomes conventional case-based reasoning (CBR) systems depending on word knowledge to index and search cases from its memory.

For sharing knowledge of different systems, domain ontology is considered as the basis of knowledge structure and the concrete case knowledge. This strategy is represented as the instance of relevant concept of domain ontology, through which knowledge of different systems is shared, knowledge management becomes more flexible and simple, and case retrieval becomes more precise and reasonable [10].

Park and his colleagues [11] propose an ontology-based fuzzy CBR support system for ship's collision avoidance to prevent the cumbersome tasks of creating a new solution each time a new situation is encountered. The first level of the ontology-based CBR identifies the dangerous ships and indexes the new case. The second level retrieves cases from the ontology and adapts the solution to solve the new situation for the output. The CBR's accuracy depends on the efficient retrieval of possible solutions, and the proposed algorithm improves the effectiveness of solving the similarity to a new case.

A proposal presented in [5] aimed at knowledge reuse, during the decision activities by means of interwoven concepts from the knowledge management, CBR and ontologies research.

In [12] the constructed decision support CBR prototype system of marketing strategy contains more than 600 cases. The evaluation shows that with the support of semantics, they can not only carry out data matching retrieval, but also perform semantic associated data access.

Kobti and Chen construct domain ontology of mold design and propose an ontology-based search model with semantic distance measures to improve the traditional keyword-based search for the mold design domain. The ontological search is compared against traditional keyword-based search in the mold design domain and shows more fault tolerance and flexibility in maximizing the accuracy and number of detected matches [13].

In [14], the authors proposed an approach based on the integration of three techniques: a CBR-personalized retrieval mechanism designed to provide a user with an optimum itinerary that meets his personal needs and preferences; a semantic web rule language considered to provide the system with enhanced semantic capabilities and support personalized case representation; and a user-oriented ontology used as source of knowledge to extract pertinent information about stakeholder's preferences and needs.

To facilitate decision making within collaborative design, a Decision Support Ontology (DSO) is developed in [15]. The structure of the information model developed reflects a priori knowledge of decision making and supports the communication of information independent of any specific decision method.

A case-based reasoning (CBR) system for the Semantic Web called Tuuurbine is presented in [16]. Tuuurbine is built as a generic CBR system able to reason on knowledge stored in RDF format. It uses Semantic Web technologies like RDF/RDFS, RDF stores, SPARQL, and optionally Semantic Wikis. Tuuurbine implements a generic case-based inference mechanism in which adaptation consists in retrieving similar cases and in replacing some features of these cases in order to obtain one or more solutions for a given query.

In [17] the authors propose a knowledge base for the Process Equipment Failures (PEFs) through semantic feature, embedded in the ontological approach and to construct a base frame for its further applications in the PEFs and process equipment related incident investigations and other knowledge extraction processes.

A knowledge-based approach to support decision making in human resource management is proposed in [18]. The appropriate support of decision making is implemented using case-based reasoning and ontology. The problems of knowledge and case representation are considered, as well as the algorithm of case retrieval.

Overall research consists in searching the solution of a problem similar to the target one. Ontology is used to bring semantics to the attributes describing the target problem, and upon which the retrieving step can be realized in the case base. The goal of retrieving step is to retrieve the closest source case in the case base given the semantic enrichment of the attributes of target problem thanks to ontology.

Many research efforts for decision modelling and support have been systematically applied to the field of ontologies. However, there is no complete method that would define how to model decisions in ontologies, and a few isolated cases in which an established decision making method was used in ontology for a specific domain, and often the reasoning procedure is based only on domain ontology.

In our approach, we consider particularly the case where the reasoning process is enriched by exploring ontology. Thereby the purpose is to retrieve and provide a set of possible solutions relating to source case showing the semantic relations between them. Afterwards, it is the duty of the decision-maker, according to his/her expertise, to opt for the decision which will seem to him appropriate to the target problem. An important goal of our work was to structure decision model in such a way that the problem solution can be obtained by reasoning upon three ontologies (domain, task, and decision). The ontologies with reasoning support can be used in the function of a case base reasoning system.

3. The Ontology-Based CBR System

The frame of our work is to integrate a knowledge capitalization tool in a Group Decision Support System (GDSS) that will be exploited by the actors (facilitator and/or decision makers) for the purpose of decision support [19][20]. We are in the context where typically incidents are not entirely identical to each other (some symptoms are not observed) but the knowledge of past incidents enables decision makers to recognize a similar situation and tailor their strategies by taking a course of action that experience has shown is effective and successful. This can happen when there is failure at some sensors so that lights or alarms cannot be triggered. The search in the database of cases can then be disoriented.

A CBR problem-solving approach is used to solve a new problem (target case) by remembering a previous similar situation (source case) and by reusing information and knowledge of that situation. The effectiveness of this approach is further improved by the application of ontologies as a mechanism for reasoning about the domain concepts and dealing with the inconsistencies that can arise in the applied vocabulary when multiple decision makers are involved.

The proposed system will assist the actors involved in a group decision making session by offering them a set of decisions for the new problem and it is for the actor to situate each solution in its semantic context and then choose a particular solution based on his expertise. The initial problem is decomposed into sub-problems where solving each of which will be more powerful than solving the entire problem [21].

The benefits of using the system is to provide a more convenient retrieving process in information retrieval system in order to reach conclusions and give recommendations based on knowledge from previous cases (experiences) and ontologies.

A. *The Case Base*

Case representation is essential in the realization of a CBR system since on this presentation depends the effectiveness and the fastness of the system case retrieving mechanism. It is therefore necessary to well identify information to be stored in each case and to choose the more efficient representation scheme of this information. We consider a case as being formed by two parts: problem and solution. Each of both parts is represented by a set of simple or complex descriptors among which some are defined in a dedicated ontology:

- Problem part: the task to be solved, the problem causes and its symptoms;
- Solution part: the solution, the problem solving method used and, the object concerned by recommended solution

Knowledge considered in our CBR system is represented by cases and ontologies. The case base is composed of all the structured cases which will be explored during retrieving step (recall stage). Every case consists of a breakdown problem already experienced and solved. Figure 1 shows the UML classes diagram relating to the modelling of the case base. The descriptors are entries to the ontologies (e.g. Id-Task, Id-Symp and Id-Cause are entries for the task ontology; the descriptors Id-Object is an entry for the domain ontology, and the descriptor Id-Solution-Id is an entry for the application ontology).

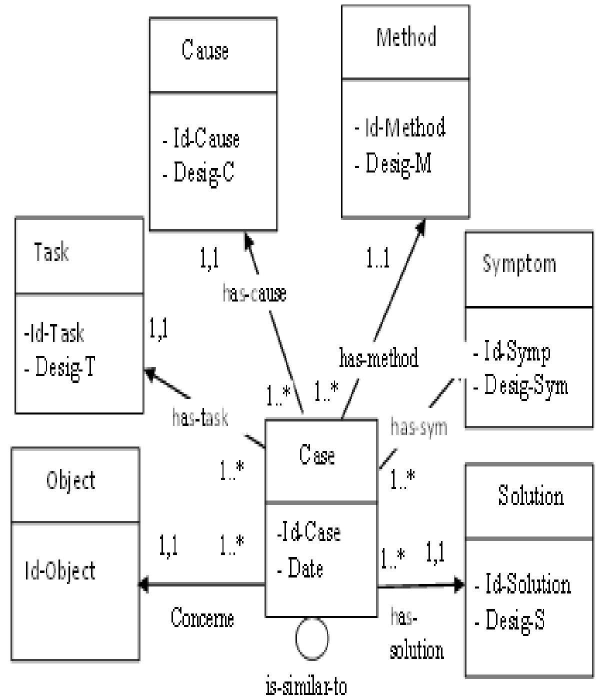

Figure 1. UML Class Diagram of the Case Base

B. *Ontologies Modelling*

*1) Ontologies Conceptualization:*We used the METHODOLOGY [22] to build the ontologies. The ontologies are created based on documentation resources as all the potential decisions that might be made by the decision makers are listed in an appropriate documentation. Similarly, the description of the equipment to be maintained is get from specific documentation while the specification of the task ontology is built with the support of an expert in industrial maintenance.

The proposed approach to improve cases retrieval is based on the three ontologies. Figures 2, 3 and 4 present respectively UML classes diagrams of Application Ontology, Domain ontology and task ontology.

a) Domain ontology: It consists of the vocabulary used in expressing decisions in terms of equipment components. The ontology constitutes a specification of the concepts relating to the equipment to maintain as well as the relations between these concepts. The latter are principally aggregation and composition relations between the equipment components.

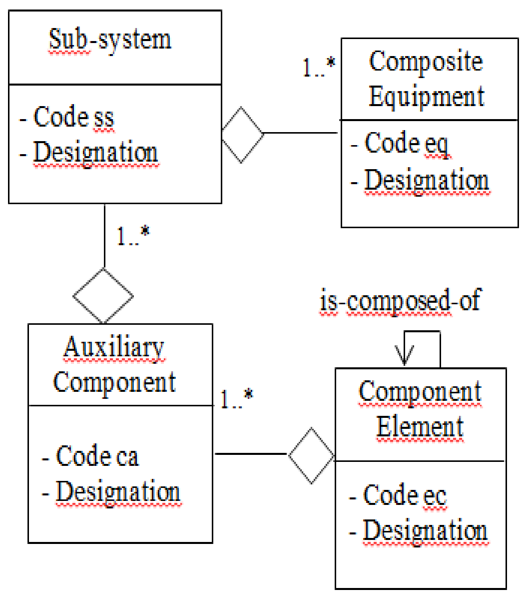

Figure 2. Conceptual model of the domain ontology

b) Application ontology: represents the domain of decisions in terms of concepts which are decisions, equivalent decisions, main decisions, as well as objects related to the decisions and, semantic relations between decisions in relation to considered application:

- "Contradiction Link" relation: it links a main decision with all the main decisions which are incompatible to it within the breakdowns diagnosis application context;
- "Generalization Link" relation: it specifies the relation of subsuming between main decisions. This relation is transitive;
- "Is Synonymous of" relation: it links an equivalent decision to a corresponding main decision.

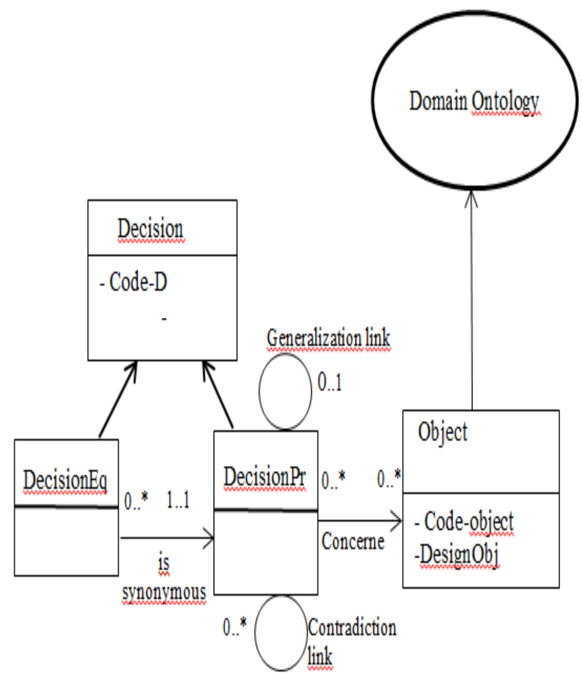

Figure 3. Conceptual model of the application ontology

c) Task ontology: this ontology described all the faulty diagnosis problems related to the machine (equipment) in terms of task, symptom, cause and solution concepts, and the relations between them.

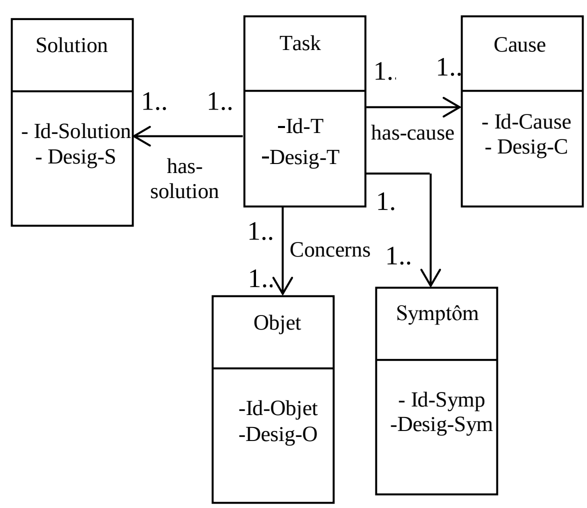

Figure 4. Conceptual model of the task ontology

*2) Ontologies Formalization:*The ontologies are created using Protégé before their generation in OWL format. Figure 5 illustrates a partial view of the decision ontology.

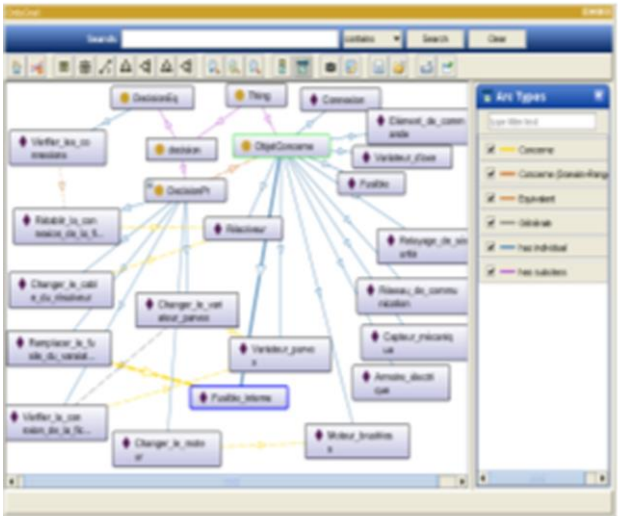

Figure 5. Partial view of the decision ontology

3) Ontologies Operationalization: An operationalized ontology is expressed in an operational language and endowed with operational semantics. In this sense the ontology operationalization consists of a computer specification of all the operations made on concepts in an operational language. The use of an operational ontology assumes its representation in an operational but also formal language, i.e. providing reasoning mechanisms appropriate to the targeted knowledge manipulations. To do this, we used the NetBeans developing environment associated to Java language [23].

Furthermore, we used the Jena framework [24] to manage the ontology. Jena provides a programming environment for RDF, RDFS [25] and OWL [26] as well as a query engine allowing SPARQL queries execution (Simple Protocol And RDF Query Language) [27] which is a RDF query language.

OWL language [26] is used to represent the case base. This would allow managing the case base as a knowledge base upon which inferences may be made. It is possible to define semantic relations between cases as for instance the transitive relation "is-similar-to" which relates the source cases already identified as being similar. Furthermore, as the remained knowledge (i.e. the ontologies) is also expressed in OWL, this would allow having to some extent compatibility between languages formalizing the different knowledge manipulated by the system, as well as, the knowledge operating tools such as SPARQL.

Example of case T3 in the case base:

<owl:NamedIndividual
rdf:about="http://www.basedecas.org/ontologycases# 3">
<rdf:type rdf:resource="http://www.basedecas.org/ontologycases#Cases"/>
<has-as-task rdf:resource="http://www.basedecas.org/ontologycases#T3"/>
<has-as-cause rdf:resource="http://www.basedecas.org/ontologycases# Failure to turn up the variator"/>
<has-as-method
rdf:resource="http://www.basedecas.org/ontologycases# M1"/>
<concerns
rdf:resource="http://www.basedecas.org/ontologycases# Internal fuse"/>
<has-as-solution
rdf:resource="http://www.basedecas.org/ontologycases#change internal fuse"/>
<possesses
rdf:resource="http://www.basedecas.org/ontologycases#display variator off"/>
<possesses
rdf:resource="http://www.basedecas.org/ontologycases# Failure to turn up the variator, the machine is shut down"/>
<is-similar-
tordf:resource="http://www.basedecas.org/ontologycases #15"/>
</owl:NamedIndividual>

4. THE ONTOLOGY-BASED CBR PROCESS

The proposed case based system should reflect human knowledge by storing data about previous significant events as “cases” within a computerized system. In this regard, the system uses the case base to retrieve similar cases to the problem to be solved. But, when the retrieving process fails or the cases retrieved are not satisfactory for the decision maker, the system uses ontologies. It makes use semantic relations between concepts within the same ontology or entries from an ontology to another to derive other solutions to the problem. By making use of the decision ontology, the system derives more specific or more general decisions to that or those made by the retrieving process. It can also set the solution relating to the equipment by visualizing the concerned component. Then, it uses the equipment ontology to set the involved component relating to the neighboring ones or to the component in which it’s comprised. Similarly other case descriptors may be used as entries to ontologies to enlarge or reduce solution space. When a solution is retained, then tested and validated, it is stored in the case base as a new case (with all its descriptors).

The reasoning process consists of the following steps (Figure 5):

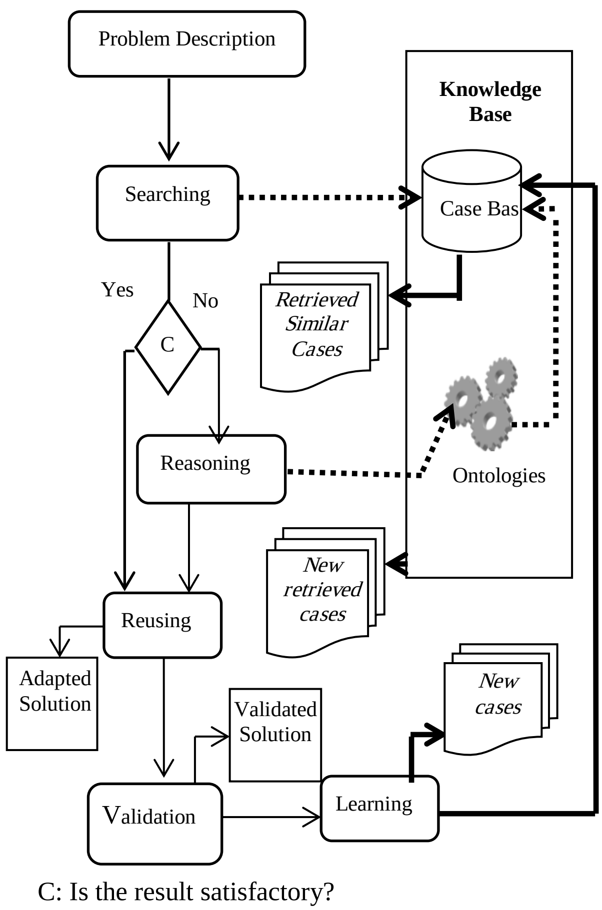

Figure 5. Ontology-based CBR Process

- Problem description: the participant describes the problem to be solved. This description can be made of different ways: by providing the task to be solved, the observed symptoms, or the faulty object, etc.
- Retrieving: it consists to search in the case base and retrieve similar cases to the problem to be solved. Here, we consider the usual local and global similarities measures to retrieve similar cases to the targeted problem.
- Reasoning: this step consists of the use of ontologies to enlarge or to reduce the solution search space. According to the object of widening, one of the three ontologies is used. For example when the object of widening is a task or a symptom, the task ontology is used; when the object of widening is a faulty component, the equipment ontology is used, but when the object of enlargement is the problem solution then the decision ontology is used.
- Validation: once the decision is made, executed and validated the process will skip to the next step.
- Learning: the new case is added to the case base. It referees to all the similar source cases if exist.

The reasoning step is useful as it allows revealing semantic knowledge from ontologies between the different parameters of the problem to be solved. Given a problem to be solved, this would allow:

- Converging to the semantically close case in the case base, or
- Retrieving first a structurally close case from the case base then, according to the case descriptors, exploiting ontologies in order to derive other possible solutions to the problem. The participant will choose among the suggested solutions that he considers being the most appropriate one to the problem.

5. ILLUSTRATIVE EXAMPLE

To illustrate the feasibility and the applicability of our approach, we consider the following case base describing the faults (Table 1) with their related symptoms (Table 2):

Let's consider the following description of the problem: "failure of the variator", the observed symptoms are: (Symp1, Symp8) where Symp1 is "Impossible to turn up the capacity" and Symp8 is "No information displayed". We try to retrieve the similar cases to the targeted problem. According to our example, the case related to T3 is the most similar.

TABLE I. THE CASE BASE

IdT	Task	Cause	Method	Object	Solution
1	T1	Resolver failure	M3	Resolver cable	Check resolver variator
2	T2	C2	M2	O1	S2
3	T3	Failure to run up variator	M1	Internal fuse	Change internal fuse
4	T4	Variator internal failure	M4	Variator	Change variator

TABLE II. THE LIST OF RELATED SYMPTOMS

IdT	Symptoms
1	Symp 3
1	Symp 1
2	Symp 1
2	Symp 2
3	Symp 18 (no variator dispaly)
3	Symp 1(Failure to turn up the variator, the machine is shut down)
3	Symp20 (Electric failing, variator supply failure)
4	Symp 1 (Failure to turn up the variator, the machine is shut down)
4	Symp 20 (Electric failing, variator supply failure)
4	Symp 21(READY absence (E1 supply)) (symptom displayed on the computer screen)

The similar problem retrieved from the case base is presented to the decision maker. The latter may want to widen the search space. The search widening consists then to retrieve another solution more general to the retrieved solution. An example of search widening is to consider the retrieved solution and then, using the decision ontology, search decisions more general to the retrieved solution. Considering the decision ontology, the retrieved solutions are S4: Change the internal fusible (Decision), S1: Change the variator (More general decision). When searching in the case base, we obtain the case (T4) and symptoms (Symp 1, Symp 20, Symp 21) related to the solution 1. This result corresponds to a new retrieved source case obtained after the search widening using the semantic relation « more general decision » defined between the decisions in the decision ontology. The role of the decision maker is to choose one of the delivered options.

6. CONCLUSION

In this paper, we proposed to integrate ontology in case based reasoning system. The used CBR approach to search in a case base of faulty diagnosis problems already solved a similar case to the problem to be solved. In this context, we considered that the latter may be not fully defined. The purpose in that case is not to retrieve one case similar to the target problem, but rather to provide the decision-maker (or the facilitator) a set of source cases with their solutions and it is the duty of the decision-maker (or the facilitator), based on his expertise, to opt for a solution to the target problem. To develop this tool, we used jointly a case base and three ontologies representing each an aspect of the domain knowledge of faulty diagnosis problem.

We believe that our approach is useful in several aspects. First, it enables to formalize the case base in OWL what allows managing it as a knowledge base. Indeed, by exploiting the semantic relations within the case base such as "is-similar-to", it is possible to derive new knowledge from those stored. Also, as a result of memorizing a source case base on its descriptors, the ontologies exploration will allow deriving new knowledge which will serve for a new research cycle in case base. The final result is the presentation of a set of source cases which solutions are presented in semantic context evidence the relations between them. Other semantic relations are also evidence those existing between objects involved in the provided solutions.

In future, we aim to develop a holistic decision making tool (diagnosis and repair) that helps the stakeholders to diagnose and repair remotely breakdowns in networked distributed plants using embedded diagnosis system [28].

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