Experience based configuration

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Abstract

This paper aims at presenting a way to integrate Case Based Reasoning and Constraint Satisfaction techniques in order to guide a configuration process according to past experiments. We suggest a methodology in three steps: first find relevant cases in the past experiments case base, then determine a relevant domain to adapt the selected solution to the new problem, and at last use constraint propagation in order to guide the adaptation. We illustrate our proposal on an example in the field of machining operation configuration.

Keywords: Case Based Reasoning, Adaptation Guided Retrieval, fuzzy similarity

1. Introduction

In the field of configuration [Browne, 1996], in order to deal with the problem complexity, much research work is based on various constraint models and propagation techniques. However, these methods are generally blind and do not enable to take into account the results of past experiences in order to guide the search of a relevant solution. Nevertheless, in many configuration problems, such as machining operation configuration, it may be very useful to reuse and adapt the solutions to previous similar solved problems in order to accelerate and to improve the configuration process.

In such cases, the Case Based Reasoning (CBR) approaches offer several means to help to find solutions to previously solved similar problems. However, since the problem to solve is often not exactly the same as the one already solved, an adaptation of the solution is often mandatory.

The basic idea developed in this paper, illustrated in figure 1, is that the CBR technique can be used to find relevant cases and that the adaptation should be carried out in a neighborhood of the found solution by using constraint propagation techniques in order to support the adaptation.

Therefore, the configuration process can be divided in three main steps:

1. Find similar situations in the case base by using the similarity measure and search algorithm proposed in [Geneste & al., 2000] ,

2. Determine the adaptation domain as a neighborhood of a selected case

3. Use constraint satisfaction techniques to guide the adaptation process

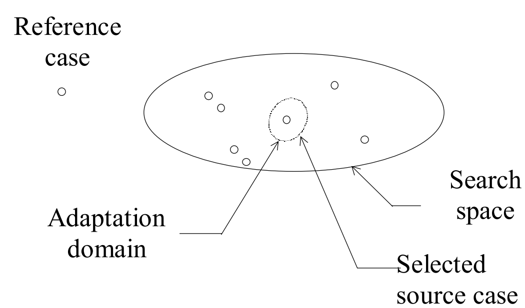

Figure 1: Adaptation domain

We proposed in [Perpen, 1999] a way to model technical knowledge in an enhanced object oriented formalism integrating the concept of constraint defined as a generalization of the notion of association in which the linked attributes are not compulsorily primary keys of the linked classes. The schema of the knowledge base is described with a class diagram whereas the knowledge base in an instanciation of the class diagram.

The problem of the search of a relevant similar case in such knowledge base has been addressed in [Geneste & al., 2000] thanks to the use of a recursive similarity measure.

The main elements of this search step are given in section 2 of this paper. Section 3 aims at presenting the problem of the characterization of the adaptation domains. The fourth section briefly describes the adaptation of the solution thanks to constraint satisfaction techniques. Then, in a last section an example of configuration is given in the field of machining operation configuration in order to illustrate the proposed configuration process.

2. Search of a similar case

The basic search algorithm is recursive and propagates inside the object structure. The user can weight the attributes in order to describe their respective contribution to the global similarity. The result of the search is a possibility and a necessity degrees that represent to which extent a case stored in the object structure is close to the reference case. The object structure is used:

- first at the class level in order to achieve a quick filtering of the candidate classes,
- then at the object level in order to make a more precise selection among objects of the selected classes.

In the literature, most CBR systems use indexing techniques in order to quickly filter the cases in the case base. The indexing strategies are numerous and often complex to implement [Kolodner, 1993], [Aamodt and Plaza, 1994]. They are based on the use of an index that must be correctly defined in order to find all the cases potentially similar to the reference case. The filtering mechanism that we propose does not use such a indexing strategy but relies on the class structure of the experience base. The filtering is achieved by comparing the characteristics of the class of the reference object (labeled O) with the characteristics of each class of the experience base class model (labeled O'). According to the similarity between classes O and O', we may decide or not to explore the objects of the class O' (by giving an acceptation threshold for instance). This filtering step aims at determining the more promising classes for case search. When the whole set of candidate classes is selected we can launch the search of cases similar to the reference case among the objects that are instances of these candidate classes, commonly called source cases. There exists a large number of similarity measures that are often very specific to the context of application. The similarity measure that we propose takes into account the object oriented structure of the knowledge base and enables the use of possibility distributions in order to represent the imprecise and/or uncertain characteristics of the cases. We distinguish the local similarity defined at the attribute level (i.e. on a single domain) and the global similarity defined at the object level (i.e. on a cartesian product of domains)

The local similarity is computed thanks to a similarity membership function μ_L that enables the user to associate to an attribute a specific similarity measure. In particular we have μ_L (x,y)=1 if x is completely similar to y, μ_L (x,y)=0 if x is totally different to y, and $0<\mu_L$ (x,y)<1 for intermediate similarities.

Notations:

- R denotes the reference case and S the source case
- $att_{R,L}$ the name of attribute L of case R
- $val_{R,L}$ the value of attribute L of case R
- D_L the domain of attribute L and U = DL x DL
- w_L the weight associated to attribute L for the search
- μ_L the membership function describing the local similarity for attribute L
- π_R the possibility distribution describing the reference case
- π_S the possibility distribution describing the source case
- π_D the possibility distribution defined by $$\pi_D(x, y) = \min(\pi_R(x), \pi_S(y)) .$$

At the level of each attribute L, the possibility and necessity degrees corresponding to a local similarity are computed as follows:

$$\Pi_L\left(val_{R,L}, val_{S,L}\right) = \sup_{u\in U} \min(\mu_L(u), \pi_D(u))$$

$$\mathrm{N}_L(val_{R,L}, val_{S,L}) = \inf_{u\in U} \max(\mu_L(u), 1-\pi_D(u))$$

After the evaluation of each local similarity at the level of the object attribute, the evaluation of the global similarity is then achieved, taking into account the weights associated to each characteristic of the reference object and by computing the min of the max of the obtained similarities. Therefore, the possibility and necessity degrees at the object level are:

$$\Pi(R, S) = \min_{i=1,n} \max(1-w_i, s_i)$$
$$\mathrm{N}(R, S) = \min_{i=1,n} \max(1-w_i, s'_i)$$

with :

$$s_i = \begin{cases} \Pi_L(val_{R,i}, val_{S,j}) & if \quad \exists j \in \{1,\dots,n\} att_{R,i} = att_{S,j} \\ 0 & else \end{cases}$$
$$s'_i = \begin{cases} \mathrm{N}_L(val_{R,i}, val_{S,j}) & if \quad \exists j \in \{1,\dots,n\} att_{R,i} = att_{S,j} \\ 0 & else \end{cases}$$

3. Determination of the adaptation domain

When several source cases are found as similar to the reference case, one of them must be selected and adapted to provide a solution to the reference problem. Our idea is, at this level, to enable an adaptation in the neighborhood of the selected case and therefore we need first to define such a neighborhood. The use of the similarity membership function is a convenient support to do so. Let us note $val_{S,L}$ the found value of the attribute L of the source case S. In order to find a neighborhood of $val_{S,L}$ we can look for a domain that includes values similar to $val_{S,L}$ at a given level. If $val_{S,L}$ is a crisp number, the α-cut of the membership function $\mu_L(x, val_{S,L})$ can represent such a domain as illustrated in figures 2, where is shown the intersection between $\pi_D(x, val_{S,L})$ and $\mu_L(x, y)$, and 3 where the α-cut of the resulting membership function is estimated leading to an interval domain $[\inf \alpha, \sup \alpha]$.

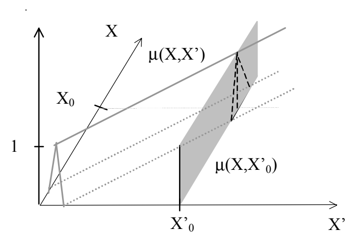

Figure 2: Intersection between $\pi_D(x, val_{S,L})$ and $\mu_L(x, y)$

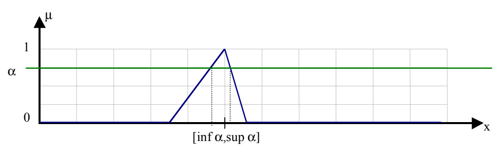

Figure 3: α-cut of the resulting membership function

More generally, if $val_{S,L}$ is described by a possibility distribution, the intersection between $\pi_D(x, y)$ and $\mu_L(x, y)$ is a volume, as shown in figure 4, volume that we project on the x-axis (figure 5). On this projection, we determine the a-cut which represents the adaptation domain.

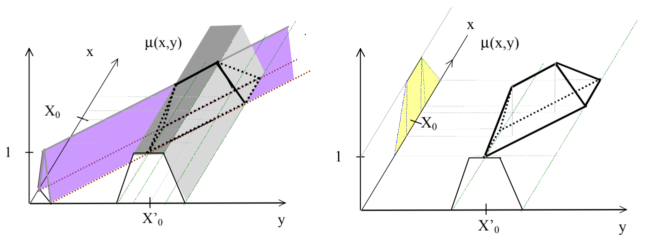

Figure 4: Intersection between $\pi_D(x, y)$ and $\mu_L(x, y)$

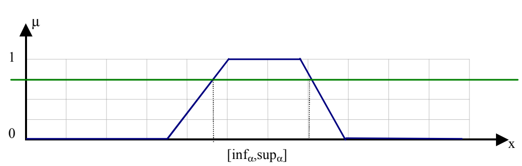

Figure 5: α-cut of the resulting membership function

When the adaptation domains are determined for each attribute it is possible to find the adaptation domain of an object as the cartesian product of these attribute domains.

We can observe that the ability of a case to be adapted may be an important criterion for the selection of the case to adapt, as suggested in [Smyth & Keane, 1995] or [Purvis & Pu, 1996] with the notion of AGR (Adaptation Guided Retrieval). We therefore defined an adaptability measure of a case as the specificity [Dubois & al., 1999] of the fuzzy set resulting of the projection on the X axis of the intersection volume between $\pi_D(x, val_{S,L})$ and $\mu_L(x, val_{S,L})$.

Figure 6 illustrates various adaptability values for an attribute. The adaptability is a value between 0 and 1. When the adaptability of each attribute of an object is evaluated, it is possible to determine the adaptability of an object as the aggregation of its attribute adaptability thanks to an operator such as min or *.

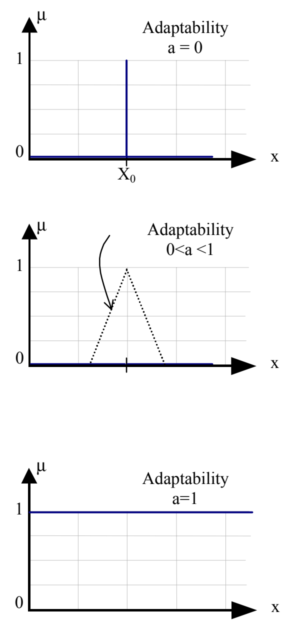

Figure 6: Examples of adaptability values

4. Constraint propagation on adaptation domain

When the adaptation domain is determined by the method proposed in section 3, the adaptation process can begin. In order to limit the choices of the user, we propose to achieve this adaptation along with a propagation of the constraints of the domain explicited in the knowledge model. The various domains of the constraints (discrete/continuous/both), the arity of the constraints (binary, n-ary), and the dynamic of the constraint application enables to select between several propagation techniques such as [Bessière, 1991], [Dechter, 1996], [Gelle, 1998], [Sam, 1995] as suggested in [Monteiro et al, 1999].

5. Example

In order to illustrate the proposed mechanism, let us consider the following example, in the field of machining operation configuration.

In this example, a machining operation is represented according to the class diagram of figure 7.

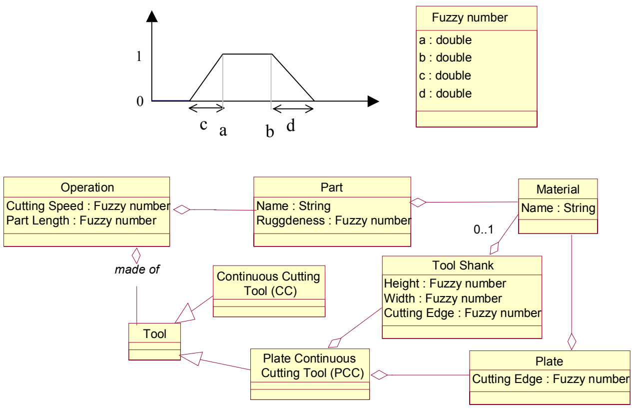

Figure 7: Schema of the knowledge base

An instance of such a class diagram is described in figure 8, in which we can see 3 different operations recorded in the knowledge base.

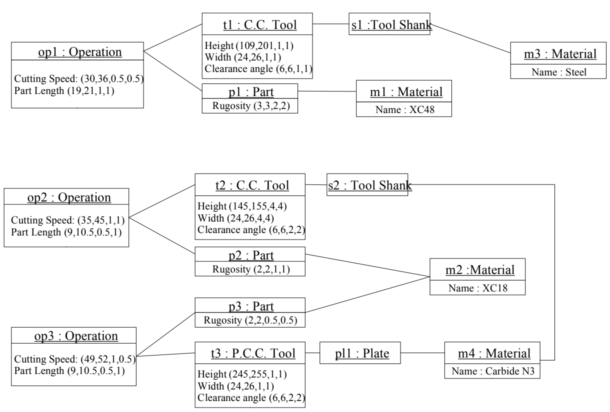

Figure 8 : Knowledge base

The problem to solve is to find a configuration for the operation OpX described in Figure 9.

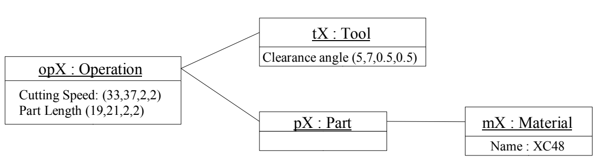

Figure 9 : Operation to configure

Three different kinds of similarity measures are used in this example :

- similarity "close to" defined by

$$\mu\ (x, y) = 1 - \frac{|x - y|}{\Delta} \text{ if } 0 \le |x - y| \le \Delta$$
$$\mu\ (x, y) = 0 \text{ else}$$

- similarity "true/false" defined by

$$\mu\ (x, y) = 1 \text{ if } x = y$$
$$\mu\ (x, y) = 0 \text{ else}$$

- "ad hoc" similarity for instance for the comparison of material defined as follows :

μ	XC18	XC25	XC38	XC48	XC60
XC48	0.7	0.8	0.9	1	0.3

The results of the similarity and adaptability of each operation of the knowledge base is given in the following table :

	Op1	Op2	Op3
Similarity with OpX	Π=1 N=0.25	Π=0.5 N=0.25	Π=0.25 N=0.25
Adaptability	0	0.386	0.385

We can observe that from a similarity point of view, operation Op1 is the best but that this operation can not be adapted to configure operation OpX (since its adaptability is equal to 0). However, operation Op2 is less similar to operation OpX than operation Op1 but is more adaptable and therefore is an interesting target for our configuration process. Operation Op3 is equally adaptable but is less similar and should therefore not be privileged.

When operation Op2 is chosen, we determine the adaptation domains for the operation at level α = 0.5. The values for the example are given for each attribute on figure 10.

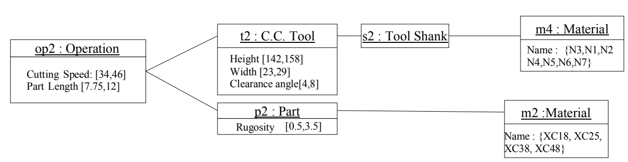

Figure 10: Adaptation domains

6. Conclusion

We proposed in this article a way to achieve the configuration of an item according to past experiences. This approach mixes classical configuration techniques with case based reasoning in order to support the configuration process. The use of a membership function for the similarity enables both to describe precisely the semantics of the similarity and to determine the adaptation domain in the neighborhood of the selected case. We also pointed out the interest of taking into account not only the similarity but also the adaptability of the source case for the selection.

The results of this first attempt to combine CBR and CSP is very promising and we expect to implement the whole approach in a knowledge management tool.

7. References

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