Categorizing Approaches Combining Rule-Based and Case-Based Reasoning

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Abstract. Rule-based and case-based reasoning are two popular approaches used in intelligent systems. Rules usually represent general knowledge, whereas cases encompass knowledge accumulated from specific (specialized) situations. Each approach has advantages and disadvantages, which are proved to be complementary in a large degree. So, it is well-justified to combine rules and cases to produce effective hybrid approaches, surpassing the disadvantages of each component method. In this paper, we first present advantages and disadvantages of rule-based and case-based reasoning and show that they are complementary. We then discuss the deficiencies of existing categorization schemes for integrations of rule-based and case-based representations. To deal with those deficiencies, we introduce a new categorization scheme. Finally, we briefly present representative approaches for the final categories of our scheme.

Keywords: hybrid intelligent systems, intelligent integrated systems, combination of rule-based and case-based reasoning, rule-based reasoning, case-based reasoning.

1. Introduction

The combination of (two or more) different problem solving and knowledge representation methods is a very active research area in Artificial Intelligence (Medsker 1995; Nauck, Klawonn and Kruse 1997; McGarry, Wermter and MacIntyre 1999; d'Avila Garcez, Broda and Gabbay 2002). The aim is to create combined formalisms that benefit from each of their components. It is generally believed that complex problems are easier to solve with hybrid or integrated[1] approaches. The effectiveness of various hybrid or integrated approaches has been demonstrated in a number of application areas.

One of the popular types of combination involves the combination of rule-based reasoning (RBR) and case-based reasoning (CBR). The efforts to combine symbolic rules and cases have yielded advanced knowledge representation formalisms. The effectiveness

[1] We use the terms 'hybrid', 'integrated' and 'combined' as more or less synonymous in this paper.

of those approaches stems from the fact that rules and cases are complementary in representing application domains and solving problems. Rules represent general knowledge of the domain, whereas cases specific knowledge. Rule-based systems solve problems from scratch, while case-based systems use pre-stored situations to deal with similar new instances. Therefore, the combination of both approaches turns out to be natural and useful. The complementarities of the advantages and disadvantages of the two intelligent methods intensify the usefulness of their combination.

To the authors' best knowledge, a categorization scheme and a survey of such hybrid or integrated approaches that take into account the most recent advances are missing. The usefulness of (or the need for) a good categorization scheme is three-fold. First, it gives a more formal and structured description of the types of approaches/systems involved in a field, in our case in that of RBR-CBR integrations. This increases the understanding of the field and the ways RBR and CBR are integrated. Second, it may lead to the discovery of new ways of integration of RBR and CBR. Third, it is a useful guide to developers/designers of such systems.

A serious early effort for a categorization scheme is presented in (Golding and Rosenbloom 1996), but it is unable to accommodate recent developments. A more recent work (Marling et al. 2002) presents a survey of combinations of various AI methods (such as rule-based reasoning, constraint satisfaction problem solving and model-based reasoning) with case-based reasoning. Thus, it does not focus on combinations of RBR and CBR. It presents, alongside other things, a very general categorization of systems integrating RBR and CBR, which however does not cover all aspects of such combinations. On the other hand, a categorization scheme concerning any combined approaches in general, like that of Medsker (Medsker 1995), is not adequate, due to its generality.

In this paper, we present a (new) categorization scheme for approaches integrating RBR with CBR. This new scheme effectively remedies the deficiencies of existing categorization schemes. We also present representative systems in some detail.

The paper is organized as follows. Section 2 briefly describes the main characteristics of symbolic rules focusing on their advantages and disadvantages. Section 3 does the same for case-based reasoning. Section 4 demonstrates the complementarity of RBR and CBR, as far as their advantages and disadvantages are concerned, and presents application areas of the integrated approaches. Section 5 deals with existing categorization schemes for approaches/systems integrating RBR and CBR and discusses their problems. Section 6 introduces our categorization scheme. Finally, section 7 concludes the paper.

2. Rule-Based Reasoning

Symbolic rules are one of the most popular knowledge representation and reasoning methods (Ligeza 2006). Their popularity stems mainly from their naturalness, which facilitates comprehension of the represented knowledge. The basic form of a rule is the following:

if <conditions>
then <conclusion>

where <conditions> represents the conditions of a rule, whereas <conclusion> represents its conclusion. The conditions of a rule are connected between each other with logical connectives such as, AND, OR, NOT, etc, thus forming a logical function. When sufficient conditions of a rule are satisfied, the conclusion is derived and the rule is said to fire (or trigger). Rules represent general knowledge regarding a domain.

Expert systems constitute the most well known type of rule-based systems (Buchanan and Shortliffe 1984; Gonzalez and Dankel 1993). The first rule-based expert system was DENDRAL (Buchanan, Sutherland and Feigenbaum 1969) and its application domain concerned organic chemistry. An influential early expert system was MYCIN (Shortliffe 1976), a system used for medical diagnosis from which the first expert system shell called EMYCIN (Buchanan and Shortliffe 1984) originated. MYCIN was the first knowledge-based system to simultaneously adhere to three basic principles endorsed by the expert systems developed ever since: (a) the separation of knowledge from how it is used, (b) the use of highly specific domain knowledge and (c) the heuristic nature of the knowledge employed (Gonzalez and Dankel 1993). The first commercial expert system was XCON (previously called R1) developed for Digital Equipment Corporation (DEC) to help configure computer systems (McDermott 1982; Kraft 1984).

The main parts of a typical expert system are the following: the rule base, the inference engine, the working memory and the explanation mechanism. The *inference engine* uses the knowledge (i.e. the rules) contained in the *rule base* as well as the known facts concerning the problem at hand. The known facts are stored into the *working memory*. There are two main inference methods: backward chaining and forward chaining. The former is guided by the goals (conclusions to be reached), whereas the latter by the (given) data. The *explanation mechanism* provides explanations regarding the conclusions reached by the inference mechanism. The provision of explanations is usually straightforward: back tracing the inference steps. The given explanations usually justify 'how' a conclusion has been reached.

Symbolic rules are usually acquired through interviews with experts. Alternative ways of acquiring rule bases are provided by using machine learning methods (Mitchell 1997) such as ID3 (Quinlan 1986). Those methods produce rules from existing empirical data.

Symbolic rules as a knowledge representation formalism, have several advantages as well as some significant disadvantages (Gonzalez and Dankel 1993; McGarry, Wermter and MacIntyre 1999).

The main advantages of rules are:

- *Compact representation of general knowledge*. Rules can easily represent general knowledge about a problem domain in autonomous, relatively small chunks.
- *Naturalness of representation*. Rules are a very natural knowledge representation method, with a high level of comprehensibility, since they look like natural language expressions. Rules can emulate the expert's way of thinking in many application domains.
- *Modularity*. Each rule is a discrete knowledge unit that can be inserted into or removed from the knowledge base, without taking care of any other technical detail (as long as other rules are not affected). This characteristic grants flexibility during the development of rule-based systems, because it enables incremental development of the knowledge base as well as partial testing.

- *Provision of explanations*. The ability to provide explanations for the derived conclusions in a straightforward manner is a vital feature, given that explanations in certain application domains (e.g. medicine) are considered necessary. This feature of symbolic rules is a direct consequent of their naturalness and modularity.

The main disadvantages of rules are:

- *Knowledge acquisition bottleneck*. The standard way of acquiring rules through interviews with experts is cumbersome and time-consuming. The chief reasons are the inability of an expert to express his/her knowledge and/or the unavailability of experts. Therefore, the acquired knowledge may be incomplete or even partially correct. Rule induction methods from machine learning can deal with some knowledge acquisition problems, but are still unable to recognize exceptions in small, low frequency sections of the domain (Cercone, An and Chan 1999). Furthermore, certain application domains are very complicated and may require a large number of rules.
- *Brittleness of rules*. It is not possible to draw conclusions from rules when there are missing values in the input data. For a specific rule, a certain number of condition values must be known in order to evaluate the logical function connecting its conditions. In addition, rules do not perform well in cases of unexpected input values or combinations of them.
- *Inference efficiency problems*. In certain cases, the performance of the inference engine is not the desired one, especially in very large rule bases. Although fast matching algorithms, like Rete algorithm (Forgy 1982), have improved the performance of forward chaining based systems, rule-based inference usually faces the scalability problem. Inference handles each problem from scratch; no matter whether it has dealt with the same problem successfully in the past. This creates inefficiency, especially in cases that the problem-solving process is time-consuming.
- *Difficulty in maintenance of large rule bases*. The maintenance of rule bases is getting a difficult process as the size of the rule base increases. The rule base may have problems such as, redundant rules, conflicting rules, rules with redundant or missing conditions, missing rules, etc. In order to deal with such problems, complex verification and validation methods are required.
- *Problem solving experience is not exploited*. A rule-based system is not self updatable, in the sense that there is no inherent mechanism to incorporate experience acquired from dealing with past problems. Such experience could contribute decisively in the inference process, as it could assist in handling special cases or exceptions not expressed by rules. The problem-solving capabilities of a rule-based system cannot be enhanced during real-time operation, unless the expert himself/herself intervenes in order to update the contents of the rule-base, which is not desirable.
- *Interpretation problems*. The general nature of rules may create problems in the interpretation of their scope during reasoning. To effectively deal with a specific situation, rules may sometimes need to be specialized (Montani et al. 2000). Especially, in certain application domains such as legal reasoning, rules contain

‘open-textured’ (i.e., not well defined and imprecise) terms that hinder their interpretation (Rissland and Skalak 1991).

3. Case-Based Reasoning

The origins of CBR can be traced back to late 1970s (Schank and Abelson 1977; Schank 1982). In (Schank 1982) structures called MOPs (memory organization packets) were proposed that constitute both generalized knowledge repositories and organizers of cases. The first implementations of MOPs were IPP (Lebowitz 1983a, 1983b) and CYRUS (Kolodner 1983a, 1983b, 1984). IPP and CYRUS were the forerunners of CBR systems (Kolodner 1993). As reported in (Kolodner 1993), the first commercially deployed CBR system is PRISM (Goodman 1990) whose application domain concerns interbank financial telexes.

Case-based representations store a large set of previous cases with their solutions in the *case base* (or case library) and uses them whenever a similar new case has to be dealt with (Kolodner 1993; Leake 1996; Lewis 1995).

Whenever, a new input case has to be dealt with, the case-based system performs inference in four phases known as the CBR cycle (Aamodt and Plaza 1994): (i) retrieve, (ii) reuse, (iii) revise and (iv) retain. The *retrieval phase* retrieves from the case base the most relevant stored case(s) to the new case. Indexing schemes and similarity metrics are used for this purpose. Indexing enables the efficient retrieval of relevant cases from the case base, thus limiting the search time. Similarity metrics assess the relevance of the retrieved cases to the new case. A simple approach to similarity assessment is the nearest neighbor matching (Kolodner 1993). One or more retrieved cases, deemed most relevant to the new case, are used for dealing with it. In the *reuse phase*, a solution for the new case is created based on the retrieved most relevant case(s). The *revise phase* validates the correctness of the proposed solution, perhaps with the intervention of the user. Finally, the *retain phase* decides whether the knowledge learned from the solution of the new case is important enough to be incorporated into the system. Quite often the solution contained in the retrieved case(s) is adapted to meet the requirements of the new case. Usual adaptation methods are substitution, transformation and derivational replay (Mitra and Basak 2005; Kolodner 1993). For the adaptation task, domain knowledge, usually in the form of rules, is employed (Kolodner 1993). Incorporation of knowledge during the operation of a case-based system enhances its reasoning capabilities. This is a major advantage, since the knowledge base of intelligent systems employing other representations remains rather static during operation.

The main advantages of case-based representations are:

- *Ability to express specialized knowledge*. This feature of cases among other advantages circumvents interpretation problems suffered by rules (due to their generality).
- *Naturalness of representation*. Cases are a simple knowledge representation method and very comprehensible to the user.
- *Modularity*. Each case is a discrete, independent knowledge unit that can be inserted into or removed from the case base, without any problem.

- *Easy knowledge acquisition*. Knowledge acquisition in case-based representations is not usually a problem, due to the fact that in most application domains cases are available. However, there are domains where they are not (see disadvantages further on).
- *Self-updatability*. Knowledge in the form of new cases faced during real-time operation can be incorporated into the case base extending the effectiveness of the system. This self-updatability also facilitates the maintenance of the case base.
- *Handling unexpected or missing inputs*. A case-based system can handle unexpected cases not recorded in the system or missing input values by assessing their similarity to stored cases and reusing relevant cases. The self-updatability of the system enhances handling of unexpected cases.
- *Inference efficiency*. Adapting preexisting cases to handle new problems is usually more efficient than having to solve a problem from scratch as in rule-based systems (Kolodner 1993). However, this is not always true since for instance in (Jarmulak, Kerckhoffs and van Veen 2001) is reported that a rule-based system (having very few rules though) was much more efficient than a corresponding case-based system with a large case base.

Issues of case-based representations that may give problems are:

- *Inability to express general knowledge.* Cases, by nature, express specialized knowledge. So, they cannot express general knowledge. This is a disadvantage compared to rule-based systems.
- *Knowledge acquisition problems*. Although knowledge acquisition is not a problem when a sufficient number of cases are available in a domain, various knowledge acquisition problems may arise when dealing with domains, where cases are either unavailable or are available in a limited (insufficient) amount (Sabater, Arcos and Lopez de Mantaras 1998; Marling, Petot and Sterling 1999). The lack of a sufficient amount of cases hinders the construction and inference process of a case-based system. Moreover, case-based systems usually require considerable case adaptation knowledge (Kolodner 1993; Mitra and Basak 2005). Insufficient adaptation knowledge compromises the effectiveness of the overall system. As concluded in a recent survey concerning case adaptation (Mitra and Basak 2005), to make a precise adaptation, the adaptation knowledge needs to be domain-specific. Due to the fact that adaptation knowledge is generally rule-based, the knowledge acquisition bottleneck of rules is 'incorporated' into case-based systems affecting their development and operation. For this reason, some researchers propose the exclusion of adaptation from the CBR cycle while others propose mechanisms for automatically acquiring this knowledge (Kinley 2001).
- *Inference efficiency problems*. The efficiency of the inference process in CBR is not always the desirable. Efficiency problems involve two main aspects: case retrieval and adaptation. Degradation of the time efficiency of case retrieval is associated with the utility problem, a problem occurring in learners when knowledge learned in an attempt to improve a system's performance degrades performance instead (Francis and Ram 1993). Swamping is the most usual type of the utility problem in CBR and occurs when the case base is very large and

the case retrieval cost encumbers inference efficiency (Francis and Ram 1993). The case base size is closely associated with two competing efficiency parameters: mean retrieval time and mean adaptation time. As the case base size increases, retrieval time becomes progressively greater and savings in adaptation time progressively less. There is a saturation point in the case base size after which the increases in the retrieval time are not offset by savings in adaptation time (Smyth and Cunningham 1996). To deal with this problem there can be three ways (Francis and Ram 1993): restricted insertion of new cases to the case base, carefully devised indexing schemes to guide search and proper case base maintenance policies (see e.g. Smyth and Keane 1995). Automated case adaptation can cause efficiency problems due to its complexity in certain applications. Automated case adaptation without the intervention of the user has been shown to be infeasible in practical applications. However, efficient and effective approaches to automated case adaptation have been implemented (Kinley 2001).

- *Provision of explanations.* Some kind of explanations can be provided for the reached conclusions, but not in a straightforward manner as in rule-based systems. It is difficult to explain all reasoning steps.

4. Combining Rule-based and Case-based Reasoning

Approaches combining RBR and CBR are becoming more and more popular. A reason for that popularity is that rules and cases offer complementary capabilities. Table 1 outlines a comparison between rule-based and case-based approaches based on the discussion presented in sections 2 and 3. Comparison is based on a number of characteristics (shown in columns). For each characteristic, the symbol +(resp. -) means advantage (resp. disadvantage), whereas the symbol +/- indicates that there is no clear advantage or disadvantage for the rule-based or case-based approach. Table 1 demonstrates that the advantages and disadvantages of rule-based and case-based approaches are complementary in a large degree. Complementary advantages and disadvantages of two knowledge representation methods is a good justification for their possible combination. From Table 1, it is clear that the combination of rules and cases can offer significant benefits, if their advantages are exploited and their disadvantages are eliminated in an adequate degree. Combination of RBR and CBR is also justified by the fact that it closely emulates the human way of thinking in a variety of complex application domains (e.g. legal reasoning and medicine). When dealing with a new situation, an expert usually combines general (rule-based) knowledge with specialized (case-based) knowledge gained from experience. This is a claim based on practical consideration besides intuitive evidence. Firstly, systems combining RBR and CBR (such as the ones shown in Table 2) have been shown to work and outperform systems based purely on RBR and CBR. Secondly, there is an abundance of research work in other fields of AI (besides CBR) demonstrating that synergies from using both (rule-based) domain theory and empirical data may result in powerful systems (e.g. (Towell and Shavlik 1994); (Fu 1993); (Mahoney 1996); (Ourston and Mooney 1994); (Kuncicky, Hruska and Lacher 1992); (Omlin and Giles 1996); (McGarry, Wermter and MacIntyre 1999); (d'Avila Garcez, Broda and Gabbay 2002)). In addition, there is psychological evidence that people rarely learn purely from theory or examples (i.e., empirical data) (Wisniewski and Medin 1991). Of course, the goal of a combination is to derive a combined representation that augments the positive aspects of the integrated formalisms and simultaneously minimizes their negative aspects.

So, approaches combining RBR and CBR have given interesting and effective hybrid or integrated schemes (Aha and Daniels 1998; Freuder 1998; Marling et al. 2002). Such a system usually consists of two integrated components (i.e., a rule-based and a case-based component). However, there are more complicated systems, which combine several rule-based and case-based modules, although such systems are infrequent. Such a system is IDS (Wylie et al. 1997).

Table 1. Advantages and disadvantages of rule-based and case-based approaches

	Expression of General Knowledge	Expression of Specialized Knowledge	Naturalness	Modularity	Knowledge Acquisition	Unexpected\ Missing Inputs	Inference Efficiency	Maintenance	Updatability	Provision of Explanations
Rule-based approach	+	-	+	+	-	-	+/-	+/-	-	+
Case-based approach	-	+	+	+	+/-	+	+/-	+	+	+/-

The pioneering combination efforts can be traced back to the end of 1980s and the beginning of 1990s, such as CABARET (Rissland and Skalak 1991) and GREBE (Branting 1991). Several integrated approaches in various application domains were developed during the following years. Legal reasoning and medicine seem to be popular application fields for the approaches integrating rules and cases. Examples of hybrid or integrated legal systems are CABARET (Rissland and Skalak 1991), DANIEL (Bruninghaus 1994), GREBE (Branting 1991, 2003), IKBALS III (Zeleznikow, Vossos and Hunter 1994) and SHYSTER-MYCIN (O'Callaghan, Popple and McCreath 2003a, 2003b). Rules in hybrid or integrated legal systems are usually based on legislation, whereas cases on previously tried cases. The reason for the popularity of rule-based and case-based combination in legal reasoning is due to the existence of 'open-textured' (i.e., not well defined and imprecise) rule terms. Furthermore, rules may have unstated prerequisite conditions and exceptions or circularities in definition (Rissland and Skalak 1991). Examples of hybrid or integrated systems used in medicine are (Bichindaritz, Kansu and Sullivan 1998; Bichindaritz et al. 2003; Marling and Whitehouse 2001; Montani et al. 2000; Montani and Bellazzi 2002; Phuong et al. 2001; Rossille, Laurent and Burgun 2005; Evans-Romaine and Marling 2003). The reason for the popularity of rule-based and case-based combination in medicine is due to the fact that decision making follows a combination of general knowledge and experience gained from abundant patient cases.

Other applications, where combination of rules and cases has been used, include agriculture (Zhou, Messermith and Harrington 2005), aircraft design (Rentema 2004), aircraft fleet maintenance (Wylie et al. 1997; Halasz et al. 1999), automobile construction (Ding, Hu and Jiang 2004), biomedicine (Park, Oh, Jeong and Park 2000), construction

(Dzeng and Lee 2004), design of nutrition menus (Marling, Petot and Sterling 1999), equipment failure analysis (Wang and Wang 2005), finance (Dutta and Bonissone 1993; Chen and Wilkinson 1998), life insurance (Lee 2002), modeling event-based dynamic situations (Jakobson, Buford and Lewis 2004), music (Sabater, Arcos and Lopez de Mantaras 1998), personnel performance evaluation (Chi and Kiang 1993), real-time marine environment monitoring (Vafaie and Cecere 2005), surname pronunciation (Golding and Rosenbloom 1996), service fault diagnosis to guarantee Quality of Service (Hanemann 2006) and ultrasonic rail inspection (Jarmulak, Kerckhoffs and van Veen 2001). Table 2 shows the application domains and the corresponding integrated systems (in alphabetical order). It should be mentioned that in the aforementioned approaches a CBR system as a whole (with its possible internal modules) is integrated 'externally' with a RBR system in order to create an improved overall system (see section 6).

Table 2. Application domains and systems integrating rules and cases

Application Domain	*Integrated Approaches*
Agriculture	HIDES
Aircraft design	AIDA
Aircraft Fleet Maintenance	IDS
Automobile construction	(Ding, Hu and Jiang 2004)
Biomedicine	(Park, Oh, Jeong and Park 2000)
Construction	ScheduleCoach
Design of Nutrition Menus	CAMPER
Equipment Failure Analysis	EFAES
Finance	ECLAS, MARS
Legal Reasoning	CABARET, DANIEL, GREBE, IKBALS III, SHYSTER-MYCIN
Life Insurance	CCAR
Medicine	CARE-PARTNER, (Marling and Whitehouse 2001), (Montani et al. 2000; Montani and Bellazzi 2002), (Phuong et al. 2001), (Rossille, Laurent and Burgun 2005), WHAT
Modeling Event-based Dynamic Situations	(Jakobson, Buford and Lewis 2004)
Music	GYMEL
Personnel Performance Evaluation	MCRS
Quality of Service	Hanemann 2006
Real-Time Marine Environment Monitoring	CORMS AI
Surname Pronunciation	ANAPRON
Ultrasonic Rail Inspection	URS-CBR

As reported in the corresponding papers, research prototypes of most of the above integrated systems have been implemented and successfully evaluated with real domain data. For a few of them (DANIEL, ECLAS, MCRS) no evaluation is reported. Also, a few of them (Jakobson et al, 2004; Rossille et al, 2005) are still under development. Finally, only two of them are reported to be operational (CORMS AI, URS-CBR).

Another aspect of interest is the specification of some criteria to judge whether a hybrid RBR/CBR solution could be applied to a problem. Such criteria can be the following:

(1) *Existence of (or ability to acquire) both rule-based and case-based knowledge sources concerning the application field.* Obviously this criterion is obligatory. No hybrid scheme can be implemented unless both types of knowledge are available (or obtainable).

(2) *Neither general nor specialized knowledge alone seems sufficient for responding appropriately to a significant part of the encountered situations.* Appropriate response means that the produced output should (more or less) comply with the response of the domain expert to the encountered situations. To assess if this criterion is satisfied, prototypes of a rule-based and a case-based system can be used in parallel to compare the independent solutions (see standalone model in the next section).

(3) *The problem solving process can be decomposed into subprocesses (tasks or stages) for which different representation formalisms are required or available.* In such situations, the tasks or stages of the problem solving process should be examined to determine which is better formulated with rules and which with cases.

(4) *It is known from literature that hybrid RBR/CBR solutions have been successfully applied to problems of this domain (or a similar domain).* It is always useful to exploit the experience gained from the development of similar systems.

From the above criteria, the first three are necessary, whereas the fourth one is optional.

5. Existing Categorization Schemes

In this section, we critically discuss three existing schemes that categorize (or could be seen as categorizing) approaches combining RBR and CBR. The first is the categorization scheme of Medsker (Medsker 1995), which refers to combined approaches in general, not specifically to those combining RBR with CBR. The second is the scheme of Golding and Rosenbloom (Golding and Rosenbloom 1996) for combinations of RBR and CBR. Finally, the third scheme is our first attempt in categorizing such combinations (Prentzas & Hatzilygeroudis 2003, Hatzilygeroudis & Prentzas 2004). A useful contribution of such categorization schemes is that they present models of integrated systems describing their key features and highlighting key developments.

5.1 Medsker's Categorization Scheme

Medsker (Medsker, 1995) provides a general categorization for approaches/systems combining various AI technologies (i.e. expert systems, neural networks, fuzzy logic, genetic algorithms and CBR). Given that, it could be used as a categorization scheme for approaches integrating RBR and CBR too. Although Medsker's categorization scheme is generally acceptable by the research community of hybrid intelligent systems, researchers working towards the integration of RBR and CBR seem to be not aware of it. Medsker distinguishes five main combination models: standalone, transformational, loose coupling, tight coupling and fully integrated models. Distinction between those models is based on the degree of coupling between the integrated components. Underlying categories for some of these models are also defined. Each one of the five models is briefly presented below.

Standalone models do not essentially describe hybrid or integrated systems, because in such systems independent components of each approach are developed that do not interact with each other during reasoning. They can be used in parallel to compare the independent solutions. Standalone systems provide an opportunity to compare the capabilities of each approach.

In the *transformational model*, a system based on one approach (e.g. rules) is completely transformed to a system based on the other approach (e.g. cases). Transformation is made for various reasons such as, better representation of the domain, enhanced inference performance, enhanced maintenance, etc. The transformational model, just like the standalone model, does not actually describe hybrid or integrated systems.

Loose coupling model concerns systems in which there are separate integrated components based on each representation method. Communication between the components is achieved via data files. Main categories of loose coupling are: *pre-processing*, *post-processing* and *co-processing* models. In the first two categories, data processing is sequential; one component is the main problem solver and the other component preprocesses/post-processes its input/output. Co-processing refers to bi-directional flow of data between the components enabling an enhanced form of interaction and cooperation between them.

Tight coupling model concerns systems in which the combined components communicate with each other via memory resident data structures. Main categories of tight coupling models are *preprocessors*, *postprocessors*, *coprocessors* and *embedded systems*. Systems belonging to the first three categories function more or less like in the case of loose coupling systems, however, the different way of communication makes interaction faster, easier and more cooperative (especially in case of coprocessors). In embedded systems, a component based on one approach is the primary problem solver embedding component(s) based on the other representation method to handle its internal reasoning tasks.

In *fully integrated model*, the integrated components share structures and knowledge representations and are virtually indistinguishable. Popular examples of fully integrated models are fuzzy neural networks (integration of neural networks and fuzzy logic), which are neural networks with fuzzified neurons.

The bulk of the approaches combining RBR with CBR belong to the (loose or tight) coupling models. Problems arise when trying to classify coupling approaches according to the underlying categories defined by Medsker (i.e., preprocessors, postprocessors, coprocessors). There are also problems with other categories of Medsker's scheme such as, the fully integrated model.

We were not able to identify coupling systems clearly belonging to the pre-processing or post-processing category. We can identify systems always (or almost always) following a sequential pattern of information processing regardless of the input case (Marling, Petot and Sterling 1999; Rentema 2004; Zhou, Messermith and Harrington 2005). There are systems following a sequential processing pattern, but not in all situations. This depends on the input case, since each component under certain conditions can produce a final result (Jarmulak, Kerckhoffs and van Veen 2001; Cercone, An and Chan 1999; Chen and Wilkinson 1998; Surma and Vanhoof 1995, 1998).

The co-processing category seems to be sufficient for describing a number of approaches such as (Branting 1991, 2003; Rissland and Skalak 1991; Bichindaritz, Kansu and Sullivan 1998; Montani et al. 2000; Montani and Bellazzi 2002; Sabater, Arcos and Lopez de Mantaras 1998; O'Callaghan, Popple and McCreath 2003a, 2003b; Jakobson, Buford and Lewis 2004). However, co-processing may entail not only cooperation but also 'competition' between the integrated components in producing the final result or assessment of their suitability in dealing with the case at hand (Golding and Rosenbloom 1996; Lee 2002; Agre 1995; Bruninghaus 1994; Dutta and Bonissone 1993.

The category related to embedded approaches describes the case-based systems embedding rule-based modules to assist the tasks of the CBR cycle. As mentioned above, most of the case-based systems usually encompass a rule-based component to perform the case adaptation task. The embedded approach may be considered commonplace in CBR (especially for case adaptation). To the best of our knowledge, we are not aware of systems following the reverse approach that is, embedding a case-based module into a rule-based system.

It is difficult to identify approaches integrating RBR and CBR that follow the fully integrated model. This is due to the inherent difficulty in fully integrating rules and cases. Full integration seems to be more suitable for approaches integrating other representation methods such as neural networks and fuzzy logic, symbolic rules and fuzzy logic, neural networks and symbolic rules.

There are also approaches following the standalone model (example approaches are briefly discussed in section 6). The transformational model (i.e. the idea of converting all cases into rules, or vice versa, and then working in a single representation) does not seem to be feasible for rules and cases. Such a conversion, either way, tend to produce an inefficient or unreliable representation (Golding and Rosenbloom 1991).

So, given that most of the approaches combining RBR and CBR follow the coupling model and there are problems with most of the underlying categories, defined by Medsker (i.e., pre-processing, post-processing), it is clear that new categories of coupling systems have to be determined. In addition, subcategories of existing coupling categories (i.e., co-processing) can be specified. Of course, inadequacy of a general categorization scheme, such as Medsker's, to accommodate all approaches integrating RBR with CBR was expected.

5.2 Categorization Scheme of Golding and Rosenbloom

Golding and Rosenbloom proposed a specialized categorization scheme, i.e. a scheme for classifying rule-based and case-based combinations (see Figure 1). Specialized categorization schemes have also been employed to classify combinations of other intelligent methods such as neural networks and fuzzy logic (Nauck, Klawonn and Kruse 1997) or neural networks and symbolic rules (McGarry et al 1999).

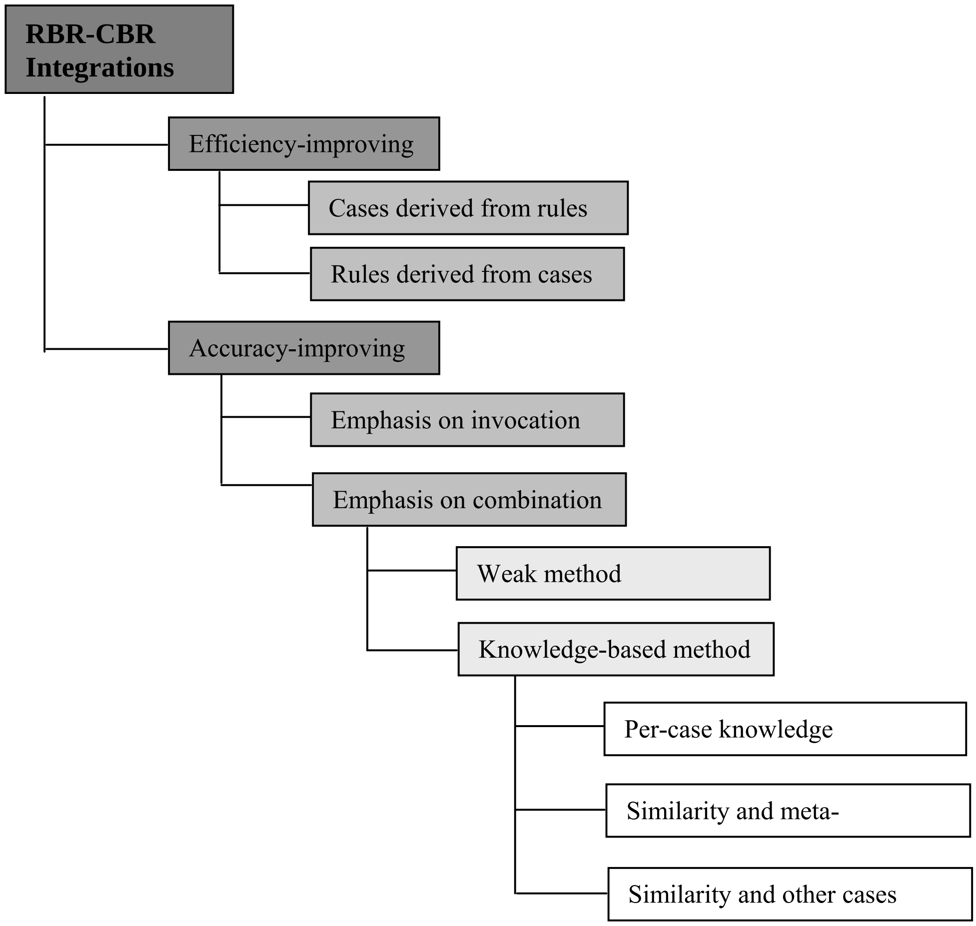

Figure1. Categorization scheme of Golding and Rosenbloom

The categorization scheme of Golding and Rosenbloom makes a basic distinction between 'efficiency-improving' and 'accuracy-improving' approaches. Efficiency-improving systems consist of dependent rule and case based components, meaning that one knowledge form has been derived from the other. Transformation of rules to cases or vice versa is made primarily for efficiency reasons. Accuracy-improving systems consist of independent rule and case based components. Their primary objective is to provide more accurate solutions by exploiting both types of knowledge. Accuracy-improving approaches are classified into two basic subcategories. The one involves approaches giving emphasis to invocation that is, emphasizing how and when to invoke the integrated components. The other involves approaches giving emphasis to combination. In these approaches, the potentially different conclusions of the rule-based and case-based components are reconciled either by employing a general (non-domain specific) method or a knowledge-based (domain-specific) method. The approaches employing a knowledge-based method for reconciliation are themselves discerned into three categories, based on the employed knowledge type: (i) per-case knowledge, (ii) similarity and meta-knowledge and (iii) similarity and other cases.

This categorization scheme, however, is not adequate for classifying recent approaches combining RBR and CBR. The main deficiencies derive from the fact that it bases its high-level classification on combined criteria. It supposes that (a) efficiency improvement goes with systems consisting of dependent rules and cases and (b) accuracy improvement goes with systems consisting of independent rules and cases. This hypothesis is not always true and gives problems when try to classify systems integrating RBR with CBR:

- Dependency or independency of the integrated knowledge types does not necessarily result in efficiency or accuracy improvement respectively. For instance, ELEM2-CBR (Cercone, An and Chan 1999) consists of dependent rules and cases (rules derived from cases) and improvement of accuracy (instead of efficiency) is the main achievement of the combination. ECLAS (Chen and Wilkinson 1998) on the other hand, consists of independent rules and cases, but the result of the combination is efficiency improvement.
- There are integrated systems resulting in both efficiency and accuracy improvement. For example, DIAL (Kinley 2001) is an integrated system resulting in both efficiency and accuracy improvement with both being primary objectives of the combination and thus cannot be clearly regarded as an 'efficiency-improving' or an 'accuracy-improving' approach. ANAPRON (Golding and Rosenbloom 1996) and URS-CBR (Jarmulak, Kerckhoffs and van Veen 2001) also improve both accuracy and efficiency, but accuracy improvement is their primary objective and so they can be considered as 'accuracy-improving' approaches.
- The transformation of rules into cases and vice versa can be done for other reasons besides efficiency (as mentioned in section 5.1 when discussing about the transformational model of Mesker's scheme) depending on the application domain. For instance, transformation of rules into cases results to systems with improved maintenance and adaptability besides inference efficiency (Macdonald 1998).
- There may be an overlapping between the underlying categories of the 'efficiency-improving' and 'accuracy-improving' approaches. In some approaches, where rules and cases are dependent and transformation is not complete, as in ELEM2-CBR (Cercone, An and Chan 1999), the distinct integrated components may behave like the components of the systems belonging to the 'accuracy-improving' approaches.

Also, other problems related to the Golding and Rosenbloom's scheme are:

- It totally disregards Medsker's scheme by not taking into account the degree of coupling between the integrated components.
- Approaches following a sequential or semi-sequential pattern of information processing have to be included in the 'emphasis on invocation' category, which does not seem to be very prudent.

- The three subcategories of the 'emphasis on combination' approaches that use a knowledge-based reconciliation method are quite restrictive. This is because each subcategory corresponds to a specific approach.

So, it is clear that the categorization scheme of Golding and Rosenbloom needs to be revised and extended in order to accommodate recent developments.

5.3 Our Early Categorization Scheme

In a previous effort of ours, we introduced another classification scheme, based on the importance of each of the two integrated schemes in the inference process (Prentzas and Hatzilygeroudis 2003; Hatzilygeroudis and Prentzas 2004). According to that scheme, which is based on a similar consideration to that in (Marling et al 2002), approaches combining RBR and CBR are discerned into three categories: (i) rule-dominant, (ii) balanced and (iii) case-dominant. Similar categorizations have also been presented in (Dutta and Bonissone 1993; Marling, Petot and Sterling 1999; Cercone, An and Chan 1999; Marling et al. 2002).

Table 3. Approaches integrating rules and cases based on component dominance

Rule-dominant	*Balanced*	*Case-dominant*
ANAPRON	AIDA	CAMPER
Montani et al. 2000	CABARET	ECLAS
CCAR	CARE-PARTNER	GYMEL
CoRCase	DANIEL	Marling & Whitehouse 2001
CORMS AI	EFAES	
Ding et al, 2004	ELEM2-CBR	
Hanemann 2006	GREBE	
IDS	HIDES	
MARS	IKBALS III	
ScheduleCoach	Jakobson et al, 2004	
SHYSTER-MYCIN	MCRS	
Surma and Vanhoof 1995,1998	Park et al, 2000	
Rossille et al, 2005	Phuong et al, 2001	
	URS-CBR	
	WHAT	

In rule-dominant approaches, the rule-based component prevails in the inference process, whereas the case-based component plays a complementary role. These approaches usually focus on the rule-based component and invoke the case-based component only when necessary (usually in specialized or exceptional situations). In balanced approaches, the role of the integrated components is balanced that is, none of the integrated components plays a supportive role. In case-dominant approaches, the case-based component plays a more important role and the rule-based component is less significant (supportive). This scheme is useful, for instance, when the case library contains a limited number of cases (Sabater, Arcos and Lopez de Mantaras 1998; Marling, Petot and Sterling 1999).

Table 3 shows (alphabetically ordered) representative approaches for each of those three categories. A problem with this categorization scheme is the difficulty of classifying approaches consisting of more than two integrated components. This scheme (to some degree) implicitly assumes that the combined approach will integrate only two components (one for each representation method). In addition, the boundary lines between the balanced category and the other two categories are not very clear. Finally, it is difficult to define subcategories for those three categories. This last disadvantage of this scheme is the most important, because it inhibits it from covering other aspects of rule-based and case-based combinations, apart from component dominance.

6. A New Categorization Scheme

To remedy the shortcomings of the aforementioned categorization schemes, we introduce here a new scheme. This scheme provides a more consistent view to modeling approaches/systems combining RBR and CBR compared to the other schemes. Furthermore, it accommodates recent developments not covered by existing schemes. The scheme is based on a task analysis of the problem solving (or reasoning) process of systems combining RBR and CBR. We identified the tasks (or stages or views) that the problem solving (or reasoning) process has been partitioned into, which representation scheme was selected to represent each of them and the functional (or architectural) relations between them.

The new scheme along with representative systems/approaches for each category is depicted in Figure 2. We also give architectural models of each leaf category in its description below. Our scheme mainly refers to coupling approaches (in terms of Medsker's categorization), which, as we noticed earlier, are the systems that truly combine RBR and CBR. Such approaches consist of two or even more integrated rule-based and case-based modules. Two main categories are distinguished in our scheme: (a) standalone and (b) coupling approaches. Coupling approaches are themselves distinguished in three main categories: (i) sequential processing, (ii) co-processing and (iii) embedded processing approaches.

6.1 Standalone

The standalone category refers to approaches where the RBR and CBR components do not interact with each other but are invoked independently and the user compares the independent solutions. Example approaches are EFAES (Wang and Wang 2005) and WHAT (Evans-Romaine and Marling 2003). In EFAES, a system for equipment failure analysis, the separate recommendations of RBR and CBR can give more information in recognizing the failure types. In WHAT, a system training medicine students to design exercise regimens for patients, exercise regimens are derived in two ways, one rule-based and one case-based and displayed separately. This approach has been found useful in teaching medicine students how to apply standard rules and simultaneously adjust to the individual needs of patients. Also the construction of CAMPER (Marling, Petot and Sterling 1999) was guided by a detailed evaluation and comparison of two independent systems, a CBR and an RBR. Furthermore, in (Chae et al. 1998) four different knowledge models were compared for leukemia diagnosis: RBR, CBR, neural network and a statistical classification method. The RBR one was proved to be the most accurate.

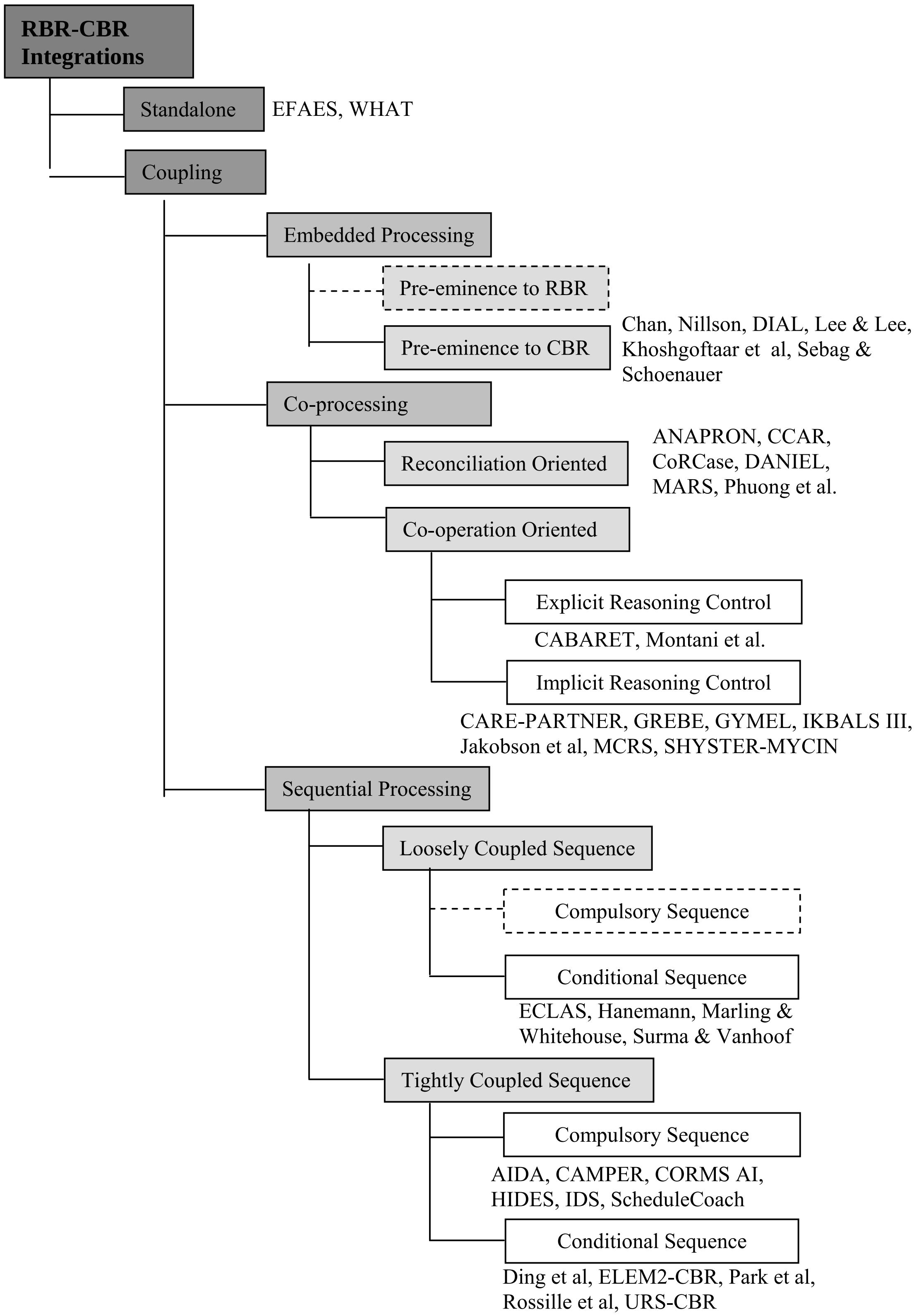

Figure 2. The new categorization scheme for integrations of RBR and CBR

The standalone model is a solution when both RBR and CBR schemes can cover the whole reasoning process (or a large part of it). This model can be applied to application domains in which the user is satisfied by simply examining the two solutions and is not interested in applying a more complex model. The standalone model can also be a step prior to the adoption of a coupling model, as in CAMPER for instance, because the application of a coupling model may require a prior thorough investigation of the strengths and weaknesses of the combined representations.

6.2 Coupling

6.2.1 Sequential Processing

The *sequential processing* category refers to coupling approaches in which the flow of information (produced by reasoning) between the integrated modules is sequential or semi-sequential. It includes approaches in which information necessarily passes sequentially through some or all of the integrated components in order to produce a final result. This means that the reasoning process of an integrated component must end before reasoning in the next component can start.

Not all the integrated components in the sequence need to be invoked, because the final result can be produced by intermediate components in the sequence. This depends on the input case. It should be noted that the 'sequential processing' category can accommodate, by definition, pre-processing or post-processing approaches (if such approaches appear in the future). We distinguish two subcategories of the 'sequential processing' category, based on the importance of the information (besides the input case) passed between the coupled modules: the 'loosely coupled sequence' and the 'tightly coupled sequence' subcategory.

The *loosely coupled sequence* subcategory refers to approaches in which the information passing to a component from a previous one in the sequence does not play an important role in its reasoning process (see Fig. 3). In such approaches, the reasoning process of each component is almost independent of the reasoning process of the previous component in the sequence. The output of the one component may be used as input knowledge to the next component, but does not play an important role in the (internal) reasoning process of the next component; it is mainly used as triggering information. Approaches belonging to this category are (Surma and Vanhoof 1995, 1998), ECLAS (Chen and Wilkinson 1998), (Marling and Whitehouse 2001). The approach described in (Surma and Vanhoof 1995, 1998) starts reasoning with the rule-based component, which refers to general cases, and if it is not successful in producing a final result the case-based component, which concerns exception to general cases, is invoked. Something similar happens in (Hanemann 2006). ECLAS, a system that accepts or rejects loan applications, invokes first the rule-based component to reduce the amount of processing in the case-based module by filtering input cases to be rejected and passing to the case-based module the remaining ones. In (Marling and Whitehouse 2001), a medical system for Alzheimer's Disease patients, the case-based module is invoked to determine if a neuroleptic drug should be prescribed to a patient and if this is so, the rule-based module is invoked to select one of five such drugs.

All existing integrations of loosely coupled sequence follow a conditional way of sequence; that is the second component is invoked if the first fails to give an acceptable solution (see Fig. 3). Therefore, they constitute the *conditional sequence* subcategory (see Fig. 2). Given that, it seems reasonable to think of integrations where a *compulsory sequence* is followed: the second component is invoked unconditionally after the first (see Fig. 4), as it happens with the tightly coupled sequence (see below). Although the fact that only minor information is passed from the first to the second component is not in favor of that, it seems that this can be considered as an unexplored type of RBR-CBR integration, therefore it is indicated by a dashed rectangle in Fig. 2.

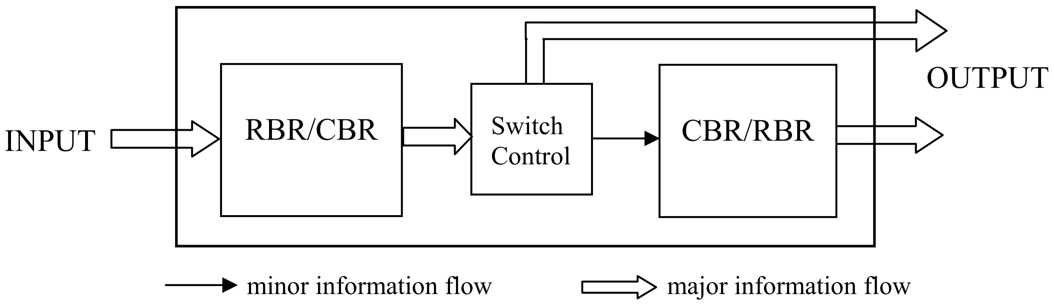

Figure 3. Loosely Coupled Conditional Sequence Model

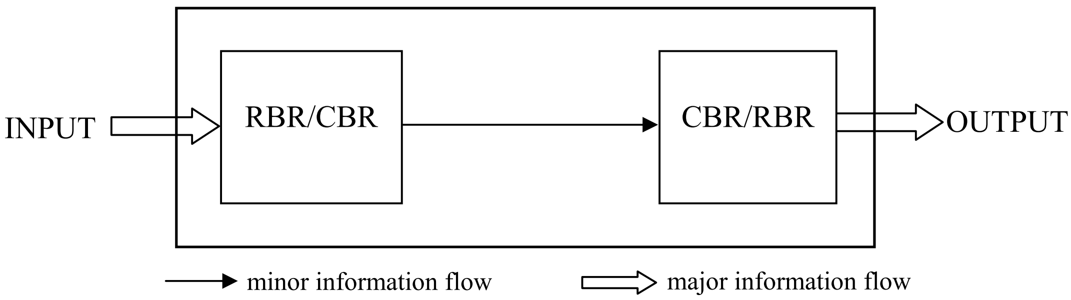

Figure 4. Loosely Coupled Compulsory Sequence Model

The loosely coupled conditional sequence model can be used for systems where the problem solving process can be viewed as two partially complementary and almost independent sub-processes. The second process complements the first in some cases, not in all cases. In those cases, some of the results of the first component are passed as input information to the second component.

The *tightly coupled sequence* subcategory refers to approaches in which the information passing to a component from a previous one in the sequence plays an important role in its reasoning process. Approaches belonging to this subcategory are more closely coupled than approaches in the 'loosely coupled sequence' subcategory. Such approaches are those used in AIDA (Rentema 2004), CAMPER (Marling, Petot and Sterling 1999), CORMS AI (Vafaie and Cecere 2005), ELEM2-CBR (Cercone, An and

Chan 1999), HIDES (Zhou, Messermith and Harrington 2005), IDS (Wylie et al. 1997), ScheduleCoach (Dzeng and Lee 2004), URS-CBR (Jarmulak, Kerckhoffs and van Veen 2001), (Marling and Whitehouse 2001), (Park, Oh, Jeong and Park 2000), (Ding, Hu and Jiang 2004) and (Rossille, Laurent and Burgun 2005). We further distinguish tightly coupled sequence category into two subcategories, namely 'compulsory sequence' and 'conditional sequence'. AIDA, CAMPER, CORMS AI, HIDES, IDS and ScheduleCoach belong to *compulsory sequence* category, which represents systems that usually invoke both modules to produce an output (see Fig. 5). AIDA, a system for aircraft design, first invokes CBR to create an initial aircraft concept, which is then passed to RBR to perform functional studies on its primary parameters and modify the initial aircraft concept into a feasible aircraft concept. CAMPER, a menu planner, usually invokes both modules, first invoking the case-based module to create an initial menu, which is passed to the rule-based module for further processing. ScheduleCoach, a system critiquing construction schedules, first invokes the rule-based module to identify possible objects violating the schedule and passes the objects for which there are no predetermined revisions to the case-based module to suggest revisions. CORMS AI, a real-time monitoring system, first invokes the rule-based module to identify problems and then the case-based module to identify the source and the remedial actions for the identified problems. IDS invokes rule-based modules to identify possible faults in aircrafts and then invokes the case-based module to acquire remedial actions for those faults. HIDES, a system for herbicide injury diagnosis, first invokes RBR to identify suspect herbicide(s) for causing the observed injury and determine possible sources of the suspect herbicide(s) and passes the results to CBR to propose a probable cause of injury.

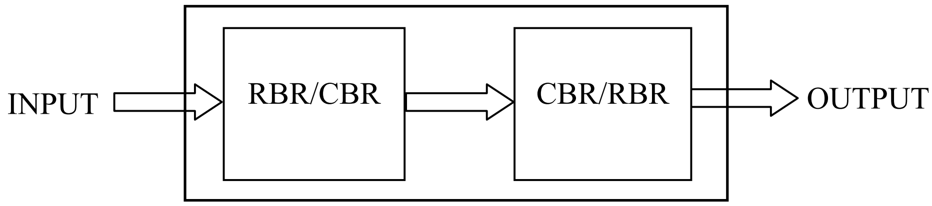

Figure 5. Tightly Coupled Compulsory Sequence Model

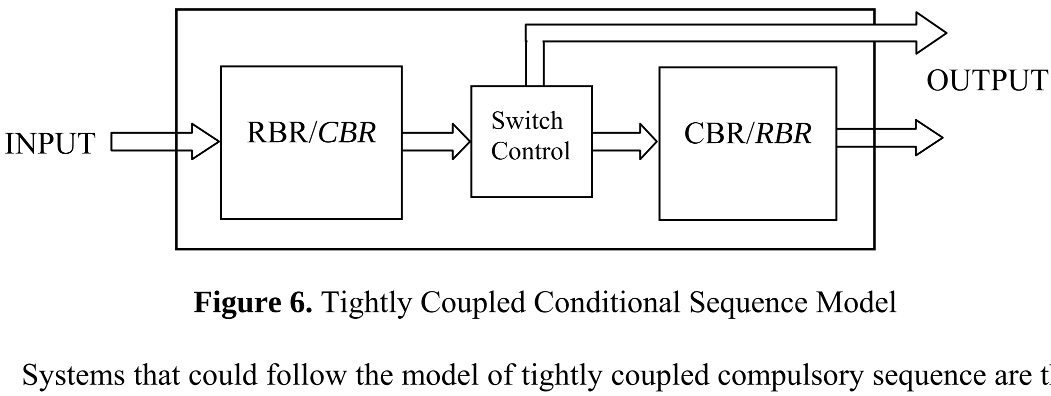

Figure 6. Tightly Coupled Conditional Sequence Model

Systems that could follow the model of tightly coupled compulsory sequence are those in which the problem solving process can be distinguished in two consecutive stages. In the first stage, a rough solution is given (e.g. by finding the type of the solution), and in the second, the precise solution is given by refining the rough one.

On the contrary, ELEM2-CBR, (Park, Oh, Jeong and Park 2000), (Ding, Hu and Jiang 2004), URS-CBR and (Rossille, Laurent & Burgun 2005) belong to the *conditional sequence category* (see Fig. 6), because they first invoke the rule-based component and if it is not able to produce a final result, the case-based component. ELEM2-CBR passes reasoning results of the rule-based module to the case-based module, which are useful for similarity assessment (i.e. calculation of attribute weights). In (Park, Oh, Jeong and Park 2000), a system used for automated sleep stage scoring, the reasoning results of the rules play a role in case similarity assessment, since cases include attributes related to the applied rules and the conclusions of the RBR process. In (Ding, Hu and Jiang 2004), a collision-solution support tool used in automobile steering machine cooperation design environment, the rule-based module sets preconditions used by the case-based module to retrieve cases. URS-CBR, a system used in Dutch Railways to classify images acquired from ultrasonic railway inspection, passes intermediate inference results of the rule-based module to the case-based module, which are useful for case retrieval (i.e., classification of the input case to an appropriate case cluster determining potentially relevant stored cases). In (Rossille, Laurent & Burgun 2005), a medical system for oncology, the results of RBR are used to determine similar cases to the input case.

In existing tightly coupled conditional sequence approaches, the RBR component is invoked first and then the CBR one, in contrast to the compulsory sequence case. It seems that there is no obvious reason for not invoking the components in the other way round. So, this latter type of tightly coupled conditional sequence approaches can be considered as an unexplored integration type, indicated by the italics font in Fig. 6.

Systems where the reasoning process can be viewed as two partially complementary, but tightly related sub-processes can use this model. The second process complements the first in several cases, but not in all cases. In those cases, the results of the first component play a significant role in the reasoning process of the second component.

6.2.2 Co-processing

The *co-processing* category refers to approaches in which the components closely interact (as partners) in producing the final result. In such approaches, information flow between the components is bi-directional. The integrated components may also work in parallel for the solution of a problem. Systems belonging to this approach are discerned into two types: *cooperation oriented*, which give emphasis on cooperation, and *reconciliation oriented*, which give emphasis on reconciliation. In the former type, the integrated components cooperate with each other (usually by interleaving their reasoning steps) for the production of the final result (see Fig. 7). In the latter, each component produces its own conclusion, possibly differing from the conclusion of the other component, and thus a reconciliation process is necessary (see Fig. 8).

C*ooperation oriented* approaches are further distinguished in those employing *explicit reasoning control* and those employing *implicit reasoning control*. Approaches of the first type employ an explicit controller or explicit control knowledge during inference (see Fig. 7a). Approaches of the second type do this implicitly (see Fig. 7b). Examples of the first category are CABARET (Rissland and Skalak 1991) and (Montani et al. 2000; Montani and Bellazzi 2002). CABARET, a system for legal reasoning, achieves an interleaving combination of the reasoning steps of the RBR and CBR components in a blackboard architecture, using a separate control module that applies heuristic control rules. The approach described in (Montani et al. 2000) employs a rule-based supervisor controller to decide if CBR will be invoked to assist in specific reasoning steps of the rule-based component. Cases in this approach are used to dynamically refine certain parameters of the rules (e.g., numeric thresholds appearing in conditions), which are too general to deal with the specific situation.

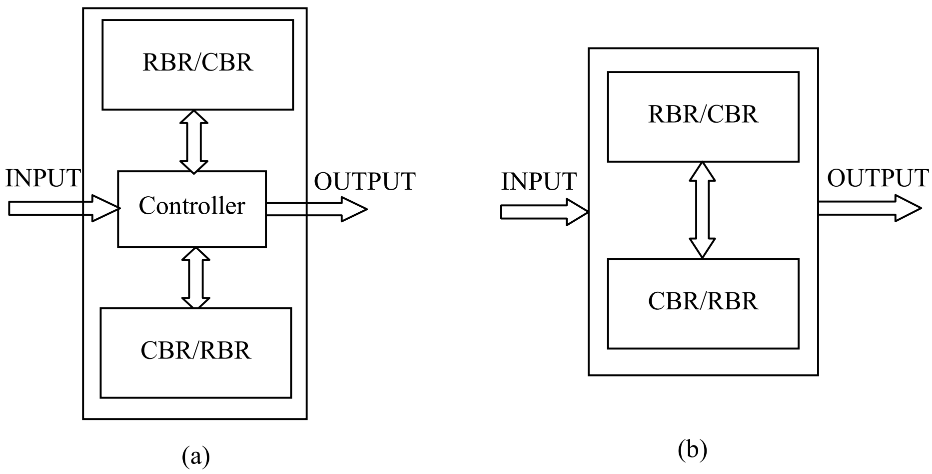

Figure 7. Cooperation Oriented (a) Explicit Control Model, (b) Implicit Control Model

Examples of the second category are CARE-PARTNER (Bichindaritz, Kansu and Sullivan 1998; Bichindaritz et al. 2003), GREBE (Branting 1991, 2003), GYMEL (Sabater, Arcos and Lopez de Mantaras 1998), IKBALS III (Zeleznikow, Vossos and Hunter 1994), MCRS (Chi and Kiang 1993), SHYSTER-MYCIN (O'Callaghan, Popple and McCreath 2003a, 2003b) and (Jakobson, Buford and Lewis 2004). CARE-PARTNER, a system applied to a medical domain, merges the reasoning steps of both methods by using a common knowledge representation language. GREBE, a legal reasoning system, invokes both rules and cases to solve its goals providing all the found solutions. SHYSTER-MYCIN, a legal reasoning system combining a case-based system (i.e., SHYSTER) and a modified version of a rule-based expert system (i.e., MYCIN (Buchanan and Shortliffe 1984)), occasionally turns to cases during inference whenever RBR faces problems due to open-textured terms and resumes RBR after retrieving results from CBR. GYMEL handles each input problem as a set of simple problems and for each simple problem it turns to rules whenever CBR faces problems resuming CBR after retrieving results from RBR (the process for simple problems may involve backtracking). In IKBALS III, a legal reasoning system, an RBR and CBR module act as agents communicating through messages. MCRS constitutes a multi-agent architecture in which the case-based and rule-based modules send and receive messages to communicate with each other and solve problems according to a predetermined invocation pattern. In (Jakobson, Buford and Lewis 2004), an architecture concerning the analysis of event-based dynamic situations, the rule-based and case-based module act in a distributed fashion with each module dynamically invoking the other during inference.

The co-operation oriented co-processing model can be used for systems where the reasoning process can be decomposed in a number of tasks (steps) each of which can be better realized by a different formalism (one of RBR, CBR). So, there is an interleaving mode of reasoning, using RBR or CBR in different steps, where the choice of the formalism in each step can be done either explicitly, using a separate mechanism, or implicitly, using a kind of common representation scheme.

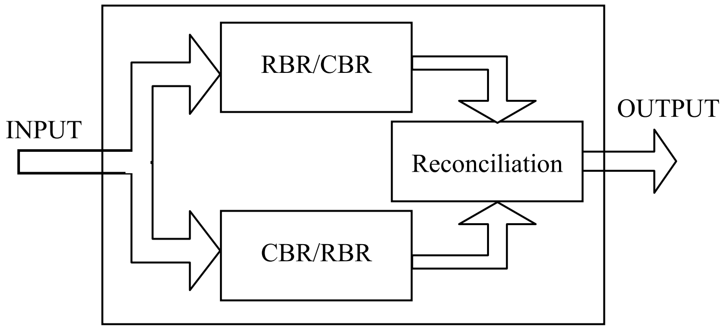

Figure 8. Reconciliation Oriented Model

Example approaches belonging to the *reconciliation oriented* category are ANAPRON (Golding and Rosenbloom 1996), CCAR (Lee 2002), CoRCase (Agre 1995), DANIEL (Bruninghaus 1994), MARS (Dutta and Bonissone 1993) and (Phuong et al. 2001). In ANAPRON, rules index cases, supporting them or contradicting them (exception cases). The indexed cases are used to confirm or disconfirm the solutions of RBR. CCAR handles inference as ANAPRON with the difference that only exception cases (and not cases supporting rules) are stored in the case base in order to improve case searching efficiency. CoRCase can be thought of, more or less, as an extension to the combination approach of ANARPON since different types of indices are employed for the cases according to all the roles they play in rule-based problem solving. DANIEL invokes rule-based and case-based reasoning in parallel and in case of contradicting conclusions evaluates their results using a rule-based coordinator. MARS aggregates evidence from rules and cases through possibilistic reasoning. In (Phuong et al. 2001), a medical system for lung disease diagnosis, the RBR and CBR modules are invoked in parallel and a type of numeric reconciliation is performed: the similarity value of the most relevant case and the conclusion degree of the fired rule are averaged to produce a more accurate and realistic conclusion degree.

The reconciliation oriented co-processing model can be used for systems where the problem solving process can be seen by two complementary and rather independent views. Each view can be implemented by a different approach (RBR or CBR), but the results of the two approaches should be combined in some way to give the final solution.

6.2.3 Embedded Processing

In *embedded processing* approaches, a component based on one representation method is the primary problem solver, embedding one or more components based on the other representation method to handle its internal reasoning tasks (see Fig. 9). This is in contrary to the other coupling categories that represent approaches in which a CBR system as a whole (with its possible internal modules) is integrated 'externally' with a rule-based system in order to create an improved overall system. It should be also mentioned here that, most of CBR systems usually include one or more rule-based components to perform tasks of their CBR cycle. So, this type of hybridism can be considered as quite common in CBR (especially for case adaptation) and thus not of great interest as far as hybridism is concerned. As argued in (Watson 1999), such systems should not be considered as hybrid CBR systems, since a CBR system adheres to a set of principles, but can be implemented using a number of different techniques.

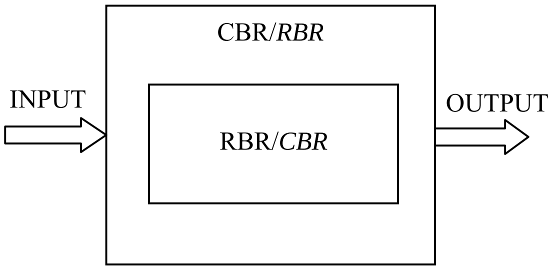

Figure 9. Embedded Processing Model

Existing embedded processing approaches use RBR within the CBR framework, so they can be called approaches that give *pre-eminence to CBR* (see Fig. 2). The 'embedded processing' approach would have been more interesting, as far as hybridism is concerned, if systems following the reverse approach that is, embedding a case-based module into a rule-based system (to assist in tasks such as conflict resolution) had been developed. However, at the moment, such systems seem not to exist. This unexplored direction, if activated, could create approaches that give *pre-eminence to RBR* (indicated by a dashed rectangle in Fig. 2 and italics in Fig. 9).

Given the above view, the 'embedded processing' category has not been further analyzed into any subcategories. However, for completeness reasons, we give in the following a brief overview of the basic aspects of such type of 'internal' integration.

The functions of each task of the CBR cycle require careful consideration in order to create an effective CBR system in terms of time efficiency and accuracy. It is not unusual that CBR systems embed more than one rule-based components to assist the tasks of the CBR cycle. For example, the system in (Chan 2005) uses a rule-based module to assist case retrieval and another one to guide case adaptation. Rules can assist in any task of the CBR cycle; however, they have been usually applied in two tasks: retrieval and adaptation. Indicative roles that rules can play in those tasks are briefly discussed in the following. It should be mentioned that we do not intend to review here all corresponding CBR systems embedding rules (the systems mentioned are only indicative).

Case retrieval includes functions requiring common sense such as situation assessment, exclusion of cases prior to matching, matching and ranking. Rules can be employed for situation assessment as in (Chan 2005), a system used in electroplating industry. In situation assessment, the description of the new problem situation is analyzed to figure out the features that will be considered most important for handling it (Kolodner 1993). Those features will indicate which indices are most important in case retrieval.

Rules can also be used to focus case retrieval on specific parts of the case base and filter all remaining cases. This may depend on characteristics of the specific domain or the case base organization. Such an approach has been employed in (Nilsson 2004), a medical system for the classification of Respiratory Sinus Arrhythmia (RSA). Case classes are clustered into larger groups and a class is not limited to one group. The new case is matched only with cases belonging to classes of the specific cluster determined by RBR.

Rule-based similarity schemes can be used as in (Sebag and Schoenauer 1993) and DIAL (Kinley 2001). In DIAL, rule-based similarity knowledge corresponds to predefined domain-specific criteria. In (Sebag and Schoenauer 1993), a redundant rule set induced from cases derives the similarity measure. Such a rule-based similarity is more flexible than a weight-based similarity because it recognizes the significance of particular combinations of factors rather than considering each feature independently.

It should be mentioned that matching and ranking processes, besides similarity measures, include functions that could require (rule-based) common sense such as finding correspondences between features of the input and stored cases, determining important dimensions, choosing importance criteria and selecting relevant cases according to certain preferences (Kolodner 1993). For instance, in (Lee and Lee 2006) there is a preference in selecting cases requiring the least modification effort, estimated based on the syntactic structure of modification rules (that is, the adaptation effort guides case retrieval).

Case adaptation can be a complex task usually requiring highly domain-dependent knowledge (Kolodner 1993; Mitra and Basak 2005). Substitution and transformation methods are considered knowledge-intensive adaptation methods (Mitra and Basak 2005). Rules constitute a popular type of adaptation knowledge. There can be two types of rule-based adaptation knowledge: abstract (or general) knowledge and domain-specific knowledge. Also in some systems the experience of adaptation can be used to convert the abstract rules to domain-specific rules (Mitra and Basak 2005). A main issue involves the acquisition of adaptation rules. Besides acquiring adaptation rules from experts, methods have been developed to automatically produce adaptation rules from the case base such as in (Hanney and Keane 1997).

Many CBR systems have been developed that employ adaptation rules. An approach differing from the usual ones is DIAL (Kinley 2001). DIAL is a system developed for disaster response planning and effectively deals with issues such as the acquisition and adaptation of case adaptation knowledge. The innovative idea of this system is to acquire adaptation knowledge during its operation in the form of cases. Furthermore, similarity measures are dynamically adapted based on the acquired case-based adaptation knowledge. Multiple cooperating rule-based and case-based components are incorporated into the case-based planner in order to perform the adaptation and similarity tasks. Rule-based adaptation knowledge consists of general abstract rules and rule-based similarity knowledge corresponds to predefined domain-specific criteria. The system tries to perform each task by calling the case-based component falling back on the rule-based component in case of failure. The advantages of the system are the improved inference efficiency and the generation of better plans compared to a conventional case-based system.

Finally, rules could be also used for (offline) tasks, such as case deletion (Khoshgoftaar, Bullard and Gao 2003). Case deletion is an important process as it can improve the time efficiency and the accuracy of a CBR system. In (Khoshgoftaar, Bullard and Gao 2003) rules have been used to improve the accuracy of a CBR classification model by detecting outliers that is, cases having correct attribute values but an incorrect class value.

7. Conclusions

In this paper, we present a new categorization (or classification) scheme for classifying approaches integrating RBR and CBR. This scheme came out of a critical review of three existing categorization schemes: a general one, concerning hybrid intelligent systems integrating various types of problem solving methods, and two specific ones, concerning rule-based and case-based combinations. We focus on approaches of coupling type, which are the vast majority of existing combinations of rules and cases and the most fruitful type of integration. We propose categories and subcategories not included in the two existing schemes. We also present representative integrated approaches for each final category.

The new categorization scheme remedies the shortcomings of the aforementioned categorization schemes and accommodates all existing (and some unexplored) approaches integrating RBR and CBR. It also covers various aspects of combinations such as, degree of coupling between the integrated components, information flow, reasoning mode and reasoning control. Furthermore, it takes into consideration Medsker's categorization scheme which, as already mentioned, although is generally endorsed by hybrid intelligent systems community, it has not been paid attention to by the community working towards integration of CBR with RBR.

So, the usefulness of such a classification scheme is also remarkable. First, it presents a structured representation of various RBR and CBR integrations, which gives a clear understanding and a clear insight of the structure of such integrations. This makes evaluation of such systems much easier. Second, it can serve as a guide for developers of such systems. What they should do is (a) identify different tasks (or stages or views) in the problem solving process of their application, (b) select which of RBR or CBR is appropriate for each task (or stage or view), based on the criteria specified in Section 4, (c) specify the functional relations between those tasks (or stages or views) and (d) find which category matches better their findings. Finally, a third use of the categorization scheme is to identify possible unexplored cases, such as those of 'loosely coupled compulsory sequence', 'embedded processing giving pre-eminence to RBR' and 'tightly coupled conditional sequence' where the CBR component is invoked first.

The above categorization could be also used to classify approaches such as the one presented in (Hatzilygeroudis & Prentzas, 2004). That approach integrates rules, neurocomputing and cases. However, rules and neural networks are fully (or totally) integrated in a seamless way in the form of neurules, a kind of integrated rules. The integration of the two components, RBR and neurocomputing, in neurules makes them indistinguishable between each other. Then, neurules and cases are combined as in coupling approaches. So, that approach can be classified as reconciliation oriented approach.

RBR and CBR are complementary ways of expressing knowledge. Approaches integrating the two formalisms have become popular during the last years. The hybrid approaches have managed to solve problems in application domains where rules and cases are available and the one representation formalism needs the assistance and/or completion of the other to work effectively. This trend is very likely to carry on in the following years. We believe that our scheme will help in it.

In the following years, it is expected that approaches integrating RBR and CBR will be applied to even more application domains. A domain in which the application of rule-based and case-based combinations may produce fruitful results concerns intelligent tutoring. Till now, few Intelligent Tutoring Systems (ITSs) have employed hybrid knowledge representation schemes in general. The combination of RBR and CBR satisfies most of the requirements for knowledge representation in an Intelligent Tutoring System (Hatzilygeroudis and Prentzas 2006). We can mention CARE-PARTNER, which has been extended into an ITS as a teaching assistant (Bichindaritz and Sullivan 2002). Also, in (Bittencourt and Costa, 2006) an ITS that uses a combination of RBR and CBR is presented. Moreover, the Web is a domain of increasing interest and Web-based systems integrating RBR and CBR can exhibit advantages. Such Web-based systems have already been developed (e.g., Bichindaritz, Kansu and Sullivan 1998; Montani and Bellazzi 2002; Rossille, Laurent and Burgun 2005) and it is expected that even more such systems will be developed in the coming years.

Finally, an open issue is to apply and evaluate the combinations of RBR and CBR in different application domains. This will enable a better and thorough assessment of their strengths and weaknesses. Such a process can lead to the development of general-purpose knowledge engineering tools based on the combination of RBR and CBR. General-purpose tools are deemed necessary in knowledge engineering because they facilitate the development of knowledge-based systems.

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