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INTEGRATING MULTI-CASE-BASE-REASONING WITH DISTRIBUTED CASE-BASED REASONING

Surjeet Dalal*

Dr. Vivek Jaglan**

Dr. Kamal Kumar Sharma***

Abstract: *Case-based analogical reasoning is a pedagogical technique that improves problem solving by helping learners identify a common structural principle shared among multiple cases. Identification and transfer of the shared principle facilitates solving novel problems or patient cases. When cueing is coupled with the process, transfer of the structural principle to the problem is enhanced. The case-based reasoning supports lazy learning through exploitation of past problems solution's in solving original complication. In this paper, the multi-case-base reasoning is being integrated with distributed case-based reasoning approach to enhance the performance of the case-based reasoning application. Various retrieval strategies are implemented to find the similar cases from the case base. This model computes performance of the conventional case-based reasoning approach.*

***Key words**: Case-based Reasoning, Distributed Case-based reasoning, Distributed case base, Multi-case-base reasoning.*

*Assistant Professor, Department of Computer Science & Engineering, E-max Institute of Engineering & Technology, Ambala, India

**Assistant Professor, Department of Computer Science & Engineering, Amity School of Engineering & Technology, Amity University, Gurgaon, India

***E-max Institute of Engineering & Technology, Ambala, India

1. INTRODUCTION

Case-based reasoning is one of supplementary estimated problem solving approach used in many decision-taking situations. This approach may determine origin difficulty faced in other approaches etc Knowledge-based system (KBS) as given below:

- knowledge elicitation is a difficult process, often being referred to as the knowledge elicitation bottleneck;
- implementing KBS is a difficult process requiring special skills and often taking many man years;
- once implemented model-based KBS are often slow and are unable to access or manage large volumes of information; and
- Once implemented they are difficult to maintain.

The case-based reasoning finds the solution in prescribed cycle of various phases. It consists following phases as given below:

- **Retrieve phase**: The similar cases are selected from case base regarding new problem.
- **Reuse phase**: The knowledge of selected cases is utilized to build proposed case.
- **Revise phase**: The proposed case is verified if it fulfills all constraints of new problem. If not, then it is modified to fulfill all constraints of the problem.
- **Retain phase:** The modified case is stored in the case base for future use [1].

All the phases of the case-based reasoning is being illustrated in the figure 1 as given below.

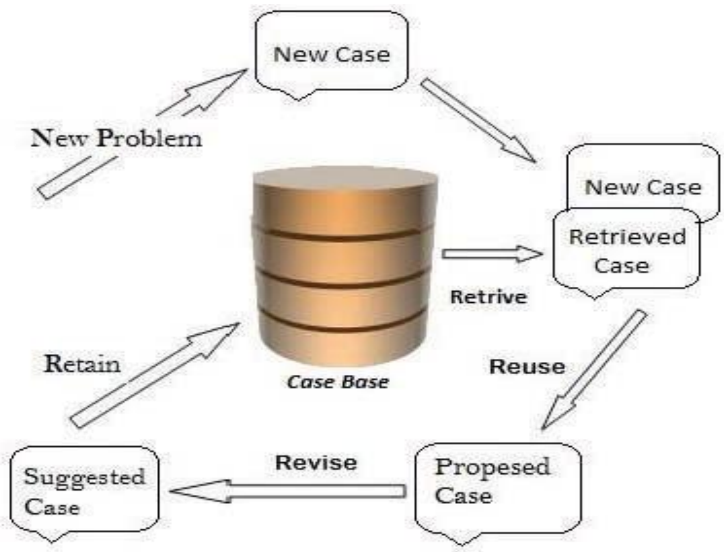

Figure 1: Case-based reasoning cycle (Aamodt and Plaza 1994)

The CBR system primarily builds up experiences, its case library may be diminutive, potentially limiting its performance. If external case-bases previously exist for analogous tasks, drawing on those case-bases may help in conquering the system's preliminary knowledge gaps. Even in a system with a pervasive case library, exterior case-bases may contain dedicated expertise that would be constructive in handling problems outside of the system's normal range of tasks. Unfortunately, it may be difficult to know when to draw on an external case-base and which external case-bases to access. It may also require supplementary endeavor to apply cases from an exterior case-base, due to inter-case-base differences reflecting differences in tasks or execution environments [2].

The predictable CBR systems consists solitary agent involving the sole case base problem solving approach where one, usually well-maintained, case base functions as the central knowledge resource. The major issues faced in the conventional case-based reasoning are described as below:

1. The manner in which knowledge is being organized/managed within the system
2. The mechanism of proceeding knowledge by the system.

Thus, making efficient utilize of the information in numerous case-bases necessitates a reasoning process. Such approach is known as the multi-case-base reasoning. This reasoning approach is oriented on the access of the exterior case-bases and how to affect their cases. The accomplishment of these processes depends on picking the accurate strategies for exacting case-bases and task domains. This paper enlarges the MCBR methods by which the distributed case-based reasoning system can mechanically decide between case-bases and pick constructive cross-case-base adaptation strategies.

2. RELATED WORK

Plaza et al. (1996) examined potential approaches of collaboration among harmonized agents with knowledge capabilities. They focused on agents that gain knowledge of resolving problems using Case-based Reasoning (CBR), and presented two modes of cooperation among them: Distributed Case-based Reasoning (DistCBR) and Collective Case-based Reasoning (ColCBR). They demonstrated these modes with an appliance where dissimilar CBR agents talented to counsel chromatography techniques for protein purification cooperate [3].

Arcos et al. (1999) presented the system for supportive retrieval and composition of a case in which subcases were distributed across different agents in a multi-agent system. From a Gestalt standpoint, a high-quality generally case may not be the one derivative from the summary of best subcases. Each agent's limited view might consequence in best local cases, which when assembled may not effect in the best generally case in terms of global procedures. They suggested a negotiation-driven case retrieval algorithm as a loom to energetically resolving contradiction between dissimilar case pieces during the retrieval procedure [4].

Martin et al. (1999) presented the Auction-based Retrieval ABR approach for distributed case retrieval based on the monetary allegory of auction on agent-based electronic trading. They focused on agent-mediated systems where each agent was intelligent to rationale from a (privately owned) case-base, has own benefit, and nevertheless it was competent to assist with the other to crack new problems. In this situation (called CoopCBR) case retrieval has an added difficulty, namely the coordination of case retrieval processes from numerous case-bases [5].

Prasad et al. (1996) argued the process of viewing corporate memories as distributed case libraries provided the advantage from presented techniques for distributed case-based reasoning for resource discovery and exploitation of previous expertise. We present two techniques developed in the context of multi-agent case-based reasoning for accessing and exploiting past experience from corporate memory resources. The first approach, called Negotiated Retrieval, covenanted with retrieving and assembling case pieces' from different resources in a corporate memory to form a good overall case. The second approach, based on Federated Peer Learning, deled with two modes of cooperation called DistCBR and ColCBR that exploited the experience and expertise of peer agents to accomplish a confined task [6].

3. DISTRIBUTED CASE BASE

The distributed case bases perform rote learning by storing superior cases, where every agent stores its individual limited case in its case base. Each agent could have acquired its individual self-governing problem-solving familiarity by contributing in dissimilar panel of agents. The case base is a foundation of multifarious data stored in standard formats. Any formless database like a text database can also be converted to a case base by generating semantic descriptors characterizing each document in the database. The deposit of databases with inter-related data can be treated as distributed case bases.

In these approaches, all cases are divided into subcases or snippets and a snippet is indexed using both comprehensive objectives and the limited circumstance of that snippet within the case. This kind of complicated engineering in the variety of indexing the case pieces using both comprehensive and limited problem solving contexts may not be practicable for multi-agent CBR systems. The agents may only have an incomplete scrutiny of the comprehensive problem solving perspective and the internal perspective of a case piece. The case pieces are iteratively retrieved and assembled into a case, energetically resolving any inconsistencies that occur during the process through negotiation among the participant agents [7].

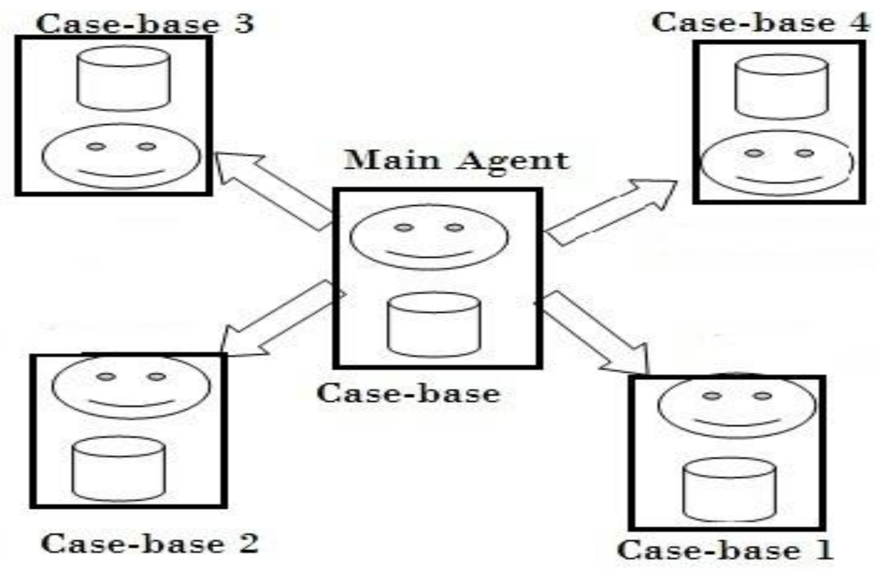

Figure 2: Distributed Case base

In distinction to single-agent CBR systems, multi-agent systems share out the case base itself and various phases of the CBR cycle among numerous agents. The most important premise in multi-agent along with multi-case-base systems is the self-sufficiency of the agents. This type of the configuration consists major factors as given below:

- Potential to conclude whether it is proficient to crack a problem.
- Potential to interrelate with other agents to achieve a comprehensive clarification for a given problem.

Without resolving these factors, the performance of the DCBR system can be not achieved. Distributed CBR strategies can advance both the recital and maintainability of CBR systems. There are two imperative factors that may cause to be this approach inappropriate as given below:

- Privacy refers to the circumstances where cases, owned by dissimilar users may not always be eager to give them to a central case repository.
- The scalability worries the impracticability of processing a central case base when dealing with very large amounts of data [8].

So resolving these factors we are going to integrate the concept of the multi-case-base with the distributed case-based reasoning having the facilities of accessing multiple case bases which can locate at different location. This approach makes the collaboration strategies for case base access at precise time.

4. WHY IS MULTI-CASE-BASE REASONING NEEDED?

The efficient exploit of exterior case-bases requires strategies for the multi-case-base reasoning as given below:

- For making the decision when to *dispatch* problems to an exterior case-base.
- For performing *cross-case-base adaptation* to recompense for differentiation in the tasks and environments that each case-base reflects.

When dissimilar resources cause the different case bases, keeping the case-bases different also facilitates an expected separation of preservation endeavor, with each resource maintaining its individual case-bases, and other users repeatedly benefitting as they repossess their cases from the most recent description of the exterior case-bases. Compared to simply gathering and merging cases from all accessible case-bases, MCBR has three main advantages for this task as given below:

- MCBR selectively adds only those cases required to crack the problems faced by system essentially through keeping the case-base more compacted.
- It avoids enthusiastic merging which gives the flexibility to illustrate on any innovative case-bases that may become obtainable.
- It probably facilitates the system to prefer to use higher-quality cases than would have been imported by enthusiastic merging.

- When cross-case-base adaptation is required, the MCBR introduce cases as needed can perk up solution superiority compared to performing cross-case-base adaptation on all external cases and eagerly merging them.
- Because cross-case-base adaptation may be defective, occasionally solving a problem using a local case for a fewer similar problem will give better results than solving it using a cross-case-base-adapted version of an external case generated for a more similar problem.

The case-dispatching strategies of MCBR acquire their decisions about when to illustrate on external case-bases, but eager merging by simply performing cross-case-base adaptation on all cases and merging the case-bases looses that potential.

5. INTEGRATION OF DCBR WITH MCBR

For applying MCBR approach the system necessitates augmenting normal CBR with methods to make a decision at what time to dispatch problems to exterior case-bases, where to dispatch them, and how to perform cross-case-base adaptation of the returned cases. For this purpose the MCBR approach builds the Knowledge-Light Cross-Case-Base Adaptation Strategies based numerical prediction. This approach consists following two case dispatching strategies as given below:

- The threshold-based dispatching dispatches problems to an exterior case-base if local cases are not presented for satisfactorily related problems. This method can be used to choose whether a problem is processed nearby or dispatched to an exterior case-base. Because concert depends on setting the accurate dispatching threshold for the case-bases and cross-case-base adaptation strategies.
- The case-based dispatching dispatches problems to the case-bases that best solved related problems in the precedent. This strategy can be used to dispatch to an uninformed numeral of case-bases, and because it support its choices on tests using the current case-bases which involuntarily reflects the distinctiveness of the precise case-bases and cross-case-base adaptation strategies.

On the time of receiving the key problem during customary processing, the problem is dispatched to the case-base (local or external) with maximum probable effectiveness. With the help of this approach, multiple CBR agents distribute stuffing of their individual case-bases as required and have considered elemental issues for efficient access of distributed case-bases.

6. CONCLUSION

When external case-bases are accessible to complement local case knowledge, the distributed case base can offer a precious supplementary source particularly during the early on stages of the enlargement of a case-base. The cases from exterior case-bases may not be instantly applicable requiring the cross-case-base adaptation. These cross-case-base adaptation strategies provide the way to judge whether the consequences of applying those strategies will be sufficient. The benefits of MCBR depend stalwartly on the essentials of the problem.

More broadly, a motivating area for future research is the relevance of analogous methods to facilitate traditional CBR systems to adjust themselves by testing which strategies work best for upcoming problems.

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