THE ROLE OF FUZZY LOGIC IN CASE-BASED REASONING: A SURVEY

Nabanita Choudhury

Department of Computer Science, Assam University
Silchar, Assam, India
nabaniitaa@gmail.com

Dr. Shahin Ara Begum

Department of Computer Science, Assam University
Silchar, Assam, India
shahin.ara.begum@aus.ac.in

Abstract

Case-based Reasoning (CBR) is an Artificial Intelligence (AI) paradigm that attempts to solve new problems based on its past experiences of solving similar problems. Due to the intrinsic similarity of CBR with human reasoning process, it is used for automated problem-solving. The effectiveness of CBR can be enhanced by combining it with other AI techniques. One such approach is the inclusion of fuzzy logic in CBR. This paper surveys the application of fuzzy logic in each of the four phases of CBR. We also present a brief overview on some of the fuzzy-CBR systems developed for a wide range of real world applications.

***Keywords*:** case-based reasoning; artificial intelligence; fuzzy logic; fuzzy-CBR.

1. Introduction

Case-based Reasoning (CBR henceforth) is an Artificial Intelligence (AI) methodology for solving problems by utilizing previous experiences. It works by retaining a memory of previous problems and their solutions, and solving new problems by referencing these [1]. The computational model of CBR methodology is very close to human reasoning, which makes CBR intuitive and easy to understand [2]. When solving problems people draw on past experiences and can readily solve problems that are similar to ones that they have encountered earlier. This leads to the fact that CBR can be based on shallow knowledge, thus requiring lesser knowledge engineering [3] than alternative AI techniques like Rule-based Reasoning. Case-bases in CBR can be developed without passing through the knowledge-acquisition bottleneck, as prevalent in Rule-based Reasoning.

As an effective problem-solving methodology, CBR needs to deal with some degree of fuzziness and uncertainty which are almost always encountered while dealing with complex real-world applications. But the core CBR methods are not powerful enough to address these. As a result, there has been an upsurge in the integration of CBR with other paradigms [4]. One such integration is that of fuzzy logic with CBR. Fuzzy set theory introduced by Zadeh in the year 1965 [5] provides an effective and flexible way of representing, manipulating, and utilizing data and information that are defined in a vague manner [6]. The fundamental similarity between CBR and fuzzy sets further suggests the use of the latter in CBR [7].

This paper surveys the role of fuzzy sets and fuzzy logic in the various phases of CBR, and how the performance is enhanced when CBR systems are hybridized with fuzzy concepts. Section 2 briefly describes the basic notions of CBR. This is followed in Section 3 by a description of how fuzzy sets and fuzzy logic are implemented in the phases of CBR. Section 4 lists some successful fuzzy-CBR systems in a wide range of application domain. Section 5 concludes the paper with a discussion on future directions of research.

2. Case-based Reasoning

2.1. *History of CBR*

The roots of CBR spread across various disciplines like cognitive science, machine learning, and knowledge-based systems. The cognitive science concepts *viz.* experience, memory, and analogy have had major influences on early CBR research [8]. Roger Schank's work on dynamic memory and situation patterns (scripts and mops) [9] was the earliest contribution in the development of CBR, where much inspiration came from the human reasoning approach. J. L. Kolodner's CYRUS [10] can be referred to as the first CBR system, which was based on Schank's dynamic memory model. Three CBR workshops in 1988, 1989, and 1991 organized by U.S. Defense Advanced Research Projects Agency (DARPA) officially marked the birth of the discipline of CBR, prior to which CBR research was regarded as a high-level model for cognitive processing.

2.2. *CBR Life Cycle*

The life cycle of CBR consists of four stages, commonly known as four R's, *viz.* Retrieve, Reuse, Revise, and Retain [11]. This cycle, depicted in Fig. 1 is also termed as R^4 cycle.

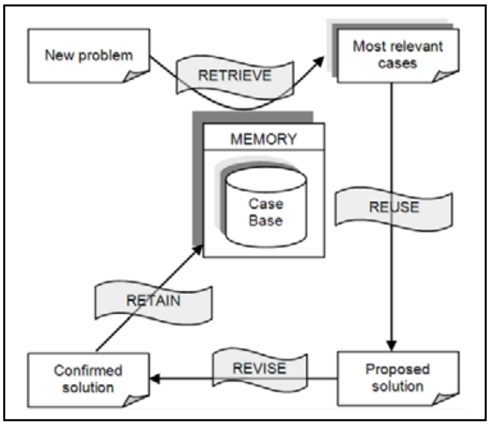

Fig. 1. CBR Life Cycle [11].

2.2.1 *Retrieval*

When the CBR system encounters a new problem, it carries out a search for the most similar case(s) in the case-base, and the most relevant case(s) is/are retrieved. To carry out effective case retrieval, there must be a selection criterion that determines how a case is chosen to be suitable for retrieval and a mechanism to control the searching of case-base. The most commonly investigated retrieval techniques include nearest neighbor retrieval, inductive approaches, knowledge guided approaches, and validated retrieval [12], [13]. CBR systems typically rely on similarity-based retrieval (SBR) that exploits similarity knowledge. In SBR, similarity knowledge approximates the usefulness of cases for solving a new problem [14]. But its limitation is that it tends to rely strongly on similarity knowledge only, ignoring other available knowledge that can be additionally provided for improving its retrieval performance [15]. In addition, SBR approaches do not suffice when the cases are very close [16].

Some alternatives [17] to SBR are Adaptation guided retrieval [15], Diversity conscious retrieval [18]-[20], Compromise-driven retrieval [21], Order based retrieval [22], and Explanation oriented retrieval [23], [24]. The cost of each decision can be taken into account while retrieving new cases from a case-base by using the concept of benefit of each solution. This leads to better results in terms of sensitivity [25]. The case-base in a CBR system needs to store many cases to meet the user's need for knowledge. However, with the growth in the number of cases in case-base, the retrieval mechanism gets slower thereby lowering the efficiency. This phenomenon is known as the swamp phenomenon [26]. To get rid of this, faster non-sequencing indexing algorithms can be applied [27].

2.2.2 *Adaptation*

The next two phases called reuse and revise are often combined into a single phase called adaptation in most of the practical implementations of CBR. Case adaptation involves transformation of a retrieved solution into a solution appropriate for the current problem. After a solution is retrieved and revised, what is changed in the retrieved solution and how this change has been achieved are the two aspects of classifying various adaptation methods [17], [28]. Adaptation is used in cases where the previous solutions cannot always be directly applied. However, acquiring the adaptation knowledge and successfully applying this knowledge is a great challenge [29]. The case that is retrieved for reuse should be the easiest one to be adapted, so the retrieval should be directed by adaptation. This method, known as adaptation-guided retrieval, makes use of information about the adaptability of case features rather than the similarity of these features [30].

In poorly understood domains, or those which are difficult to codify, developing adaptation rules is particularly difficult. One such domain is that of medical diagnosis. The problem is so acute that experts argue that it may not be always practical to deploy CBR applications with automatic adaptation. Consequently, new methods are needed for acquiring case adaptation knowledge [31], [32].

2.2.3 *Maintenance*

The final confirmed solution is retained in the case-base. But merely storing the cases in the case-base leads to an uncontrolled growth of the case-base. So, a case-base needs to be maintained. As defined by Leake & Wilson [33], case-base maintenance 'implements policies for revising the organization or contents (representation, domain content, accounting information, or implementation) of the case-base in order to facilitate future reasoning for a particular set of performance objectives'.

There have been various attempts in the past to address various aspects of case-base maintenance. Smyth [34] for instance, suggests deletion of 'harmful' cases, and the suggested model at the same time ensures that both competence and efficiency are preserved. Smyth and Keane suggest a deletion strategy that takes competence and performance into consideration [35]. Rather than focusing on case deletion, Zhu and Yang focus on case addition. They describe an algorithm that has the additional advantage of providing a guaranteed lower bound on the resulting competence [36]. Wilson & Leake [33], [37] develop a framework for categorizing case-base maintenance policies in terms of how they collect data when maintenance operations are triggered, the types of maintenance operations available, and how are these executed. Yang & Wu [38] use clustering so that the case-base is maintained without using sophisticated structures and the method is kept transparent. Here the cases are grouped in such a way that cases in the same cluster are more similar than cases in other clusters. These clusters are then converted to new smaller sized case-bases.

Adaptation can also be involved in maintenance, as proposed by Leake & Wilson [39]. They add adaptation rules as a 'lazy' strategy for updating the case-base as future cases are retrieved. The adaptive CBR model developed by Salamo & Lopez-Sanchez [40] maintains the case-base by using a measure of 'case goodness' in various retention and forgetting strategies, which in turn improves the classification accuracy, efficiency, and the size of case-base. Maintenance strategies can be used for case acquisition as well. Ferrario & Smyth [41] describe a maintenance framework, which they call collaborative maintenance. It uses interactive processes where users recommend case updates.

3. Fuzzy Logic in Case-based Reasoning

As prevalent in the ongoing discussion, there is a substantial uncertainty and incompleteness that pervades all the phases of the CBR process. This happens due to the usage of abstract features for indexing, evaluation of the similarity measures computed across these features, and the like [42]. This suggests the need of combining CBR with a methodology which can deal with uncertainty. Fuzzy logic is one such technique because in general, fuzzy logic deals with imprecision and uncertainty in a nearly appropriate manner [43]. In terms of fuzzy relations denoted by S and T, CBR principle can be expressed as – 'The more similar are the problem description attributes in the sense of S, the more similar are the outcome attributes in the sense of T' [44].

3.1. *Fuzzy Case Representation, Indexing, and Retrieval*

A case, which denotes a problem situation in CBR, can itself be fuzzified, where some of the attribute-values are of fuzzy character [2]. The features prevalent in a case could also be fuzzified into fuzzy linguistic terms and fuzzy numbers [12]. The case-base can also be considered as a fuzzy set as the usefulness of the cases in the case-base is a matter of degree. Assigning indexes to cases for future retrieval and comparison is known as case indexing. Proper indexing leads to the retrieval of correct case, where retrieval involves the process of finding cases in the case-base that are most similar to the current case. Cases can be indexed using fuzzy sets.

Using fuzzy logic has a number of advantages [45] in the indexing and retrieval phases of CBR, which are as follows:

- Conversion of numerical features to fuzzy terms to simplify comparison.
- Multiple indexing of a case on a single feature with varying degrees of membership.

- Easier transfer of knowledge across domains.
- Use of term modifiers to increase flexibility in retrieval.

Fuzzy logic is particularly useful in domains with cases having quantitative attributes [1]. Case indices defined with fuzzy sets provide an interval for matching; and at the same time provides for higher level abstraction of symbolic information from surface features [46]. Fuzzy retrieval can also be implemented through fuzzy integrals, and was first discussed in [47] and then extended in [48]. The use of fuzzy sets in case representation allows flexible encoding of case characteristics as fuzzy numbers and fuzzy objects [49]. During the retrieval phase, cases most similar to the input query are selected from the case-base. So, fuzzy similarity of a case can be calculated using a fuzzy membership function for each feature [50], [51].

Cases when partitioned into several clusters often lead to easier and faster matching and retrieval of cases from a case-base, as compared to searching the entire case-base when no clustering is used. This can be done with fuzzy classification and clustering algorithms [6]. CBR when combined with fuzzy decision trees can be successfully used to classify large databases [52].

3.2 *Fuzzy Adaptation and Maintenance*

Case adaptation involves transforming a retrieved solution into a solution appropriate for the current problem. It consists of finding out the difference between the case retrieved, and the query case, and modifying the existing solution(s) if required. A set of fuzzy adaptation rules can be generated using fuzzy decision trees for adaptation knowledge [53], [54]. For maintenance tasks, fuzzy rules can be used for reducing the number of cases and for determining the competency of case-base [33]. An approach to minimize the size of case-base is by rough feature weighting and selection method applied as a preprocessing step for the generation of fuzzy rule base in the revision phase of a CBR system [55], [56]. Larger case-bases can be transformed into smaller ones by the use of adaptation rules generated by hybridizing rough sets with fuzzy sets in a distributed CBR system [57]. With the use of fuzzy logic into CBR, case-based decision making [58] and elicitation [59] also improves.

4. Fuzzy Case-based Reasoning Systems

The use of fuzzy logic in CBR systems dates back to 1990’s [43]. Since then, many hybrid fuzzy-CBR systems have been developed, in order to solve a wide range of real world problems. Table 1 lists some of these systems in chronological order.

Table 1. Fuzzy CBR Systems

Sl. No	Systems/Author(s)	Area of Application	Year	Reference
1	ARC	Case-based apprentice	1990	[49]
2	BOLERO	Medical diagnosis	1993	[60]
3	CAREFUL	CBR assistant	1994	[61]
4	Lee et al.	Cash flow analysis	1995	[47]
5	PROFIT	Real estate transactions	1998	[62]
6	Hansen & Riordan	Operational meteorology	1998	[63]
7	HCBS	Medical diagnosis	1998	[64], [65]
8	Phuong et al.	Medical diagnosis (Lung disease)	2001	[66], [67]
9	Hansen & Riordan	Weather prediction	2001	[68]
10	Riordan & Hansen	Weather prediction	2002	[69]
11	Tsaganou et al.	Historical text comprehension	2003	[70]
12	Fdez-Riverola & Corchado	Weather forecasting (Red tides)	2003	[71]
13	Kwiatowska & Atkins	Medical diagnosis (Obstructive sleep apnea)	2004	[72]
14	SADEX	Fault diagnosis	2004	[73]
15	SoLIM	Soil mapping	2004	[74]
16	Georgopoulos & Stylios	Language impairments diagnosis	2005	[75], [76]
17	KASIMIR	Classification and medical diagnosis (Breast cancer)	2006	[77]
18	geneCBR	Classification and medical diagnosis (Cancer)	2006	[78]
19	Marques et al.	Fault diagnosis	2007	[79]
20	Ahmed et al.	Medical diagnosis (Stress)	2008	[80]
21	Pulkkinen et al.	Quality management (GPRS)	2008	[81]
22	Wu et al.	Product ideas	2008	[82]
23	Begum et al.	Medical diagnosis (Stress)	2009	[83]
24	Cheng et al.	Construction disputes	2009	[84]

Table 1. Fuzzy CBR Systems (Contd.)

Sl. No	Systems/Author(s)	Area of Application	Year	Reference
25	Khanum et al.	Facial expression recognition	2009	[85]
26	Jagannathan et al.	Planning (Brain cancer radiotherapy)	2010	[86]
27	Ahmed et al.	Planning (Stress)	2011	[87]
28	Cadena & Garrido	Strategic and tactical management	2011	[88]
29	Douali et al.	Medical diagnosis (Urinary tract infection)	2011	[89]
30	Ahmed et al.	Medical diagnosis (Stress)	2012	[90]
31	Khelassi & Chikh	Medical diagnosis (Cardiac arrhythmia)	2012	[91]
32	Ahmed et al.	Diagnosis, classification and planning	2012	[92]
33	Begum et al.	Classification (Physiological sensor signals)	2012	[93]
34	Chen et al.	Document tracing	2013	[94]
35	Abdul et al.	Database workload management	2014	[95]
36	Huang et al.	Emergency Management	2014	[96]
37	Zuo et al.	Reinforced Concrete Structures Accident Prevention	2014	[97]
38	Akumu et al.	Soil texture modelling	2015	[98]
39	Noori	Marketing mix planning	2015	[99]
40	Sui et al.	Machining database	2016	[100]
41	Wei & Dai	Traffic emission	2016	[101]

5. Conclusions and Future Scope

A fundamental part of the CBR methodology is learning by remembering previous experiences. Unlike other expert systems, CBR systems can start with a shallow knowledge base and incrementally acquire the knowledge automatically, but the core CBR methods are not powerful enough to address complex real world situations, which suggests hybridization of CBR with other methods. One such integration leads to fuzzy-CBR systems.

In the present paper, the role of fuzzy sets and fuzzy logic in the various phases of CBR have been studied, and fuzzy CBR systems which are applied successfully over a wide domain ranging from medical diagnosis to soil mapping are explored. From its very origin, CBR has aimed to model the human cognition process. Our study shows that the integration of fuzzy logic in CBR results in successful hybrid systems, which are robust and more tolerant of noise. One of the challenges of automated CBR systems is the adaptation phase. Most of the CBR systems focus on retrieval, and adaptation is normally done by the human expert. The inclusion of fuzzy logic in the adaptation phase could result in automatic adaptation, making CBR systems solve problems more precisely and resemble the human decision making process more closely.

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