Multi-modal and multi-purpose case-based reasoning in the health sciences

MOBYEN UDDIN AHMED, SHAHINA BEGUM, PETER FUNK, NING XIONG
School of Innovation, Design and Engineering,
Mälardalen University
PO Box 883 SE-721 23, Västerås, Sweden
SWEDEN
{firstname.lastname}@mdh.se

Abstract: - Case-based reasoning systems for medical application are increasingly multi-purpose systems and also multi-modal, using a variety of different methods and techniques to meet the challenges from the medical domain. In this paper, some of the recent medical case-based reasoning systems are classified according to their functionality and development properties. It shows how a particular multi-purpose and multi-modal case-based reasoning system solves these challenges. For this a medical case-based reasoning system in the domain of psychophysiology is used.

Key-Words: - Case-based reasoning, Health science, Multi-modal, Multi-purpose, Fuzzy logic, Diagnosis, Classification and Treatment.

1 Introduction

Case-based reasoning (CBR) is inspired by the way humans reasoning e.g. solve a new problem by applying previous experiences adapted to the current situation. An experience (a case) normally contains a problem, a diagnosis/classification, a solution and its results. For a new problem case, a CBR system matches the problem part of the case against cases in the so called case library and retrieves the solutions of the most similar cases that are suggested as solution after adapting it to the current situation.

The origin of the CBR stems from the work of Schank and Abelson in 1977 [33] at Yale University. According to Schank [34], "remembering is at the root of how we understand... at the root of how we learn." CYRUS [21] is the first CBR system developed by Janet Colodner. She employed knowledge as cases and use an indexed memory structure. Many of the early CBR systems such as CASEY [22] and MEDIATOR [35] have implementations based on CYRUS. The early work exploiting CBR in the medical domain are by Konton[22], and Braeiss[6] in the late 1980's.

The clinical domain is a suitable and challenging application domain for CBR. Clinicians often explain that they reason in terms of similar cases and adapt them to the current situation. A clinician may start his/her practice with some initial past experience (own or learned solved cases), then try to utilize this past experience to solve a new problem and simultaneously increases his/her experience. One main reason that CBR is seen as suitability for the medical domain is its adequate cognitive model and cases may be extracted from the patient's records [18]. The advantages of CBR in medical domain have been identified and explored in several research works i.e. in [18, 9, 26].

Medical applications offer a number of challenges for CBR researchers and drive research advances. Important research issues are:

- Feature extraction- desire to let medical CBR systems handle increasingly complex data format, such as image, sensor signals etc.
- Limited number of available cases- in the initial phase of a medical CBR system there are often a limited number of cases available which. This may reduces the performance of the system. If past cases are missing or very sparse in some areas the accuracy is reduced.
- Adaptation- medical domains are often complex, knowledge and recommendation change in medical knowledge; cases often have large number of features; risk analysis for an automatic adaptation strategy [26].

In section 3 we discussed how some of these challenges are overcome in recent research and give examples on how the medical CBR system Integrated Personal Health Optimizing System (IPOS)[1] project [7, 2, 3] overcomes some of these challenges.

CBR is applied in a wide variety of medical scenarios and tasks such as diagnosis, classification, tutoring, treatment planning, as well as knowledge acquisition and management. Also hybrid CBR systems are frequent where CBR on combined with other AI methods and techniques such as rule-based reasoning, data mining, fuzzy logic, as well as probabilistic and statistical computing. This enables the adoption of CBR for solving problems previously to complex to solve with one single method. An example of a multi-purpose and multi-modal case-based reasoning system is given in section 3. In section 2 we show list some recent CBR systems, their purpose and what methods and techniques they use. In section 2 it is also shown that case-based

[1] http://www.mdh.se/ide/iss/index.php?choice=projects&id=0081

reasoning for health science today is both a recognized and well established method and the domain offers researchers in the CBR community worthy challenges driving the research area of CBR forward.

1.1 Case-based Reasoning Cycle

Aamodt and Plaza has introduced a life cycle of CBR [1] which is a four-step model with four RE-s, as shown in Fig 1. Retrieve, Reuse, Revise and Retain present key tasks to implement such kind of cognitive model.

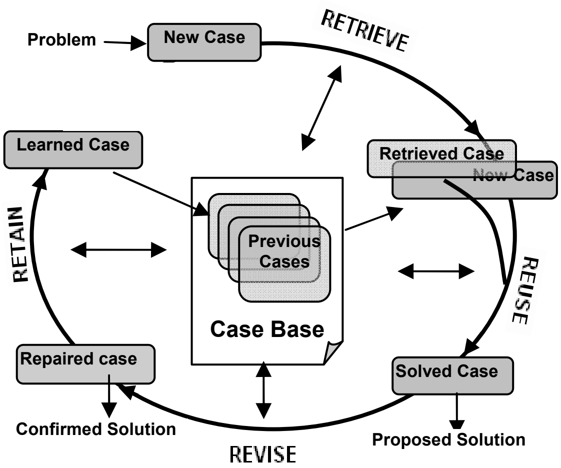

Fig 1. CBR cycle. The figure is introduced by Aamodt and Plaza [1]

In the retrieve step, the system tries to retrieve the most similar case(s) by matching previous cases from a case base. If it finds any suitable case that is close to a current problem then the solution is reused (after some adaptation and revision, if necessary). A clinician may revise the selected case with solution and retain this solution along with the new problem into the case base. In many medical CBR systems feature extraction is a relative large issue due to complexity of the data. In medical CBR systems, the use of complete CBR cycle is still rare.

This paper contains a result of the investigation of CBR in medical domains between 2004 and 2008 focusing the recent trends in systems and systems development. As an example, we will show a recent medical CBR system that combined other AI techniques to assist multi-purpose in making decision in the psychophysiological domain.

The rest of the paper is organized as follows. In the next section 'Medical CBR systems' a number of medical CBR systems' recent development followed by analysis of properties and functionalities of such systems are outlined. The section 'IPOS: a CBR system in the psychophysiology' gives a description of a system in making decision in the psycho-physiological domain.

2 Medical CBR systems

Due to the area's fast and successful development and progress there is a need to identify the trends in developing CBR systems for health science. The systems are investigated in terms of the systems properties divided into two parts: purpose-oriented properties and construction-oriented properties [28]. Purpose-oriented properties categorized the system properties into diagnosis, classification, tutoring, planning and Knowledge acquisition/management. Construction-oriented properties such as, hybridity, adaptivity, size of case-library etc. are also investigated to see the recent trends in medical CBR systems. For details about the system properties see [28]. As in some systems/projects these properties are not possible to derive from the literature review so along with the literature review the authors were asked to answer a questionnaire about the system properties by e-mail.

2.1 Overall trends

Table 1 presents CBR systems with their purpose-oriented properties and application domain. According to table 1, the majority of the recent CBR systems address more than one purpose-oriented category. In 2004, only 2 of the evaluated systems were multipurpose- systems while today most of the systems have two or more purposes [28]. Note that, Nilsson et al. [28] investigated 15 CBR systems yet did not explicitly mention overlapping among their purpose-oriented properties. So the systems today are not only concentrating on the diagnostics and treatment tasks as the early CBR systems. Recent CBR systems tend to support in other complex tasks in the health care domain. In particular, we can observe the use of CBR systems in Knowledge acquisition/management has attained increasing attention in recent years. Also planning in the medical domain offers interesting challenges to case-based reasoning researcher and/or being an application where the CBR methodology may offer valuable progress and commercial applications.

Systems and their construction-oriented properties are summarized in table 2. One of the identifiable achievements made in the medical CBR systems is that almost all have implemented their systems in a form of prototype. Only a few medical systems i.e. Perner [30] and Corchado et al. [13] showed successful commercialization of their systems. Several other projects which still are in the research phase, aim at commercial systems in future. Many of the systems have been successfully evaluated in a clinical environment. But day-to-day use in clinical setting is not common.

No	References	Purpose-oriented properties	Application domain/context
1	De Paz et al. 2008[16]	Diagnosis & classification	Cancer diagnosis
2	Perner et al. 2006[30], Perner and Bühring 2004[31]	Classification, Knowledge acquisition/ management	Object recognition
3	Cordier et al. 2007[14]	Diagnosis, Knowledge acquisition/ management	Oncology
4	Corchado, Bajo, and Abraham 2008[13]	Planning, Knowledge acquisition/ management	Alzheimer patients
5	Glez-Peña et al. 2008[19]	Diagnosis & classification	Cancer classification
6	Plata et al. 2008[32];	Classification, Knowledge acquisition/ management	Image classifier
7	Begum et al. 2008[7]	Diagnosis, classification and planning	Stress diagnosis
8	D'Aquin, Lieber, and Napoli 2006[15]	Diagnosis, classification, Knowledge acquisition/ management	Breast cancer
9	Bichindaritz 2006a[10]	Diagnosis, planning , tutoring, Knowledge acquisition/ management	Biology & medicine
10	Montani et al. 2006[27];	Classification, planning, Knowledge acquisition/ management	Hemodialysis
11	Kwiatkowska and Atkins 2004[23]	Diagnosis, planning and tutoring	Obstructive sleep apnea
12	Lorenzi, Abel, and Ricci 2004[24]	Diagnosis	Fraud detection in health care
13	Ochoa et al. 2008[29]	Diagnosis, planning & Tutoring	Tourette syndrome
14	Doyle, Cunningham, and Walsh 2006 [17]	Classification and tutoring	Bronchiolitis
15	Marling, Shubrook, and Schwartz 2008[25]	Planning	Diabetes
16	Song, Petrovic, and Sundar2007[36]	Planning	Prostate cancer
17	Zhuang et al. 2007[37]	Classification, tutoring & Knowledge acquisition/ management	Pathology ordering
18	Ahn and Kim 2009[5]	Diagnosis	Breast Cancer Diagnosis
19	Huang et al. 2007[20]	Diagnosis, Knowledge acquisition/ management	Chronic diseases diagnosis

Table 1: CBR systems with their purpose and application domain/context.

Adaptation is often a challenging issue in the medical domain. Nevertheless, the survey shows that a number of recent medical CBR systems [10,12,15,19] adapt and explore different automatic and semi-automatic adaptation strategies.

From table 2 it can be seen that several other techniques are integrated into the CBR systems such as-Hypothetico-deductive reasoning (HDR), Rule-based reasoning (RBR), Knowledge management (KM) technique, Neural network (NN), Data mining etc. Indeed few systems depend only on CBR today; almost all medical CBR systems are combined more than one method and technique. In fact, the multi-faced and complex nature of the medical domain leads to designing such multi-modal systems [26,28]. Integration of CBR and RBR was common in past CBR systems such as in CASEY [22], FLORENCE [11]. Recent trends in hybrid CBR systems today are data mining, fuzzy logic and statistics.

No	No of cases	Prototype	Adaptability	Commercialization	Clinical use	CBR and other techniques
1	212	Yes	Yes	No	Clinician evaluation	NN and Statistics
2	400	Yes	No	Planned	Clinician evaluation	Image processing
3	10	Yes	Yes	No	No	CBR
4	4000	Yes	Yes	Yes	Day-to-day use	Variational calculus
5	43	Yes	No	No	Clinical evaluation	RBR & Fuzzy logic
6	300	Yes	No	Yes	Day-to-day, clinical evaluation	Image processing & data mining
7	39	Yes	No	Planned	Clinical evaluation	Fuzzy Logic, RBR, TCBR
8	100	Some extent	Yes	No	Clinical evaluation	Semantic web, belief revision theory, fuzzy logic & ergonomy
9	122	Yes	Yes	No	Planned	RBR, Data mining & Statistic
10	1476	No	Yes	Planned	Planned	Temporal abstractions
11	37	Some extent	No	No	No	Fuzzy logic
12	70	Yes	No	No	No	CBR
13	100	Yes	Some Extent	Planned	Clinical evaluation	Data mining
14	40	Yes	Some Extent	No	Clinical evaluation	RBR
15	50	Yes	Planned	Planned	Planned	
16	72	Some extent	Yes	Planned	In progress	RBR
17	1548122	Some extent	Some Extent	No	Planned	Fuzzy logic, Dempster-Shafer theory & Simulated annealing
18	569	Some extent	Some Extent	No	No	Data mining and clustering
19	15751	Yes	Yes	No	No	genetic algorithms

Table 2: Construction-oriented properties, number of each CBR systems corresponds to table 1.

3 IPOS: a CBR system in the psychophysiology

In the medical domain, diagnostic, classification and treatment are the main tasks for a physician. The multi-faced and complex nature of the medical domain such as the psychophysiological domain often requires the development of a system applying several artificial intelligence techniques such as CBR, textual CBR, RBR, and fuzzy logic and so on. The construction of multi-purposed and multi-modal medical systems is becoming a hot topic in current applied CBR research. The research efforts in this direction can be well demonstrated by the IPOS. The aim of the IPOS project is to develop tool based methods reducing stress to levels that are safe in the long term and thus improving health of an individual. Fig. 2 presents the steps to develop a hybrid multi-purpose CBR system to support in diagnosis and treatment of stress-related disorder based on finger temperature measurements.

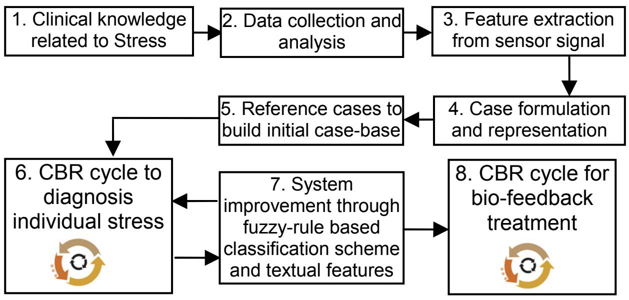

Fig 2. Schematic diagram of developing the CBR system

Step 1: The signal employed in IPOS is FT which is showed in clinical studies to generally decrease with stress, help to determine stress-related disorder. But, interpreting a particular FT measurement and diagnosing stress level is difficult even for experts in the domain due to the large individual variations and absence of general rules.

Step 2: The FT measurement is taken using a temperature sensor in six steps (i.e. Baseline, Deep-breath, Verbal-stress, Relax with positive thinking, Math-stress and Relax) in the calibration phase [8]. In this phase a number of individual parameters are identified to establish an individual stress profile.

Step 3: One of the challenges of the many CBR systems today is extracting features from the complex data format. In our IPOS project to identify key features the system uses 15 minutes FT measurements (time, temperature) in 1800 samples, together with other numeric (age, room-temperature, hours since meal, etc) and symbolic (gender, food and drink taken, sleep at night, etc) parameters. The derivative of each step of FT measurement (from calibration phase) is used to introduce "degree of changes" as a indication of the finger temperature changes. A low angle value, e.g. zero or close to zero indicates no change or stable in finger temperature. A high positive angle value indicates rising FT, while a negative angle, e.g. -20° indicates falling FT[[7]. Total signal from step2 to step6 is divided into 12 parts with one minute time interval and 12 features (i.e. *Step2_Part1*, *Step2_Part2*, *Step3_Part1*, ………, *Step6_Part1*, *Step6_Part2*) are extracted. Five other features *start temperature* and *end temperature* from step2 to step6, *minimum temperature* of step3 and step5, *maximum temperature* of step4 and step6, and *difference between ceiling and floor* are also been extracted from the sensor signal. Finally, 17 (12+5) features are extracted automatically from the fifteen minutes (1800 samples) FT measurements signal data.

Step 4: A new problem case is formulated with 19 features as a total keeping in a vector above 12 features and adding *hours since last meal and gender*. The problem description part of a case contains a vector of the extracted features from the FT measurements and the solution part provides a level of stress. The level of stress has been denotes as Very Relaxed, Relaxed, Normal/Stable, Stressed and Very Stressed by the expert of the domain.

Step 5: The case base is initialized with 39 reference cases from 24 patients classified by the domain expert. Seven woman and 17 men with the age range of 24 to 51 are participated in this study.

Step 6: To diagnosis individual stress level new FT measurement (formulated as a problem case) is put forward into the CBR cycle. The new problem case is then matched using different matching algorithms including modified distance function; similarity matrix and fuzzy similarity match [7]. The system can provide matching outcome in a sorted list of best matching cases according to their similarity values in three circumstances: when a new problem case is matched with all the solved cases in a case base (between subject and class), within a class where the class information is provided by the user and also within a subject [7].

Step 7: The cases stored in the case library should be both representative and comprehensive to cover a wide spectrum of possible situations. The composition of the case library is one of the key factors that decide the ultimate performance of a CBR system. As presented above, in the initial condition this CBR system has a limited number of cases available (only 39 cases) which reduces the performance of the system. Therefore Ahmed et al presents a fuzzy rule-based classification scheme which is introduced into the CBR system to initiate the case library, providing improved performance in the stress diagnosis task. [2] Moreover, clinicians are also considering other factors such as patients feelings, behaviours, social facts, working environments, lifestyle and so on in diagnosing individual stress levels. Such information can be presented by a patient using natural text format and visual analogue scale. Textual data of patients captures important indication not contained in measurements and also provides useful supplementary information. Therefore system added textual features in the case vector which helps to better interpret and understand sensor readings and transferring valuable experience between clinicians [4].

Step 8: Last step in fig 2 focused on CBR system in bio-feedback treatment. A three phase CBR framework is deployed to classify a patient, estimate initial parameters and to make recommendations for biofeedback training by retrieving and comparing with previous similar cases in terms of features extracted [3].

The intention of the system is to enable a patient to train himself/herself without particular supervision.

The framework of the system has been implemented and primarily validated in a prototypical system [7,3,2]. Until now the prototypal system is clinically used for the clinical evaluation. The system has no option for automatic adaptation today this is functioned manually by the clinician but our plan to include adaptability into the system. Ongoing research is looking at automatic adaptation for IPOS. Although the system is still in the research phase it aims at day-to-day use.

4 Conclusion

Case-based reasoning has been demonstrated a powerful methodology widely applied in medical scenarios for decision support. This paper makes an in-depth study of the issues and challenges of applied CBR researches in medical domains. We outlined the recent CBR systems in terms of not only their functionality but also the various key techniques that support such systems. In particular we point out that a current hot trend in CBR applications is to build multi-modal and multi-purpose CBR systems to tackle the high complexity in medical domains. The features of such multi-purpose and multi-modal CBR systems is exemplified by the demonstration of the IPOS (Integrated Personal Health Optimizing System) project, which represents on-going research efforts carried out by the authors.

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