Case-Based Reasoning Systems in the Health Sciences: A Survey of Recent Trends and Developments

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***Abstract*—The health sciences are, nowadays, one of the major application areas for case-based reasoning (CBR). The paper presents a survey of recent medical CBR systems based on a literature review and an e-mail questionnaire sent to the corresponding authors of the papers where these systems are presented. Some clear trends have been identified, such as multipurpose systems: more than half of the current medical CBR systems address more than one task. Research on CBR in the area is growing, but most of the systems are still prototypes and not available in the market as commercial products. However, many of the projects/systems are intended to be commercialized.**

***Index Terms*—Case-based reasoning (CBR), construction-oriented properties, medical system, purpose-oriented properties, survey.**

I. Introduction

CASE-BASED reasoning (CBR) is today both a recognized and well-established method for the health sciences. The health science domain offers the CBR community worthy challenges and is driving CBR research forward by offering a variety of complex tasks, which are difficult to solve with other methods and approaches.

The origin of CBR can be traced to Yale University and the work of Schank and Abelson in 1977 [54]. Early work exploiting CBR in the medical domain was performed by Koton [56] and Bareiss [57] in the late 1980s. The CBR is inspired by human reasoning, i.e., solving a new problem by applying previous experiences adapted to the current situation. A case (an episodic experience) normally contains a problem, a solution, and its result. The CBR is an appropriate method to explore in a medical context where symptoms represent the problem, and diagnosis and treatment represent the solution. Aamodt and Plaza [1] have outlined a life cycle of CBR with four main steps (retrieve, reuse, revise, and retain), as shown in Fig. 1.

In the retrieval step, a new problem is matched against the previous cases in the case library. Domain knowledge is used to determine how similar a case is to a previous one, and the degree of similarity leads to an estimate of how suitable the previous solution is for the current problem. The most relevant solutions are proposed to solve the current problem (after some adaptations if necessary). The selected solution is revised before it is reused. Then, the new problem and its solution are retained in the case library for future use.

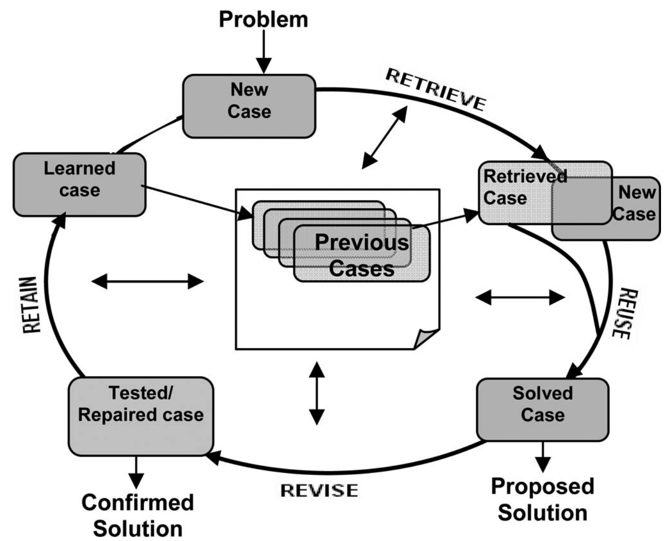

Fig. 1. CBR cycle, introduced by Aamodt and Plaza [1].

Prior to the case formulation, some CBR systems typically need preprocessing and filtering. For example, if the data are collected from sensor signals, images, free-text sources, etc., then the system may require feature extraction, feature mining, indexing, weighting, etc.

In the medical domain, clinicians or doctors may start their practice with some initial experiences (solved cases). Afterward, they use these past experiences to solve a new problem. This may involve some adjustment of the previous solutions to solve the new problem. Thus, a new experience (case) has been created, which enriches the clinician's/doctor's set of experiences. In fact, this is how the traditional CBR cycle works. So, the CBR is a reasoning process, which is medically accepted and also getting increasing attention from the medical domain. A number of benefits of applying CBR in the medical domain have already been identified [13], [24], [36]. However, the medical applications offer a number of challenges for the CBR researchers and drive advances in research. Important research issues are given in the following.

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1) Feature extraction is becoming complicated in the recent medical CBR systems due to a complex data format where the data are coming from sensors [6] or images [43] or as time series [49] or free-text format [4]. Key-sequence-discovery approach was proposed in [23] to find characterizing features of time series cases and it was also shown that case indexing and similarity matching based on discovered key sequences resulted in improved performance of case-based classification of symbolic time series data [67].
2) Feature selection and weighting are two other important factors for which many CBR systems depend on expert knowledge. Cases with hidden features could also affect the retrieval performance.
3) The component that plays a central role in the CBR systems is the case base or case library. A case base can be considered as concrete knowledge of a model consisting of specific cases. The cases stored in a case library should be both representative and comprehensive, so as to cover a wide spectrum of possible situations. As an initial step in the creation of a medical CBR system, the case base is often launched with a limited number of cases, which may reduce the system performance. Therefore, the case-library maintenance [2] and case mining have become increasingly important issues in the CBR research.
4) Many CBR systems avoid automatic adaptation strategies due to a number of problems, such as the complexity of medical domains, rapid changes of medical knowledge, the large number of features, reliability, risk analysis, etc. [36]. As a result, the adaptation step in the medical domain is often performed manually by an expert of the domain.

Interesting publications which looked at the early influential CBR systems in the health sciences include [7], [11], [13], [26], [37], [48]. A survey of the medical CBR systems before 1998 was done by Griel *et al*. in [24]. Another survey for the medical CBR systems/projects reported between the years 1999 and 2003 was done by Nilsson and Sollenborn in [38].

Due to the area's fast and successful development, there is a need for a systematic survey to identify recent trends in medical CBR systems. This paper focuses on the medical CBR systems/projects created or reported on between 2004 and 2008. Through a literature review, the discussion is extended for the systems/projects reported on in the year 2009. The aim of the survey is to investigate the recent trends, in particular, why the recent systems are being built, i.e., their purpose, and how they are constructed. The aim of this review is to provide the reader easier access to the current state of the art. We have done an exhaustive literature search in the proceedings of CBR conferences, i.e., ICCBR/ECCBR 2004–2009 and their adjunct workshops on CBR in medicine. Some of the references from other journals such as the *Journal of IEEE Intelligent Systems*, *Computational Intelligence*, *Artificial Intelligence in Medicine*, *the International Journal of Hybrid Intelligent Systems*, *Transactions on CBR on Multimedia Data*, *Applied Intelligence*, *Knowledge-Based Systems*, *the European Journal of Operational Research*, *IEEE Transactions on Knowledge and Data Engineering*, *Applied Soft Computing*, and *Expert Systems and Applications* are also included. An e-mail survey to the authors of the papers was conducted mainly to find out about the construction-oriented properties, which may not always be available in the corresponding research papers describing the systems. The number of medical CBR systems published in different journals shows a rapid growth of the field in recent days. It is possible that there are other systems/projects, which we failed to identify although we sought to be as comprehensive as possible in our literature search. Nevertheless, the 34 systems/projects included in this paper represent certain significant trends with respect to the medical CBR systems.

The paper is organized as follows: in Section II, we describe the categorization of the system properties on the basis of which the different systems are compared. Section III presents the survey results and summarizes the recent trends in tables based on purpose-oriented and construction-oriented properties. Section IV discusses the overall trends. Section V contains a conclusion and a short summary of and references to the systems included are provided in the Appendix.

II. Categorization of System Properties

This survey was conducted by following the approach of Nilsson and Sollenborn in [38], where the development of the systems is followed by analyzing a set of distinctive system properties.

The system properties are divided into two parts.

1) Purpose-oriented properties: the function or functions, such as diagnosis, classification, tutoring, planning, knowledge acquisition/management, that is/are performed by a system.
2) Construction-oriented properties: how the systems are constructed, i.e., case type, adaptability, hybridization, etc.

A. Purpose-Oriented Properties

1) Diagnosis: This property assists a clinician in the process of identifying a disease or medical condition. Most of the medical systems provide various degrees of assistance in the diagnostic process.
2) Classification: Classification is a method by which new situations are distributed or categorized into groups (i.e., items are arranged in classes or categories).
3) Tutoring: A tutoring system acts as a trainer, which generates individualized instructions or feedback for students. Some CBR systems attempt to function as tutoring systems, typically by using a case library.
4) Planning: In the medical domain, planning generally refers to treatment procedure or therapy management. For instance, the RHENE system [34] provides planning expertise for patients with end-stage renal disease by monitoring and adjusting the treatment over time.
5) Knowledge acquisition/management: A system can assist in leveraging the knowledge within an organization. This property is defined according to [51], where knowledge acquisition is labeled as one of the activities of knowledge management.

B. Construction-Oriented Properties

1) Subjects: The number of persons/patients used in the evaluation of the system.
2) Number of cases: The quantity of cases for each CBR system.
3) Case type: The nature, e.g., real, prototypical, generic, of a case or group of cases used for the purpose of evaluation.
4) Prototype: This property shows whether and to what extent a system has been implemented, i.e., in the form of a model or a trial product.
5) Adaptability: To what extent the systems are using automatic adjustments of the cases in the medical domain.
6) Hybridization: This property explores the synergy between the CBR and other artificial intelligence (AI) methods. This often enriches the reliability and efficiency of a system.
7) Autonomy: This indicates the degree of autonomy or the level of human intervention needed to complete and/or evaluate a system's performance. A fully independent system can provide results without any human intervention, which is particularly rare in medical diagnosis and planning systems.
8) Commercialization: Successful commercialization of CBR systems is still not common in the medical domain. This property refers to the status of the medical CBR systems that are targeted for commercial production.
9) Clinical use: This property differentiates the systems/projects with respect to their use in clinical environments, i.e., whether or not they are used in a clinical/hospital environment for evaluation and/or routine clinical use.
10) Reliability: This is an important property of a medical CBR system, referring to how trustworthy or dependable a system is. The functionality of a system should be tested to see if it provides an accurate solution when needed.

The method used in this survey for examining the recent trends is based on the aforementioned distinctive properties in system development, so as to differentiate one system from another. Furthermore, it also takes the application domain or the context of the system into account, to provide information on how well CBR is suited for the medical domain. We are also interested in investigating the different matching techniques applied in the case retrieval. All this has been done with the aim of discovering the trends in the development of recent medical CBR systems as compared to previous years.

III. Survey Results: Trends in Medical CBR

The results from the survey are summarized in tables to give a clear picture of recent trends in the development of medical CBR systems. Table I presents the different CBR systems with their application domains/contexts and the purpose-oriented properties. The systems and their construction-oriented properties are summarized in Tables II and III.

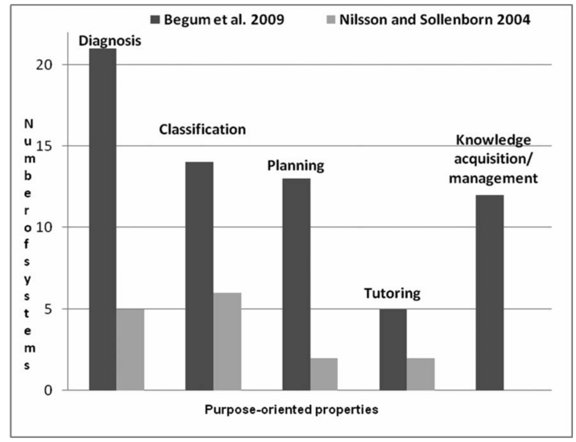

Fig. 2. Number the systems belonging to each purpose-oriented category.

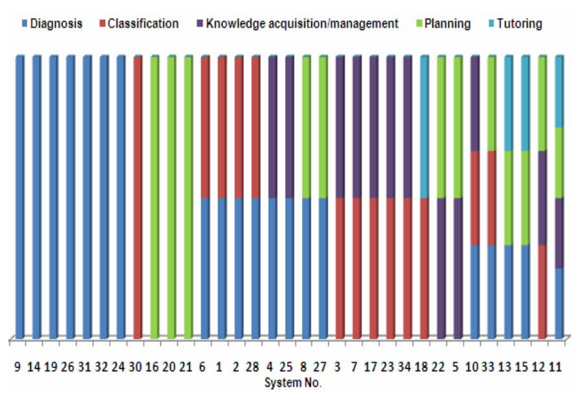

Fig. 3. Purpose-oriented properties in the different systems studied. *X*-axis denotes the system no. s according to Table I.

A. Purpose-Oriented Properties

Fig. 2 illustrates a comparison, on the basis of the purpose-oriented properties, between the survey performed by Nilsson and Sollenborn in [38] (i.e., the medical CBR systems reported or created between 1999 and 2003) and the survey presented in this paper (i.e., the medical CBR systems reported or created after 2003). It shows that besides covering a new category, namely, knowledge acquisition/management, more systems address diagnosis and planning in recent years compared to the years 1999–2003. During the past years, the increase in classification systems has been moderate. Few systems address tutoring, while many address planning, as shown in Fig. 2. According to our survey, numerous systems are multipurpose oriented, i.e., perform more than one task in the medical domain. As can be seen from Table I, out of the 34 systems investigated, only 11 serve a single purpose while the others are multipurpose systems.

Fig. 3 illustrates the recent trend of developing multipurpose systems in the medical domain. Every purpose is given a color, though note that the share of each color within a system has no significance since we do not know the balance among the different purposes in a system. The first 11 systems in Fig. 3 are single-purpose systems, and of these seven are diagnosis, one classification, and three planning systems.

TABLE I
PROPERTY MATRIX, CBR SYSTEMS AND THEIR APPLICATION DOMAINS

No	Author/system	Purpose-oriented properties	Application domain/context	References
1	McSherry/CaseBook	Diagnosis & classification	Contact lenses	[33]
2	De Paz/ExpressionCBR	Diagnosis & classification	Cancer diagnosis	[22]
3	Perner/Fungi-PAD	Classification, knowledge acquisition/management	Object recognition	[42], [43]
4	Cordier/FrakaS	Diagnosis, knowledge acquisition/management	Oncology	[18]
5	Corchado/GerAmi	Planning, knowledge acquisition/management	Alzheimer patients	[17]
6	Glez-Peña/geneCBR	Diagnosis & classification	Cancer classification	[19], [25]
7	Perner/HEp2-PAD	Classification, Knowledge acquisition/management	Image classifier	[41], [44], [45]
8	Schmidt/ISOR	Diagnosis & planning	Endocrinology	[50]
9	Begum/IPOS	Diagnosis	Stress diagnosis	[6]
10	D'Aquin/KASIMIR	Diagnosis, classification, knowledge acquisition/management	Breast cancer	[20]
11	Bichindaritz/Mémoire	Diagnosis, planning , tutoring, knowledge acquisition/management	Biology & medicine	[8]
12	Montani/RHENE	Classification, planning, knowledge acquisition/management	Hemodialysis	[34], [35]
13	Kwiatkowska/Somnus	Diagnosis, planning, tutoring	Obstructive sleep apnea	[29]
14	Lorenzi/SISAIH	Diagnosis	Fraud detection in health care	[30]
15	Ochoa /SIDSTOU	Diagnosis, planning & tutoring	Tourette syndrome	[39]
16	Ahmed./Biofeedback	Planning	Stress management	[3]
17	Brien/ADHD	Classification, knowledge acquisition/management	Neuropsychiatries	[15]
18	Doyle/Bronchiolitis	Classification and tutoring	Bronchiolitis	[21]
19	O'Sullivan/Dermatology	Diagnosis	Dermatology	[40]
20	Marling/Type-1diabetes	Planning	Diabetes	[32]
21	Song/radiotherapy planning	Planning	Prostate cancer	[47]
22	Wu/ Dietary counseling	Planning & knowledge acquisition/management	Dietary counseling	[52]
23	Zhuang/Pathology	Classification, tutoring & knowledge acquisition/management	Pathology ordering	[53]
24	Ahn/ Breast Cancer	Diagnosis	Breast cancer diagnosis	[5]
25	Huang/ Chronic Diseases	Diagnosis, knowledge acquisition/management	Chronic diseases diagnosis	[27]
26	Chang/ children developmental	Diagnosis	Children with developmental delay	[16]
27	Houeland/Palliative care	Diagnosis & planning	Palliative care for long-term cancer	[59]
28	Nicolas/Melanoma	Diagnosis & classification	Melanoma	[60]
29	Töpel/Metabolic disease	Diagnosis & planning	Inborn metabolic disease	[61]
30	Arshadi/MOE4CBR	Classification	Biomedical domain	[62]
31	Kurbalija/multiple sclerosis disease	Diagnosis	Multiple sclerosis disease	[63]
32	Obot/Hepatitis	Diagnosis	Hepatitis	[64]
33	CBSMS/Stress management	Diagnosis, classification & planning	Stress management	[65]
34	Yuan/ HDCU	Classification knowledge acquisition/management	Diabetes	[66]

The next 16 systems are two-purpose systems, of which the first eight all have diagnosis as one of their purposes. Therefore, in Fig. 3, the systems are displayed according to the number of their purposes: first, the one-purpose systems, then the two- and three-purpose systems, etc. Note that the systems are numbered according to Table I.

B. Construction-Oriented Properties

Table II presents the different matching techniques applied in the recent CBR systems and demonstrates what other AI techniques are used along with CBR to complete a system. Among those other techniques integrated or combined with CBR in these systems/projects are rule-based reasoning (RBR), knowledge management, neural networks, data mining, etc.

The matching technique or similarity measurement between cases plays an important role during case retrieval in a CBR system. Among the matching techniques used in recent medical CBR systems are nearest neighbor, Euclidian distance, genetic algorithms, author's defined similarity algorithm, etc., as summarized in Table II.

TABLE II
SYSTEMS DEVELOPED WITH CBR AND OTHER TECHNIQUES AND THEIR MATCHING TECHNIQUES

No	Author/system	Other techniques used in conjunction with CBR	Matching techniques
1	McSherry/CaseBook	HDR(hypothetico-deductive reasoning)	Author's defined similarity algorithm
2	De Paz/ExpressionCBR	NN & statistics	Nearest-neighbour and minkowski distance
3	Perner/Fungi-PAD	Image processing	Author's defined similarity measurement function
4	Cordier/FrakaS	None	Using adaptation knowledge
5	Corchado/GerAmi	Variational calculus	Hierarchical, multivariate conglomerates analysis and mahalanobis distance
6	Glez-Peña/geneCBR	RBR & fuzzy logic	Author's defined fuzzy similarity metric
7	Perner/HEp2-PAD	Image processing & data mining	Euclidian distance, Nearest-neighbour
8	Schmidt/ISOR	Statistics	Keyword-based similarity
9	Begum/IPOS	Fuzzy logic	Fuzzy similarity, similarity matrix, Euclidian distance, cosine similarity
10	D'Aquin/KASIMIR	Semantic web, belief revision theory, fuzzy logic & ergonomy	Matching of source (general) cases using adaptation knowledge
11	Bichindaritz / Mémoire	RBR, data mining & statistics	Ontology assisted case matching including semantic information
12	Montani/RHENE	Temporal abstractions	Euclidian distance, nearest-neighbour
13	Kwiatkowska/Somnus	Fuzzy logic	Fuzzy logic, semiotic approach
14	Lorenzi/SISAIH	None	Nearest-neighbour
15	Ochoa /SIDSTOU	Data mining	Author's defined method
16	Ahmed ./Biofeedback	Fuzzy logic	Fuzzy similarity matching, similarity matrix
17	Brien/ADHD	None	Modified nearest-neighbour matching
18	Doyle/Bronchiolitis	RBR	Nearest-neighbour
19	O'Sullivan/ Dermatology	KM & image processing	IR metrics [46]
20	Marling/Type-1diabetes	RBR	Nearest-neighbour and similarity metric
21	Song/Radiotherapy planning	Fuzzy logic, dempster-shafer theory & simulated annealing	Fuzzy sets, distance function and author's defined similarity function
22	Wu/ Dietary counseling	Data mining, rule based & ontology	Nearest-neighbour
23	Zhuang/Pathology	Data mining and clustering	Kohonen's self-organizing maps
24	Ahn/ Breast Cancer Diagnosis	Genetic algorithms	Genetic algorithms, nearest-neighbour
25	Huang/ Chronic Diseases	Data mining	knowledge-guide method, weight ratio functionality
26	Chang/Children development	None	Nearest-neighbour
27	Houeland/Palliative care	Rule-based & probabilistic model-based methods	Semantic matching
28	Nicolas/Melanoma	RBR	Normalized Euclidian distance
29	Töpel/Metabolic disease	None	Similarity tables, difference-based similarity functions
30	Arshadi/MOE4CBR	Spectral clustering & logistic regression	Modified nearest-neighbour
31	Kurbalija/multiple sclerosis disease	None	Case retrieval net
32	Obot/Hepatitis	Rule base & neural networks	Binary search algorithm
33	CBSMS/Stress management	RBR, textual information retrieval & fuzzy logic	Fuzzy similarity matching, modified distance function, similarity matrix
34	Yuan/ HDCU	Support vector machine	Self-organizing map

Some of the construction-oriented properties, such as the degree of autonomy, the existence of a prototype, commercialization, reliability, etc., of the systems are not always specified in the reference papers. Therefore, an e-mail questionnaire was sent to the corresponding authors of the papers. We got responses from 24 out of 34 authors. On the basis of the answers to the questionnaire, we formulated a construction-oriented properties overview as displayed in Table III. An empty cell in Table III means that the property in question could not be determined from the specified reference papers. From Table III, it can be seen that the number of cases involved in the different systems/projects varies from 10 to 1 548 122. The case type identifies whether a system is using real or artificial cases and/or a combination of the two. The majority of the systems involved in this survey use real cases while a few systems are based either on prototypical cases or a combination of real and artificial cases. Only some of the systems develop automatic adaptation strategies whereas the majority of the systems/projects provide for manual/conventional adaptation. Almost all the systems are multimodal or hybrid, i.e., combine more than one AI technique, though a small number still depends on the CBR only. A large share of the systems addresses user interaction. Until now, only a few systems have been commercialized. However, many of the systems are intended for commercial production. Some

TABLE III
CONSTRUCTION-ORIENTED PROPERTY. SURVEY RESULTS ON CBR SYSTEMS IN THE HEALTH SCIENCES

No	Author/ System	Subjects	No of cases	Case type	Prototype	Adaptability	Hybridization	Autonomy	Commercialization	Clinical use	Reliability
1	McSherry/CaseBook					Not applicable					
2	De Paz/ ExpressionCBR	212	212	Real	Yes	Yes	Yes	Considerable	No	Clinical evaluation	Clinician
3	Perner/ Fungi-PAD	8	400	Real, prototypical	Yes	No	Yes	Considerable	Planned	Clinical evaluation	Expert level
4	Cordier/ FrakaS	Not relevant	10	Prototypical	Yes	Yes	No	Limited	No	No	Not relevant
5	Corchado/ GerAmi	20	4000	Real	Yes	Yes	Yes	Considerable	Yes	Day-to-day Use	Always right
6	Glez-Peña/ geneCBR	7	43	Real	Yes	No	Yes	Considerable	No	Clinical evaluation	Expert level
7	Perner/ HEp2-PAD	10	300	Real	Yes	No	Yes	Considerable	Yes	Day-to-day, clinical evaluation	Expert level
8	Schmidt/ISOR	-	-	Real, prototypical	Yes	Some Extent	Yes	-	-	Clinical evaluation	-
9	Begum/ IPOS	24	39	Prototypical	Yes	No	Yes	Limited	Planned	Clinical evaluation	Expert level
10	D'Aquin/ KASIMIR	Not relevant	100	Real, generic	Some extent	Yes	Yes	Limited	No	Clinical evaluation	Expert level
11	Bichindaritz/ Mémoire	Simulator	122	Real, prototypical	Yes	Yes	Yes	Considerable	No	Planned	Expert Level
12	Montani/ RHENE	37	1476	Real	No	Yes	Some extent	No	Planned	Planned	Not Tested
13	Kwiatkowska/ Somnus	37	37	Real	Some extent	No	Yes	Limited	No	No	Not relevant
14	Lorenzi/ SISAIH	5	70	Real	Yes	No	Pure CBR	Considerable	No	No	Expert level
15	Ochoa/ SIDSTOU	47	100	Real	Yes	Some Extent	Yes	Limited	Planned	Clinical evaluation	Clinician
16	Ahmed ./Biofeedback	24	39	Prototypical	Yes	No	Yes	Limited	Planned	Clinical evaluation	Expert level
17	Brien/ADHD	152	-	Real	Yes	-	No	Limited	-	Clinical evaluation	-
18	Doyle/ Bronchiolitis	400	40	Real	Yes	Some Extent	Yes	Limited	No	Clinical evaluation	Clinician
19	O'Sullivan/ Dermatology	1000	150	Real	-	-	Yes	Limited	-	-	-
20	Marling/ Type-1diabetes	20	50	Real	Yes	Planned	Yes	Limited	Planned	Planned	Testing underway
21	Song/Radiotherapy planning	6	72	Real	Some extent	Yes	Yes	Considerable	Planned	Planned	Clinician
22	Wu/ Dietary counseling	-	-	-	No	Yes	Yes	Limited	-	No	-
23	Zhuang/′ Pathology	1548122	1548122	Prototypical, generic	Some extent	Some Extent	Yes	No	No	Planned	Not relevant
24	Ahn/Breast cancer Diagnosis	569	569	Real	Some extent	Some Extent	Yes	Limited	No	No	Expert level
25	Huang/ Chronic Diseases	3	15751	Real	Yes	Yes	Yes	Limited	No	No	Always right
26	Chang/Children development	210	210	Real	Some extent	No	No	Limited	-	Clinical evaluation	-
27	Houeland/Palliative care					Not applicable					
28	Nicolas/Melanoma	-	150	Real	Some extent	-	Yes	Limited	-	-	-
29	Töpel/Metabolic disease	-	750	Real	Yes	No	No	Limited	-	Day-to-day, clinical evaluation	-
30	Arshadi/MOE4CBR	-	580	Real	Yes	Yes	Yes	-	-	Clinical evaluation	-
31	Kurbalija/Multiple sclerosis disease					Not applicable					
32	Obot/Hepatitis	70	70	Real	Some extent	Yes	Yes	Limited	-	Clinician evaluation	-
33	CBSMS/Stress management	31	53	Real, Prototypical	Yes	No	Yes	Limited	Planned	Clinical evaluation	Expert level
34	Yuan/ HDCU	-	-	-	Some extent	No	Yes	Limited	-	-	-

of the recent systems also address the standardization of CBR systems and cases (i.e., formalization, case representation, reasoning procedures, etc.) to facilitate exchange or sharing among the systems, e.g., the Memoire project [7]

IV. Overall Trends

After comparing the different CBR systems on the basis of the distinctive system properties described in the earlier sections, certain significant research trends in the health sciences can be identified.

Application areas: A wide range of application areas (see Table I) and a number of successfully implemented systems have proven that the interest in applying CBR in the health sciences is increasing. Moreover, the systems in [19], [22], [25], [52], [62] indicate an increasing use of CBR in the bioinformatics domain.

Multipurpose systems: An interesting observation concerning the purpose-oriented properties is that the systems developed today perform multiple tasks in the medical domain. 68% of the systems in this survey address more than one purpose (see Fig. 3.). By contrast, until the year 2003 [38], only two (13%) of the evaluated systems were multipurpose. Nilsson and Sollenborn [38] investigated 15 CBR systems yet did not explicitly mention overlapping with respect to their purpose-oriented properties. However, the systems today do not only concentrate on the diagnosis and treatment tasks like the early CBR systems, but tend to provide multitask facilities. In fact, the recent CBR systems even tend to support additional complex tasks in the health science domain, e.g., the standardization of CBR systems, as defined in [8].

Combination of purposes: In particular, it can be observed that the CBR systems for knowledge acquisition/management have attracted increased attention in recent years. Besides, it is popular to combine classification and knowledge acquisition/management, as evidenced by seven of the systems in Table I. At the same time, planning in the medical domain offers interesting challenges to CBR researchers and is an application where the CBR methodology may offer valuable progress and commercial applications (as shown in Table III, many systems are developed for commercialization).

Data preprocessing: The majority of the health science domains require preprocessing of datasets for feature extraction or feature mining prior to case representation. Some of the systems/projects have successfully extracted features from multimedia data, i.e., time series or images in a separate phase, as in [6]. Feature mining from multimedia data is a notable trend in the health science domain. It helps to represent cases with original implicit and complex format. An example of a system focusing on feature mining is the dietary counseling system by Wu *et al*. [52].

Prototype: One of the identifiable achievements in the medical CBR systems is that almost all the systems/projects included in this survey involved their implementation in a form of prototype. Only two medical systems, i.e., Perner [44] and Corchado *et al*. [17], have undergone successful commercialization. Several other projects, which are still in the research phase, aim at commercialization of their systems in future. Many of the systems have successfully been evaluated in a clinical environment. However, day-to-day routine use in a clinical setting is not so common.

Automatic adaptation: Adaptation is often a challenging issue in the health sciences and has traditionally been carried out manually by physicians/experts of the domain. Nevertheless, the survey shows that a number of recent medical CBR systems [8], [15], [19], [20], [25] adopt and explore different approaches to automatic and semiautomatic adaptation strategies.

Hybrid systems: Although a few systems still depend on CBR only, today almost all the medical CBR systems combine more than one AI method and technique and, thus, become hybrid systems. Among these, many systems use a CBR approach in the top-level construction and some systems apply CBR as a core technique. Besides the CBR approach, these systems apply other techniques to accomplish different tasks such as feature extraction, feature selection, feature weighting, efficient similarity matching, adaptation, case library management, and artificial case generation in a system. In fact, the multifaceted and complex nature of the medical domain motivates the design of such multimodal systems [36], [38]. The integration of CBR and RBR was already common in the early CBR systems, e.g., in CASEY [28], FLORENCE [14]. Recent hybrid CBR systems also use other techniques or methods such as data mining, fuzzy logic, statistics, and neural networks to handle the underlying complexities in the medical domains.

Matching techniques: The use of some kind of distance function to calculate similarity between a new and an old case is commonly applied in most systems. The nearest neighbor retrieval algorithm is still widely applied in medical CBR systems. As a result of this survey, we found that several other techniques have also been employed in some systems, for instance, when a source (general) case is matched using adaptation knowledge [20]. Some CBR systems integrate other AI techniques to improve the matching task, e.g., fuzzy similarity matching in [6].

Reliability: In terms of reliability, most of the systems are trustworthy or operationally secure at some degree of expert level, while others are still in earlier stages.

Data types: Most of the systems are using real medical datasets, as is evident from Table III (column "Case Type"). Some applications depend on artificial or prototypical datasets. Several of the systems employ rather generic methods or algorithms, which could be applicable using datasets from other domains, such as [15], [33]. Developing more general solutions also advances CBR as a research area.

V. Related Work and Discussion

Looking at some new systems/projects mainly reported in the year 2009, for example, [2], [5], [53], [58]–[60], [64], [65], that there are no dramatic changes with respect to system properties compared to the preceding years (2004–2008). Most of the systems are multipurpose. These systems are also reported as multimodal or hybrid. As in the preceding years, most of the systems implement feature extraction and case retrieval.

A previous survey in [11] describes the trend of integrating CBR with other AI techniques. Here, the function of CBR is explained in terms of data processing and handling in the medical CBR systems. The author also illustrates how CBR in recent systems complements statistical methods, which were widely used in early medical systems. Another review in [13] summarizes the research papers and analyzes the trends in the research presented at the workshops of CBR in the Health Sciences (ICCBR03 and ECCBR04). The trends identified are the use of CBR in bioinformatics, the standardization of CBR in biomedicine, and feature and case mining, among others. However, in our survey, we have considered the CBR conferences ICCBR/ECCBR 2004–2009 and their adjunct workshops and some of the references from other journals on CBR in medicine. Holt *et al*. [26] mention the application areas of CBR in the medical domain and address future research trends, e.g., in adaptation and case mining. The authors also talk about future areas of application. Like Holt *et al*., we have also mentioned application areas and investigated current trends in automatic adaptation, prototype building, matching techniques, adaptation, etc. The outcome of the analysis shows that automatic adaptation is increasing and about half of the systems included in this survey incorporate adaptation. The survey in [37] explains the importance of contextual knowledge in the medical CBR systems and how this knowledge has been included in the case bases of recent systems. The systems referred to there were reported on in the year 2007 or earlier. The paper in [48] contributes more to the analysis of the medical CBR systems (until 2000). The synergy between CBR and other problem-solving methods is also addressed there. Surveys of the medical CBR systems reported before 2003 were carried out by Griel *et al*. [24] and Nilsson and Sollenborn [38]. However, the survey in this paper follows the survey done by Nilsson and Sollenborn in 2003 and analyzes the systems reported between the years 2004 and 2009. Some of the findings or outcomes of the present analysis have already been stated in previous reviews, in particular with respect to application areas, multimodal or hybrid systems, and adaptation. Besides, this paper also discusses case types, the number of cases used in a system, prototype, autonomy commercialization, reliability, and clinical use for the systems/projects reported on between 2004 and 2009. The new matching trends are also investigated, which shows that the recent medical CBR systems are not only based on traditional nearest neighbor algorithm but also utilize other AI methods, e.g., Kohonen's self-organizing maps and fuzzy logic. Note that most of the previous reviews show that automatic adaptation is a weak point or a big challenge, especially for the medical domain. However, the rate of implementing adaptation strategies in recent medical CBR systems has increased. Most of the emerging systems have planned to implement automatic adaptation. If we consider the latest publication in [38] that contains information about system prototypes, then we find notable achievements in recent systems in that most of them are built as prototypes. The rate of autonomy is higher compared to previous years. As a consequence, commercialization is also more common. Although the nature of the medical domain is complex, recent CBR systems are trying to cope with the difficulties and cover a set of essential tasks in medical applications.

The ongoing research in the field indicates that the application of CBR in the medical domain is evolving well. In future, CBR systems might provide more services in the medical field and will be integrated more into the clinical environment. Another notable prospect is the development of efficient systems with generic and automatic case-adaptation strategies. The future may provide an increased availability of medical CBR systems in the market instead of them remaining only on the level of research prototypes.

VI. Conclusion

This paper presents a survey of applied research on CBR in medical domains. A number of the recent medical CBR systems were reviewed in terms of their functionalities and the techniques adopted for system construction. In particular, we outlined a variety of methods and approaches that have been used for case matching and retrieval, which play a key role in these medical CBR systems.

It was shown that CBR has been applied in many medical scenarios for various tasks, such as diagnosis, classification, tutoring, treatment planning, and knowledge acquisition/management. The survey also leaves us with the awareness that hybridization of CBR with other AI techniques, such as ontology, RBR, data mining, fuzzy logic, neural networks, as well as probabilistic and statistical computing, creates promising opportunities to enhance CBR systems by scaling them up to handle increasingly large, complex, and uncertain data in clinical environments.

Appendix

CBR Systems in the Health Sciences

1) CaseBook [33] [*Purpose: Diagnosis, Classification*] applies hypothetico-deductive reasoning (HDR) in a conversational CBR system. The HDR can rule out a hypothesis proposed by a system or user and diminish the number of tests needed. It, thus, determines the most significant hypothesis. Though the strategy is exemplified by recommending types of contact lenses in the domain of contact lens classification, it is applicable to datasets other than from the medical domain.
2) ExpressionCBR [22] [*Purpose: Diagnosis, Classification*] automatically classifies leukemia patients from the exon array data and helps in the diagnosis of different cancer types. It uses a data-filtering algorithm to take care of the dimensionality problem in the datasets. A clustering algorithm also helps to speed up the classification process in the system.
3) Fungi-PAD [43], [44] [*Purpose: Classification, Knowledge acquisition/management*] describes an object-recognition method to detect biomedical objects (i.e., airborne fungal spores) in a digital microscopic image. Due to large biological variations, it is difficult to generalize the appearance of fungal spores into a model. The

system uses image-processing techniques along with CBR to determine the identity of an object. In connection with this, a set of cases explains the appearance of an object. An object in an image is compared to the original object. This original object is produced by using a template in the form of a prototypical case. The prototypical cases are generated by a semiautomatic process.

4) FrakaS [18] [*Purpose: Diagnosis, Knowledge acquisition/ management*] is a prototype implemented using CBR in the domain of oncology. It proposes a conservative adaptation strategy for the acquisition of knowledge from experts. Here, any inconsistency between domain knowledge and an expert's knowledge is added as new knowledge and, consequently, evolves the domain knowledge. The authors emphasize the importance of proper management of the domain knowledge to avoid wrong decisions in medical-decision support systems.
5) GerAmi [17] [*Purpose: Planning, Knowledge acquisition/ management*] is an intelligent system that aims to support healthcare facilities for the elderly, Alzheimer's patients, and people with other disabilities. This system mainly functions as a multiagent system. The CBR system provides case-based planning mechanisms to optimize work schedules and present up-to-date patient information. A prototypical system has been implemented at a care facility for Alzheimer's patients in geriatric residences.
6) geneCBR [19], [25] [*Purpose: Diagnosis, Classification*] focuses on the classification of cancer based on the gene expression profile of the microarray data. Several AI techniques are combined to optimize the classification accuracy. The system also aims to keep the original set of features as small as possible. Here, each of the cases contains 22 283 features. The cases are represented using fuzzy sets. Fuzzy-prototype-based retrieval is applied in the case retrieval phase. The patients are also clustered into groups of genetically similar patients using neural networks. An explanation of the solution is provided using a set of rules.
7) HEp2-PAD [41], [44], [45] [*Purpose: Classification, Knowledge acquisition/management*] addresses a novel case-based method for image segmentation in medical-image diagnosis. The system combines CBR, image processing, feature extraction, and data mining techniques to optimize image segmentation at the low-level unit. The CBR performs the segmentation-parameter-selection mechanism based on the current image characteristics. The cases are represented with the image and nonimage information. The similarity value is also calculated using both the image and nonimage information.
8) ISOR [50] [*Purpose: Diagnosis, Planning*] identifies the causes of ineffective therapies and gives recommendations to avoid therapy inefficacy in long-term therapies. The system is exemplified with the diagnosis and therapy recommendations for hypothyroidism patients treated with hormonal therapy. Along with a case base, it uses three other knowledge components, namely, a knowledge base, prototypes (i.e., generalized cases), and medical patient histories. The knowledge base represents domain theory in a tree structure. The information of these components works in a form of dialogue, and key words are used in the retrieval of a similar case.
9) IPOS [6] [*Purpose: Diagnosis*] is a case-based decision-support system to assist clinicians in the diagnosis of individual stress based on the finger temperature sensor signal [58]. The system uses a calibration phase to generate an individual stress profile. The CBR is applied as a key methodology to facilitate experience reuse and decision explanation by retrieving previous similar temperature profiles. Further, the fuzzy techniques are incorporated into the CBR system to handle vagueness, uncertainty inherent in clinicians' reasoning, as well as imprecision of feature values. The textual data in such a system capture the different yet complementary aspects of a subject with a desire to tackle more comprehensive situation awareness. It also [4] handles the unstructured textual information and the time-series data and, thereby, provides more reliable diagnosis and decisions.
10) The KASIMIR project [20] [*Purpose: Diagnosis, Classification, Knowledge acquisition/management*] is an effort to provide decision support for breast-cancer treatment based on a protocol in oncology. It focuses on the adaptation of the protocol to provide therapeutic decisions for the cases outside the protocol. The adaptation protocol depends on a revision operator. It offers consistency between the domain knowledge and the target case. The system [18] particularly stresses the importance of proper management of the domain knowledge to avoid wrong decisions. The analysis of a failure is added as a new dimension of knowledge into the domain knowledge, providing automatic evolution of knowledge in the system.
11) The Mémoire project [8] [*Purpose: Diagnosis, Planning, Knowledge acquisition/management, Tutoring*] offers a framework to exchange case bases and CBR systems in biology and medicine. It is an effort to apply a semantic web approach in the biomedical domain. It uses the OWL representation language to make the case bases interoperable. A number of studies have been carried out [9], [12] in the Mémoire project to validate different roles of prototypical cases. In [10], the author argues that the "maintenance prototypical cases" can be generated by mining from the medical literature, which, as a result, could build and maintain case bases in an autonomous way in the medical domain. The project explores prototypical cases and how they can serve in various ways [9], [12], e.g., maintenance of memory, maintenance of knowledge, management of reasoning, and bootstrapping a case base in a CBR system.
12) RHENE [34], [35] [*Purpose: Classification, Planning, Knowledge acquisition/management*] is a case-based system in the domain of nephrology for the management of end-stage renal disease patients treated with hemodialysis. It retrieves patterns of failure over time and allows the clinician to analyze a solution within and/between the patients. The system assists in the search of consistency of a prescribed therapy plan to a proposed dialysis session and

provides an assessment of treatment efficacy. Each dialysis session is represented as a case in which the static features characterize a patient. The dynamic features are collected from the time series measurement. Further, a case-based architecture [31] is used in the RHENE system for the parameter configuration of the temporal abstractions on time-series data and, thereby, reduces the dimensionality of the features.

13) Somnus [29] [*Purpose: Diagnosis, Planning, Tutoring*] is a prototype implemented in the domain of obstructive sleep apnea (OSA). The OSA is a respiratory disorder that causes sleeping problems in patients. The intention is to assist the respiratory therapy students in the sleep disorders clinic at the University College of the Cariboo. The students can analyze the diagnosis and treatment process of a case by retrieving cases similar to the current case. The case base consists of three types of cases: *individual cases* (extracted from 37 OSA patients), *prototypical,* and *exceptional cases* (collected manually with the help of a sleep specialist). Somnus is constructed as a combined framework in which fuzzy logic is applied for the modeling of the case features and a semiotic approach is used for the modeling of their measurements.
14) Hospital Admission Authorization System (SISAIH) [30] [*Purpose: Diagnosis*] is a decision-support tool that assists in the decision-making process by the hospital admission authorities in the Brazilian public health system.It helps to manage the admission of a patient in a hospital and handles the billing errors and medical procedures, i.e., it performs a managerial job. Each case contains expert knowledge to solve a problem. Therefore, in fact, it helps in the evaluation of the hospital admission authorization (HAA) that decides whether to accept or reject a current HAA. SISAIH simplifies the problematic manual knowledge acquisition process and utilizes the resources in a cost-effective way, which, in turn, speeds up the process and makes it more accurate.
15) SIDSTOU [39] [*Purpose: Diagnosis, Planning, Tutoring*] is an intelligent tutoring CBR system for providing medical education on Tourette syndrome. It works as a tool for diagnosing Tourette syndrome and could help to minimize the need of a psychiatrist or neurologist at the initial stage. The system can learn automatically based on a number of defined predicting characteristics. An evaluation of the system compared to an expert of the domain demonstrates the reliability of the system.
16) Ahmed *et al*. [3] [*Purpose: Planning*] propose a three-phase sensor-based biofeedback decision support system to provide treatment for stress-related disorders. The biofeedback training is, most of time, guided by an experienced clinician and the results rely largely on the clinician's competence. The intention of the system is to enable a patient to train himself/herself without any particular supervision. A CBR framework is deployed to classify a patient, estimate the initial parameters, and to make recommendations for the biofeedback training. Fuzzy techniques are applied to better accommodate the uncertainty in clinicians' reasoning as well as in decision analysis.
17) Brien *et al*. [15] [*Purpose: Classification, Knowledge acquisition/management*] attempt to classify attention-deficit hyperactivity disorder (ADHD) patients in the neuropsychiatric domain. The system could function as a second option for clinicians who are currently using a multisource system to diagnose ADHD. It classifies a patient based on the hypothesis that the eye movement of a person, i.e., altered control of saccadic eye movements, contains significant information to diagnose ADHD. The paper exploits an iterative refinement strategy during the knowledge acquisition step to achieve a satisfactory performance in terms of case description and similarity assessment, which can also be applicable across other domains.
18) Doyle *et al*. [21] [*Purpose: Classification, Tutoring*] present a decision-support system for bronchiolitis treatment. It focuses on explanation in decision-making tasks. The system provides recommendations based on preceding cases. Besides this, explanatory text imparts the supporting and nonsupporting aspects of a selected case as well as indicates the level of confidence in the prediction. The system has been evaluated at the Kern Medical Center and the result shows that the recommendations with explanation are rather useful for medical professionals in their decision-making tasks.
19) O'Sullivan *et al*. [40] [*Purpose: Diagnosis*] develop a case-based decision-support system by exploiting patients' electronic health records delivered through wireless networks. It allows a user to electronically input and compare the patient's records. The system facilitates knowledge sharing in the domain and allows "remote-access health-care." The cases are represented in a multimedia data format, which contains a patient's information, i.e., medical image, annotations, endoscopies, and physician's dictations. The contextual expert knowledge for the relevant cases is also stored in the case base of the encapsulated patient cases. The textual indices generated from each of the constituent features assist in the matching process. The system is evaluated using a dataset from 100 encapsulated patient profiles in the dermatology domain.
20) Marling *et al*. [*Purpose: Planning*] describe a case-based decision-support system to assist in the daily management of patients with Type 1 diabetes on insulin pump therapy [32]. In adjusting patient-specific insulin dosage, the system considers real-time monitor of the patients' blood glucose levels and their lifestyle factors. It reduces the cumbersome manual review process for a physician by providing individual therapeutic recommendations. The best matching case is retrieved in two steps. First, a subset with potential relevant cases is retrieved and then, from this subset, the most useful similar cases are retrieved by using a standard nearest neighbor metric. An evaluation of the prototypical decision support system with 50 cases from 20 patients articulates the potential applicabil-

ity of CBR in managing diabetes for insulin pump therapy patients.

21) Song *et al*. [*Purpose: Planning*] propose a system in radiotherapy for dose planning in connection with prostate cancer [47]. The system is capable of adjusting the appropriate radiotherapy doses for an individual while, at the same time, reducing the risks of possible side effects of the treatment. The fuzzy-similarity measurement is applied in matching between cases to incorporate experts' knowledge in retrieving past similar experiences. When several retrieved similar cases provide different treatment solutions, the Dempster–Shafer theory helps to fuse multiple cases and recommend a particular dose plan for a case.
22) Wu *et al*. [52] [*Purpose: Knowledge acquisition/management, Planning*] present a CBR framework based on NutriGenomics knowledge by considering a person's genetic variation, i.e., individual gene expression, to provide personalized dietary counseling. Genetic variations in a person have an impact on the person's response to diet. The system proposes a dietary strategy that influences the individual gene expression and, as a consequence, helps to maintain health and prevent diseases. The NutriGenomics knowledge is collected through data mining and represented in a form of ontology. A distributed case base allows the system to save this knowledge and, if necessary, to generate new cases automatically using a case builder based on this stored knowledge.
23) Zhuang *et al*. [53] [*Purpose: Classification, Knowledge acquisition/management*] describe an intelligent decision-support system for pathology ordering by general practitioners. The authors integrate the data mining and CBR approaches to get an effective decision support that facilitates more informed evidential decision making in the area of pathology ordering. The system is working on 1.5 million pathology records.
24) Ahn and Kim in [5] [*Purpose: Diagnosis*] propose a computer-aided system to diagnose breast cancer using digital images. The CBR system uses genetic algorithms to improve the system's performance. It applies genetic algorithms to optimize feature weighting, instance selection, and the number of neighbors that combine simultaneously.
25) Huang *et al*. [27] [*Purpose: Diagnosis, Knowledge acquisition/management*] implement a system for chronic disease diagnosis and prognosis. Here, data on four chronic diseases—stroke, cardiopathy, hypertension, and diabetes mellitus—are investigated by the authors. In the knowledge-creation phase, data mining and decision tree induction algorithms are applied to mine out a set of rules for chronic disease prognosis.
26) Chang [16] [*Purpose: Diagnosis*] uses CBR to create a screening system for developmentally delayed children. The purpose of the screening is to determine symptoms, which show delays in the developmental status of children. Here, the CBR helps to enhance the efficiency of this screening system. It considers the language and communication, the motor skills, as well as the sensory and cognitive development of a child to diagnose developmental delay.
27) Houeland *et al*. [59] [*Purpose*: *Diagnosis, Planning*] describe a decision-support system in the domain of palliative care for long-term cancer patients. The authors propose a meta-level reasoning architecture, which effectively combines different reasoning processes. Here, the CBR is applied as a core component. RBR and probabilistic model-based reasoning are also integrated into the reasoning architecture. A meta-level control agent evaluates the solution of a current problem using the CBR method. The agent could suggest applying the current solution or using an alternative reasoning method, depending on the strengths and weaknesses of the solution. This provides an automatic improvement of the reasoning process for a specific problem at hand.
28) Nicolas *et al*. [60] [*Purpose: Diagnosis, Classification*] address a diagnostic system to assist experts in diagnosing melanoma. The system applies CBR to facilitate experience reuse in the domain. It uses two melanoma-diagnosis techniques based on images in the domain. The preprocessed rules are applied on the combined results of the images to further improve the classification performance. Two independent CBR classifiers, which follow the medical protocol are used to provide reliable diagnosis results. The preprocessing algorithm generates a set of characteristics from the melanoma dataset. The results from the two individual CBR modules are then combined using the rules.
29) Töpel *et al*. [61] [*Purpose: Diagnosis, Planning*] apply CBR in the diagnosis and therapy planning for inborn metabolic diseases. In the problem part, each case contains symptoms, lab findings, development, molecular test results, etc., and the solution part comprises diagnosis, therapy, diet, and drugs. The case library consists of 750 cases. A preselection of the cases is performed to reduce the expected computational time in the CBR retrieval phase.
30) MOE4CBR [62] [*Purpose: Classification*] is an application of the CBR method in the biological domain. It uses ovarian mass spectrometry datasets, as well as leukemia and lung microarray datasets. The author argues that the CBR is a suitable method for the application as it can function well when the domain theory is not clear enough, such as in high-dimensional biomedical domains. The system uses data mining and a logistic regression approach along with CBR to improve the classification performance. The logistic regression helps to filter out the important features to define a case. Similar cases are also clustered in a group using the data-mining technique. Thus, the system handles the "dimensionality" problem in the biomedical domain.
31) Kurbalija [63] [*Purpose: Diagnosis*] presents a diagnosis system in the domain of multiple sclerosis disease using CBR. The CaBaGe (Case Base Generator), a case-based decision-support system, is used to treat the input data source for a new problem case. The cases are created using a case retrieval net and the weights are automatically assigned for each feature in a case. Each case consists of

72 features. The implemented system could be valuable for new physicians and could also be used as a second opinion for experts.

32) Obot *et al*. [64] [*Purpose: Diagnosis*] describe a system for the diagnosis of hepatitis combining CBR, RBR, and neural networks. The proposed system handles the objective knowledge in the domain in the form of some rules and the subjective knowledge is represented using the cases. An expert in the domain determines the weights of the feature values of a case within the range of 1–5. A binary search algorithm is applied for the retrieval of similar cases. The adaptation is performed using a mapping function. If the difference between a current case and a similar case is not so important, it applies the mapping function; otherwise neural networks are used to form a set of rules.

33) CBSMS [55], [65] [*Purpose: Diagnosis, Classification, Planning*] represents a multimodal and multipurpose-oriented clinical decision-support system for stress management. It uses several AI techniques to support diagnosis and biofeedback treatment of stress. The system is based on finger temperature sensor data and also considers contextual information, i.e., human perception and feelings, in a textual format. The reliability of the diagnosis and decision-making tasks in the CBR system is enhanced through textual information retrieval with ontology. When there are limited numbers of initial cases in the case library, a fuzzy rule-based classification scheme helps to cope with the problem by generating artificial cases. Another important goal is to assist a clinician in the treatment procedure. Therefore, a three-phase computer-assisted biofeedback system is proposed, which works in a cyclic procedure and supports the biofeedback training in stress management.

34) HDCU [66] [*Purpose: Classification, Knowledge acquisition/management*] is a hybrid system that combines data mining, user modeling, and CBR in order to achieve a fast, dynamic, reliable, personalized blood glucose level prediction for diabetic patients. The support vector machine (SVM) is also introduced in this system to analyze the patient data, which is for finding patterns and regularities in the datasets.

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References

[1] A. Aamodt and E. Plaza, “Case-based reasoning: Foundational issues, methodological variations, and system approaches,” *Artif. Intell. Commun.*, vol. 7, 1994, pp. 39–59.

[2] M. U. Ahmed, S. Begum, P. Funk, and N. Xiong, “Fuzzy rule-based classification to build initial case library for case-based stress diagnosis,” in *Proc. Int. Conf. Artif. Intell. Appl. (AIA)*, V. Devedžic, Ed. IASTED, Innsbruck, Austria, Feb. 2009, pp. 225–230.

[3] M. U. Ahmed, S. Begum, P. Funk, N. Xiong, and B. V. Schéele, “A multi-module case based biofeedback system for stress treatment,” *Artif. Intell. Med.*, to be published.

[4] M. U. Ahmed, S. Begum, P. Funk, N. Xiong, and B. V. Schéele, “Case-based reasoning for diagnosis of stress using enhanced cosine and fuzzy similarity,” *Trans. Case-Based Reason. Multimedia Data*, vol. 1, no. 1, IBaI Publishing, 2008, pp. 3–19. ISSN: 1864–9734.

[5] H. Ahn and K. Kim, “Global optimization of case-based reasoning for breast cytology diagnosis,” *Expert Syst. Appl.*, vol. 36, pp. 724–734, 2009.

[6] S. Begum, M. U. Ahmed, P. Funk, N. Xiong, and B. V. Schéele, “A case-based decision support system for individual stress diagnosis using fuzzy similarity matching,” *Comput. Intell. (CI)*, vol. 25, no. 3, Blackwell, 2009, pp. 180–195.

[7] I. Bichindaritz, “Case-based reasoning in the health sciences,” *Artif. Intell. Med.*, vol. 36, no. 2, pp. 121–125, 2006.

[8] I. Bichindaritz, “Semantic interoperability of case bases in biology and medicine,” *Artif. Intell. Med.,* (Special issue on case-based reasoning in the health sciences), vol. 36, no. 2, pp. 177–192, 2006.

[9] I. Bichindaritz, “Prototypical case mining from medical literature,” *Appl. Intell.*, vol. 28, no. 3, pp. 222–237, 2007.

[10] I. Bichindaritz, “Prototypical cases for knowledge maintenance in biomedical CBR,” in *Proc. 7th Int. Conf. CBR*, 2007, pp. 493–506.

[11] I. Bichindaritz, “Case-based reasoning in the health sciences: Why it matters for the Health Sciences and for CBR,” in *Proc 9th Eur. Conf. CBR*, 2008, pp. 1–17.

[12] I. Bichindaritz, “Prototypical case mining from biomedical literature for bootstrapping a case base,” *Appl. Intell.*, vol. 28, no. 3, pp. 222–237, 2008.

[13] I. Bichindaritz and C. Marling, “Case-based reasoning in the health sciences: What’s next?” *Artif. Intell. Med.*, vol. 36, no. 2, pp. 127–135, 2006.

[14] C. Bradburn and J. Zeleznikow, “The application of case-based reasoning to the tasks of health care planning,” in *Proc. Top. 1st Eur. Workshop, Case-Based Reason. (EWCBR)*, Springer, Berlin, 1994, pp. 365–378.

[15] D. Brien, I. J. Glasgow, and D. Munoz, “The application of a case-based reasoning system to attention-deficit hyperactivity disorder,” in *Proc.6th Int. Conf. CBR Res. Develop.*, 2005, pp. 122–136.

[16] C. L. Chang, “Using case based reasoning to diagnostic screening of children with developmental delay,” *Expert Syst. Appl.*, vol. 28, pp. 237–247, 2005.

[17] J. M. Corchado, J. Bajo, and A. Abraham, “GERAmI: Improving the delivery of health care,” *IEEE Intell. Syst.* (special issue on ambient intelligence), vol. 3, no. 2, pp. 19–25, Mar./Apr. 2008.

[18] A. Cordier, B. Fuchs, J. Lieber, and A. Mille, “On-line domain knowledge management for case-based medical recommendation,” in *Proc. Workshop CBR Health Sci.*, 2007, pp. 285–294.

[19] F. Díaz, F. Fdez-Riverola, and J. M. Corchado, “GENE-CBR: A case-based reasoning tool for cancer diagnosis using microarray datasets,” *Comput. Intell.*, vol. 22, no. 3–4, pp. 254–268, 2006.

[20] M. D’Aquin, J. Lieber, and A. Napoli, “Adaptation knowledge acquisition: a case study for case-based decision support in oncology,” *Comput. Intell.*, vol. 22, no. 3–4, pp. 161–176, 2006.

[21] D. Doyle, P. Cunningham, and P. Walsh, “An evaluation of the usefulness of explanation in a CBR system for decision support in bronchiolitis treatment,” *Comput. Intell.*, vol. 22, no. 3–4, pp. 269–281, 2006.

[22] F. J. Paz, S. Rodriguez, J. Bajo, and M. J. Corchao, “Case-based reasoning as a decision support system for cancer diagnosis: A case study,” *Int. J. Hybrid Intell. Syst. (IJHIS)*, IOS press, 2008, pp. 97–110.

[23] P. Funk and N. Xiong, “Case-based reasoning and knowledge discovery in medical applications with time series,” *J. Comput. Intell.*, vol. 22, no. 3–4, pp. 238–253, 2006.

[24] L. Gierl and R. Schmidt, “CBR in medicine,” in *Case-Based Reasoning Technology, From Foundations to Applications*. Springer-Verlag: New-York, 1998, pp. 273–298.

[25] D. Glez-Peña, F. Díaz, J. M. Hernández, J. M. Corchado, and F. Fdez-Riverola, “geneCBR: multiple-microarray analysis and Internet gathering information with application for aiding diagnosis in cancer research,” *Boston Med. Center Bioinformatics*, vol. 10, pp. 187–194, 2009.

[26] A. Holt, I. Bichindaritz, R. Schmidt, and P. Perner, “Medical applications in case-based reasoning,” *Knowl. Eng Rev.*, vol. 20, no. 3, pp. 289–292, 2006.

[27] M. Huang, M. Chen, and S. Lee, “Integrating data mining with case-based reasoning for chronic diseases prognosis and diagnosis,” *Expert Syst. Appl. (SCI)*, vol. 32, no. 3, pp. 856–867, 2007.

[28] P. A. Koton, *Using Experience in Learning and Problem Solving*. Cambridge, MA: MIT Press, 1988.

[29] M. Kwiatkowska and M. S. Atkins, “Case representation and retrieval in the diagnosis and treatment of obstructive sleep apnea: A semio-fuzzy

approach," in *Proc. 7th Eur. Conf. Case-Based Reasoning*, Madrid, Spain, Aug./Sep. 2004, pp. 25–35.

[30] F. Lorenzi, M. Abel, and F. Ricci, "SISAIH: A case-based reasoning tool for hospital admission authorization management," *Proc. Workshop CBR Health Sci.*, pp. 33–42, 2004.

[31] G. Leonardi, A. Bottrighi, S. Montani, and L. Portinale, "CBR for temporal abstractions configuration in haemodyalisis," *Proc. Workshop CBR Health Sci.*, pp. 295–304, 2007.

[32] C. Marling, J. Shubrook, and F. Schwartz, "Case-based decision support for patients with type 1 diabetes on insulin pump therapy," in *Proc.9th Eur. Conf.Case-Based Reason: (ECCBR)*. Berlin, Germany: Springer-Verlag, 2008, pp. 325–339.

[33] D. McSherry, "Hypothetico-deductive case-based reasoning," *Proc. Workshop CBR Health Sci.*, pp. 315–324, 2007.

[34] S. Montani, L. Portinale, G. Leonardi, R. Bellazzi, and R. Bellazzi, "Case-based retrieval to support the treatment of end stage renal failure patients," *Artif. Intell. Med.*, vol. 37, pp. 31–42, 2006.

[35] S. Montani and L. Portinale, "Accounting for the temporal dimension in case-based retrieval: A framework for medical applications," *Comput. Intell.*, vol. 22, pp. 208–223, 2006.

[36] S. Montani, "Exploring new roles for case-based reasoning in heterogeneous AI systems for medical decision support," *Appl. Intell.*, pp. 275–285, 2007.

[37] S. Montani, "How to use contextual knowledge in medical CBR systems: A survey on very recent trends," *Proc. Workshop CBR Health Sci.*, pp. 79–88, 2008.

[38] M. Nilsson and M. Sollenborn, "Advancements and Trends in medical case-based reasoning: An overview of systems and system development," in *Proc. 17th Int. FLAIRS Conf.*, 2004, pp. 178–183.

[39] A. Ochoa, M. Meza, S. González, A. Padilla, M. Damiè, D. L. J. Torre, and F. Jiménez-Vielma, "An intelligent tutor based on case-based reasoning to medical use," *Adv. Compt. Sci. Eng. Res. Comput. Sci.,* G. Sidorov, B. Cruz, M. Martinez, and S. Torres, Eds., vol. 34, pp. 187–194, 2008.

[40] D. O'Sullivan, M. Bertolotto, D. Wilson, and E. McLoghlin, "Fusing mobile case-based decision support with intelligent patient knowledge management," *Proc. Workshop CBR Health Sci.*, pp. 151–160, 2006.

[41] P. Perner, "An architeture for a CBR image segmentation system," *J. Eng. Appl. Artificial Intell., Eng. Appl. Artif. Intell.*, vol. 12, no. 6, pp. 749–759, 1999.

[42] P. Perner and A. Bühring, "Case-based object recognition," in *Proc. Adv. Case-Based Reason., (ECCBR)*. Madrid/Spain: Springer Verlag, 2004, pp. 375–388.

[43] P. Perner, H. Perner, and S. Jänichen, "Recognition of airborne fungi spores in digital microscopic images," *J. Artif. Intell. Med.*, vol. 36, no. 2, pp. 137–157, 2006.

[44] P. Perner, "Flexible high-content analysis: automatic image analysis and image interpretation of cell pattern," *G.I. T. Med. and Microscopy*, vol. 1, pp. 2–3, 2006.

[45] C. Plata, H. Perner, S. Spaeth, K. J. Lackner, and P. V. Landenberg, "Automated classification of immunofluorescence patterns of HEp-2 cells in clinical routine diagnostics," *Clin. Chem. Lab. Med.*, vol. 46, no. 9, 2008.

[46] G. Salton and M. McGrill, *Introduction to Modern Information Retrieval*. McGraw-Hill, Inc., New York, NY, 1983.

[47] X. Song, S. Petrovic, and S. Sundar, "A case-based reasoning approach to dose planning in radiotherapy," *Proc. Workshop 7th Int. Conf. Case-Based Reason. (ICCBR)*, Belfast, Northern Ireland, 2007, pp. 348–357.

[48] R. Schmidt, S. Montani, R. Bellazzi, L. Portinale, and L. Gierl, "Cased-based reasoning for medical knowledge-based systems," *Int. J. Med. Inf.*, vol. 64, pp. 355–367, 2001.

[49] R. Schmidt and L. Gierl, "A prognosis model for temporal courses that combines temporal abstraction and case based reasoning," *Int. J. Med. Inf.*, vol. 74, pp. 307–315, 2005.

[50] R. Schmidt and O. Vorobieva, "Case-based reasoning investigation of therapy inefficacy," *J. Knowl.-Based Syst.*, vol. 19, no. 5, pp. 333–340, 2006.

[51] I. Watson, "Knowledge management and case-based reasoning: a perfect match?" *Proc. 14th Annu. Conf. Int. Florida Artif. Intell. Res. Soc.*, AAAI Press, Menlo Park, CA, 2001, pp. 118–122.

[52] D. D. Wu, R. Weber, and D. F. Abramson, "A case-based framework for leveraging nutrigenomics knowledge and personalized nutrition counseling," in *Proc. Workshop CBR Health Sci.*, 2004, pp. 71–80.

[53] Z. Y. Zhuang, L. Churilov, F. Burstein, and K. Sikaris, "Combining data mining and case-based reasoning for intelligent decision support for pathology ordering by general practitioners," *Eur. J. Oper. Res.*, New York: Elsevier, vol. 195, no. 3, pp. 662–675, 2009.

[54] R. C. Schank and R. P. Abelson, *Scripts, Plans, Goals and Understanding*. Erlbaum, Hillsdale, New Jersey, 1977.

[55] M. U. Ahmed, S. Begum, P. Funk, and N. Xiong, "Multi-modal and multi-purpose case-based reasoning in the health sciences," *Proc. 8th Int. Conf. Artif. Intell., Knowl. Eng. Data Bases (AIKED)*, Cambridge, U.K., 2009, pp. 378–383.

[56] P. Koton, "Using experience in learning and problem solving. Massachusetts Institute of Technology," Ph.D. dissertation, Lab. Computer Science, Dept. Electr. Eng. Comut. Sci., MIT/LCS/TR-441, Cambridge, 1989.

[57] R. Bareiss, "Examplar-based knowledge acquisition: A unified approach to concept, classification and learning," Academic Press Professional, Inc., San Diego, CA, 1989.

[58] S. Begum, "Sensor signal processing to extract features from finger temperature in a case-based stress classification scheme," in *Proc. 6th IEEE Int. Symp. Intell. Signal Process.* (special session on signal processing in bioengineering). Budapest, Hungary, Aug. 2009, pp. 193–198.

[59] T.G. Houeland and A. Aamodt, "Towards an introspective architecture for meta-level reasoning in clinical decision support systems," presented at 7th Workshop Case-Based Reason. Health Sci. (ICCBR), Seattle, Washington, 2009.

[60] R. Nicolas, D. Vernet, E. Golobardes, A. Fornells, S. Puig, and J. Malvehy, "Improving the combination of CBR systems with preprocessing rules in melanoma domain," presented at 7th Workshop on Case-Based Reason. Health Sci. (ICCBR), Seattle, Washington, 2009.

[61] T. Töpel, J. Neumann, and R. Hofestädt, "A medical case-based reasoning component for the rare metabolic disease database RAMEDIS," in *Proc. 20th IEEE Int. Symp. Comput.-Based Med. Syst. (CBMS)*, 2007, pp. 7–11.

[62] N. Arshadi and I. Jurisica, "Data mining for case based reasoning in high-dimentional biological domains," *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 8, pp. 1127–1137, Aug. 2005.

[63] V. Kurbalija and M. Ivanovic, "Multiple sclerosis diagnoses- case-base reasoning approach," in *Proc. 20th IEEE Int. Symp. Comput.-Based Med. Syst.*, 2007, pp. 65–72.

[64] O. U. Obot and E. F. Uzoka, "A framework for application of neuro-case-rule base hybridization in medical diagnosis," *Appl. Softw. Comput.*, vol. 9, pp. 245–253, 2009.

[65] M. U. Ahmed, S. Begum, P. Funk, and X. Ning, "A multi-modal case-based system for clinical diagnosis and treatment in stress management," presented at 7th Workshop on Case-Based Reason. Health Sci., Seattle, Washington, 2009.

[66] C. Z. Yuan, D. Isa, and P. Blanchfield, "A hybrid data mining and case-based reasoning user modeling system (HDCU) for monitoring and predicting of blood sugar level," in *Proc. Int. Conf. Comput. Sci. Softw. Eng.*, 2008.

[67] N. Xiong and P. Funk, "Concise case indexing of time series in health care by means of key sequence discovery," *J. Appl. Intell.*, vol. 28, pp. 247–260, 2008.

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