Case Studies on the Clinical Applications using Case-Based Reasoning

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Abstract—**Case-Based Reasoning (CBR) is a promising Artificial Intelligence (AI) method that is applied for problem solving tasks. This approach is widely used in order to develop Clinical Decision Support System (CDSS). A CDSS for diagnosis and treatment often plays a vital role and brings essential benefits for clinicians. Such a CDSS could function as an expert for a less experienced clinician or as a second option/opinion of an experienced clinician to their decision making task. This paper presents the case studies on 3 clinical Decision Support Systems as an overview of CBR research and development. Two medical domains are used here for the case studies: case_study_1) CDSS for stress diagnosis case_study_2) CDSS for stress treatment and case_study_3) CDSS for post-operative pain treatment. The observation shows the current developments, future directions and pros and cons of the CBR approach. Moreover, the paper shares the experiences of developing 3CDSS in medical domain in terms of case study.**

I. INTRODUCTION

DECISION Support System (DSS) that bear similarities with human reasoning have benefits and are often easily accepted by physicians in the medical domain [6, 14, 31, 32, and 33]. Hence, DSSs that are able to reason and explain in an acceptable and understandable style are more and more in demand and will play an increasing role in tomorrow's health care. Many of the early AI systems attempted to apply pure Rule-Based Reasoning (RBR) as 'reasoning by logic in AI' for decision support in the medical area. However, for broad and complex domains where knowledge cannot be represented by rules (i.e. IF-THEN), this pure rule-based system encounters several problems. Knowledge acquisition bottleneck is one of the most critical problems since medical knowledge evolves rapidly, updating large rule based systems and proving their consistency is expensive. A risk is that medical rule-based systems become brittle and unreliable. One faulty rule may affect the whole system's performance and is also important to consider [8, 40]. Artificial Neural Networks (ANN) can be used in the medical domain as "reasoning by learning in AI". However, it requires large data sets to learn the functional relationship between input and output space. Moreover, transparency is another issue since the ANN functions as a so called black box i.e. it is very difficult to understand clearly what is going on [40]. Case-Based

Reasoning (CBR) is a promising AI method that can be applied as "reasoning by experience in AI" for implementing DSSs in the medical domain since it learns from experience in order solve a current situation [16]. CBR is especially suitable for domains with a weak domain theory, i.e. when the domain is difficult to formalize and is empirical. In CBR, experiences in the form of cases are used to represent knowledge. A case is defined by Kolodner and Leake as "a contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner" [26]. In practice, clinicians often reason with cases by referring and comparing previous cases (i.e. experiences). This makes a CBR approach intuitive for clinicians. A case may be a patient record structured by symptoms, diagnosis, treatment and outcome. Some applications have explored integration of CBR and RBR, e.g. in systems like CASEY [27] and FLORENCE [7]. Moreover, some of the recent medical CBR systems are studied (based on literature review) along with a survey (e-mail questionnaire to the corresponding authors) between the year 2004 and 2009 in [43]. Here, the paper investigated the current trends and developments of CBR system in medical domain.

In this paper, three case studies on 3 CDSSs 1) CDSS for stress diagnosis 2) CDSS for stress treatment and 3) CDSS for post-operative pain treatment are presented. Here, we have discussed the power of CBR in medical domain and also presented the advancement of CBR. Moreover, our experience in order to develop the CDSSs on two different medical domains are presented and discussed.

II. RELATED WORK

The design and development of Decision Support Systems (DSSs) or intelligent systems in medicine is very challenging and complex. Even though the area is evolving day-by-day they are most often limited to research level. CDSSs using AI started in the early 1970s and produced a number of experimental systems; the MYCIN [8] was one of them. The HELP [19] system is one of the longest running and most successful clinical information systems. According to a literature study presented in [41], different AI techniques

have been applied in the clinical DSSs such as 1) rule-based reasoning [3, 4 and 8], 2) bayesian theory [9], 3) bayesian belief networks [30], 4) heuristic, 5) semantic network, 6) neural networks [10], 7) genetic algorithms [35] 7) fuzzy logic [3, 9] and 8) case-based reasoning. Some of the recent medical DSSs using CBR approach are presented below: a) ExpressionCBR [17], the system is a decision support system for cancer diagnosis and classification. It uses Exon array data and classifies Leukemia patients automatically to help in the diagnosis of various cancer patients. b) GerAmi [14] 'Geriatric Ambient Intelligence', is an intelligent system that aims to support healthcare facilities for the elderly, Alzheimer's patients and people with other disabilities. This system mainly works as a multi-agent system and includes a CBR system to provide a case-based planning mechanism. c) geneCBR [18, 20], is focusing on classification of cancer, based on a gene expression profile of microarray data. The system is aiming to deal with a common problem in bioinformatics i.e. to keep the original set of features as small as possible. d) ISOR [38], the system identifies the causes of ineffective therapies and advises better recommendations to avoid inefficacy to support in long-term therapies in the endocrine domain. The system is exemplified in diagnosis and therapy recommendations of Hypothyroidism patients treated with hormonal therapy. e) the KASIMIR project [15], is an effort to provide decision support for breast cancer treatment based on a protocol in Oncology. The adaptation of protocol is an important issue handled here to provide therapeutic decisions for cases those are out of the protocol.

III. APPLICATION DOMAINS

In order to develop such CDSSs it requires clinical knowledge of the application domain. Medical, biological and/or physical background of a particular disease and its treatment is one example. In this paper, two different medical application domains have been discussed and presented, they are: 1) stress management and 2) post-operative pain treatment.

A. Stress management

According to Hans Selye, stress can be defined as "the rate of wear and tear within the body" [39]. We have an inborn reaction to stressful situations called the "fight or flight" response. The wear and tear is a physiological reaction such as rise in blood pressure, rise in heart rate, increased respiration rate and muscles get ready for action. According to [34], there are three methods that can be used for the diagnosis of stress: questionnaires, biochemical measures and physiological measures. A face-to-face interview with questionnaires and a checklist are traditional ways to diagnose stress. Rudolf E. Noble in [34], mentioned various biochemical parameters e.g. corticosteroid hormones which can be measured from body fluids, blood, saliva and urine. Since the autonomic nervous system is activated by a

stress response various physiological parameters of the SNS can be used in the diagnosis of stress. The physiological parameters are commonly measured using skin conductance, skin temperature, respiration e.g. end-tidal carbon dioxide (ETCO2), electromyography (EMG), electrocardiography (ECG), heart rate e.g. calculating respiratory sinus arrhythmia (RSA) and heart rate variability (HRV), electroencephalography (EEG), brain imaging techniques, oculomotor and pupilometric measures etc.

There are several methods to control or manage stress e.g. exercise or training. In our everyday lives we need to control our stress in many situations, for instance when we are sitting at our desk or behind the wheel of a car getting stuck in traffic. In such situations or in other environments biofeedback training is an effective method for controlling stress. It is an area of growing interest in medicine and psychology and it has proven to be very efficient for a number of physical, psychological and psycho-physical problems [2, 29]. The basis of biofeedback therapy is to support a patient in realising their self-ability to control specific psychophysiological processes [25]. There is a correlation between skin temperature and relaxation. The changes in skin temperature reflect the state of the peripheral blood vessels which in turn are controlled by the SNS. A biological significant decrease in the SNS i.e. relaxation activity results in an increased diameter in the peripheral blood vessels.

In this research, both stress diagnosis and biofeedback treatment have been conducted using the skin temperature i.e. finger temperature (FT) since the intention of the research was to design and develop a CDSS for stress management which should be simple, inexpensive and easy to use.

B. Post-operative pain treatment

Approximately 40 million patients are undergoing minor to major surgical operations every year in Europe. At least half of these patients from children to elderly have suffered with a moderate or severe amount of post-operative pain. The degree of post-operative pain differs for various patients, operation site and the type of operation. For example, an operation on the thorax and upper abdomen is more painful than the lower abdomen [11]. There are different types of operations but in this project we will only focus on the following operations: 1. Cholecystectomy, 2. Total knee arthroplasty, 3. Knee arthroscopy, 4. Lower limb amputation and 5. Sternotomy for valve replacement or CABG. According to Hawthorn and Redmond [22], pain might often be a useful thing, a "protective mechanism", a biological signal, which is essential when we for example learn not to touch a stove in order to protect us from being injured. However, pain can also be a bad thing; pain after surgery obstructs the healing-process for example resistance to mobility, loss of sleep, decreased food intake, depression and loss of morale can be a consequence of post-operative pain among many other negative consequences that might occur.

The measurement of pain is very subjective and multidimensional experience and unique to every individual [12, 28]. For example, someone may experience heavy pain after a small operation and need extra medication since they have very low capacity to cope with pain. On the other hand, others may have better capacity for pain tolerance and be happy with small doses of medication. Post-operative pain has different levels and ranges starting from a minor pain to a very major acute pain. There are different ways to measure pain even if it is very subjective and individual. For example, for adults a Numerical Rating Scale (NRS) [21] or a Visual Analog Scale (VAS) [23] or Brief Pain Inventory (BPI) [13] is used and for children and elderly patients a Facial expression [24] approach can be used.

IV. CLINICAL APPLICATIONS

Clinicians/doctors have experience which may have been collected over many years. As an example, when a less experienced clinician is confronted with a new problem (for example symptoms that are not familiar) the clinician might start to analyse the whole situation and try to make a diagnosis by using their education and experience (with some solved cases). This may be a very time consuming task and may result in not finding a proper diagnosis. In that case the clinician needs to find other sources for help and a very common way is to ask senior colleagues who have more experience. A professional (more experienced clinician) might start to think to himself: "Have I ever faced any similar problem and in that case, what was that solution?" and refer the problem with their past solution to the less-experienced clinician. The less-experienced clinician then solves the problem and learns the new experience and saves it in their memory for future use. Thus, a clinical experience can be shared and reused to make a quick and correct diagnosis in the domain of health care.

Here in the 3 CDSS, a nearest neighbor (NN) algorithm is applied as a global similarity function to retrieve similar cases in CBR. The similarity measurement is taken to assess the degree of matching and creates a ranked list containing the most similar cases retrieved according to equation 1.

$$\text{Similarity}(C, S) = \sum_{f=1}^{n} w_f * \text{sim}(C_f, S_f) \qquad (1)$$

Where C is a current/target case, S is a stored case in the case base, w is a normalized weight defined by human expert, n is the number of the attributes/features in each case, f is the index for an individual attribute/feature and sim (C_f, S_f) is the local similarity function for attribute f in cases C and S.

A. CDSS for stress diagnosis

The system consists of a thermistor, sensing the finger temperature. A calibration phase helps to establish an individual stress profile and is used as a standard protocol in the clinical environment in order to collect the measurements. The protocol comprises different conditions

in 6 steps, they are as follows: baseline, deep breath, verbal stress, relax, math stress, and relax. The details information about the calibration phase with the six steps can found in [5]. The steps in diagnosis stress using finger temperature (FT) measurements and CBR is illustrated in figure 1.
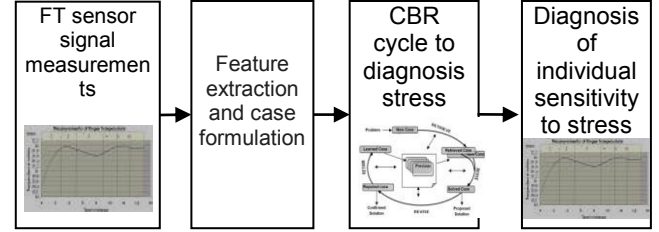

Fig 1. Steps in stress diagnosis using only FT measurements.

To determine important features the system uses 15 minute measurements (time, temperature) in 3600 samples, together with other numeric (i.e. age, room-temperature, hours since last meal, etc.) and symbolic measurements (i.e. gender, food and drink taken, sleep at night, etc.) parameters. According to closer discussion with clinicians, the derivative of each step of the FT measurement (from calibration phase) is used to introduce a "degree of changes" as an indication of the FT changes. A low angle value, e.g. zero or close to zero indicates no change or a stable finger temperature. A high positive angle value indicates a rising FT, while a negative angle, e.g. -20° indicates falling FT. The total signal, except the baseline, is divided into 12 parts each with a one minute time interval. A case is formulated with 19 features in total in which 17 features are extracted from the sensor signal (i.e. Step2_Part1, Step2_Part2, Step3_Part1, …, Step6_Part1, Step6_Part2, start temperature, end temperature, minimum temperature, maximum temperature and difference between ceiling and floor) and 2 are the human defined features (i.e. sex, hours since last meal). This new formulated case is then applied into a CBR cycle of the CDSS to assist with the diagnosis of stress.

The new problem case is then passed into the CBR cycle to retrieve the most similar cases. The case (feature vector extracted for FT signal) in this system is matched using three different local similarity algorithms [45][6]. A modified distance function uses Euclidean distance to calculate the distance between the features of two cases. Hence, all the symbolic features are converted into numeric values before calculating the distance for example, for a feature 'gender' male is converted to one (1) and female is two (2). The function similarity matrix is represented as a table where the similarity value between two features is determined by a domain expert. For example, similarity in same gender (i.e. if both are male or female) is defined by 1 otherwise 0.5. In fuzzy similarity, a triangular membership function (mf) replaces a crisp value of the features for new and old cases with a membership grade of 1. In both the cases, the width of the membership function is fuzzified by 50% in each side. Fuzzy intersection is employed between the two fuzzy sets to get a new fuzzy set which represents the overlapping area between them.

$$sim(C_f, S_f) = s_f(ml, m2) = \max(om/ml, om/m2) \qquad (2)$$

Similarity between the old case (S_f) and the new case (C_f) is now calculated using equation 2 where m1, m2 and om is the area of each fuzzy set. For the interested reader, an elaborated description of fuzzy similarity can be found through the research contributions in [6, 45].

Unlike measurement-based experience, human perceptions are usually expressed in an informal and natural language format, and they are provided important information for diagnosis. In fact, when diagnosing an individual's stress level, clinicians also consider other factors such as the patient's feelings, behaviour, social factors, working environment and lifestyle. Such information can be presented by a patient using a natural text format and a visual analogue scale. Thus, the textual data of patients capture important indications not contained in measurements and also provide useful supplementary information. Therefore, the system adds textual features in a case vector which helps to better interpret and understand the sensor readings and transfer valuable experience between clinicians [45]. The steps that combine the measurements presented in Fig. 2 that is the FT sensor signal measurement and textual information are collected, features are extracted, and a new case is formulated using extracted features and finally send to the CBR cycle for stress diagnosis.
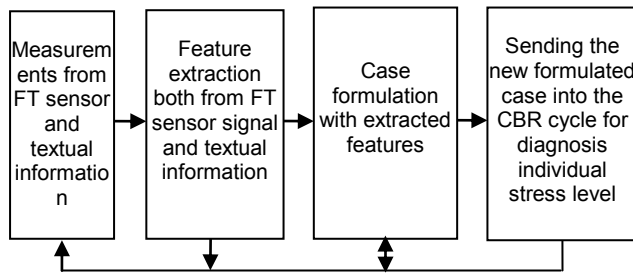

Fig 2. The steps in the stress diagnosis considering both the FT measurement and the textual information.

To enable similarity matching on less structured cases containing text, this research contributes with a proposal which combines cosine similarity with synonyms and ontology. In [45], presents a hybrid model that considers textual information besides FT sensor signal readings. For textual cases, the tf-idf (term frequency–inverse document frequency) [37] weighting scheme is used in a vector space model [36] together with cosine similarity to determine the similarity between two cases. Additional domain information that often improves results, i.e. a list of words and their synonyms or a dictionary provides comparable words and relationship within the words using classes and subclasses are also included. It uses domain specific ontology that represents specific knowledge, i.e. the relationship between words.

B. CDSS for stress treatment

The basis of a biofeedback system is that a patient gets feedback in a clear way (a patient observes a graph and knows from prior education how it should change). The feedback can behaviourally train the body and mind in a better way with a biological response. After discussions with clinicians it can be seen that most of the sensor-based biofeedback applications comprise of three phases illustrated in Fig. 3, 1) analyse and classify a patient and make a risk assessment, 2) determine individual levels and parameters, and finally 3) adapt and start the biofeedback training. If the clinician only uses sensor readings shown on a screen then the classification is highly experience-based [46].
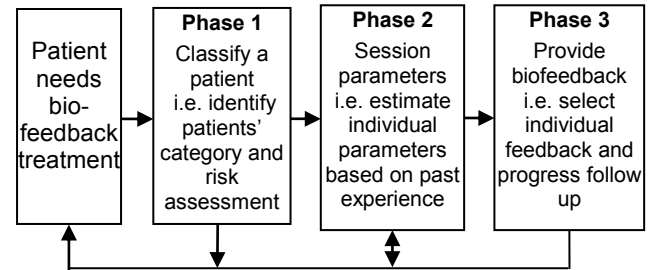

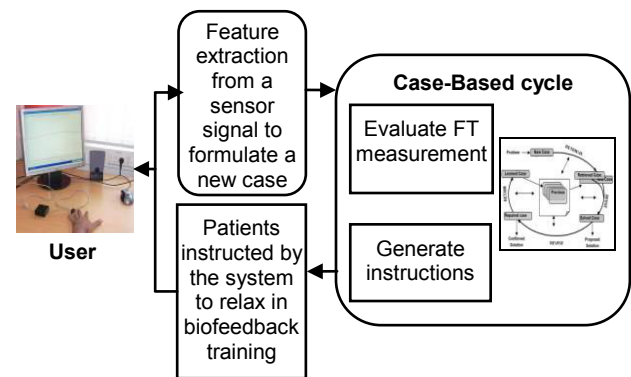Fig 3. General architecture of a three-phase biofeedback system.

Fig 4. The steps in the biofeedback treatment cycle.

In this cycle shown in Fig. 4, a user connects a sensor to their finger and can see the changes of FT during several instructions in relaxation training. The FT measurements are performed in real time and every 2 minutes the system evaluates the last 2 minutes measurement and if necessary generates instructions for the patient. A CBR cycle is applied for the biofeedback training in stress management; this training time is flexible, which means a patient can choose the duration of their training between 6 minutes (as minimum) to 20 minutes (as maximum). Nevertheless, the system generates feedback with appropriate suggestions after every 2 minutes if necessary. Thus, for each individual, the biofeedback cases are formulated with a feature vector from a biomedical signal (i.e. with 2 minutes FT measurement) in the conditional part and a suggestion for relaxation in the solution part. A new biofeedback case is compared to previously solved cases applying a fuzzy similarity matching algorithm and displays the outcome as feedback. Here, the feedback is defined with a pair i.e. it presents an evaluation of the FT measurement and a recommendation for the next training. This generated feedback is then presented to a clinician as a proposed solution. The clinician thereafter reviews the proposed cases and takes a final decision to

suggest a treatment to the patient. Thus the system assists a clinician, as a second option, to improve the patient's physical and psychological condition [46].

C. CDSS for post-operative pain treatment

A case-based system mainly depends on cases, their types and how they should be represented. The case comprises unique features to describe a problem. Cases can be presented in different ways; in the post-operative pain treatment application domain the case structure contains three parts: 1) problem, 2) solution and 3) outcome, which is slightly different from stress management domain. The cases could be defined differently on the basis of their use, manner and nature. Different DSSs might have different requirements on which type of cases are to be handled. For this domain we have proposed different types of cases namely regular cases and rare cases which is a more user-friendly format for physicians. Further, these cases are also authorised and tagged by the case owner. A short description of the different types of cases used in the system is presented in [48]. As the cases in this domain are formulated in three parts, the 'problem description' part contains around 278 attributes, and 'treatment' as a solution consists of 685 attributes, while 'outcome' as a recovery measure has 19 attributes. However, to formulate a case, feature abstraction has been done only considering the problem description and outcome information, which has been further mapped with the solution. So, out of 278 attributes only 15 features are extructed in the problem part and only 1 from 19 attributes were extracted from the outcome part. Deatailed information about feature abastruction is presented in [48]. Note that, the solution part of the cases remains unchanged since this data contains important medicine information which might modify during abstraction. Two cases are compared using NN as global similarity and different local similarity algorithms including modified distance function; similarity matrix and fuzzy similarity matching discussed earlier. Only difference in the local weight which is defined by the case author(s) or owner(s) for each stored case. The weight is assumed to be a quantity reflecting the importance of the corresponding feature individually. The reason to use individual case weighting is to combine several clinicians and experts knowledge into the system.

V. OBSERVATIONS AND DISCUSSION

The paper mainly focuses on the research of the investigation of methods and techniques in order to design and develop Clinical Decision Support Systems (CDSSs). Several Artificial Intelligence (AI) methods, techniques and approaches have been investigated and applied to develop the CDSSs. Although the CBR approach is applied as a core technique for both of the domains, other AI methods were also combined and applied with CBR. In the following section of the paper presented the several related issues and a summary of the reason behind the applied methods, techniques and approaches.

CBR is not only a powerful method for computer reasoning, but also a common human problem solving behaviour in everyday life; that reasoning is based on the past personally experienced cases. CBR is inspired by a cognitive model based on the way humans solve certain classes of problems e.g. solve a new problem by applying previous experience adapted to the current situation. Watson has reported in [40] that CBR is attracting attention because:

1. It does not require explicit domain knowledge but gathering of cases.

2. The CBR [1, 40] method can solve a problem in a way similar to the normal behaviour of human problem solving e.g. it solves a problem using experience. Such a CBR system could be valuable for a less experienced person because the case library can be used as knowledge.

3. A CBR system can start working with few reference cases in its case library and then learn day by day by adding new cases into the library. Similarly, a doctor or an engineer might start their practice with a few cases and gradually increases their experiences.

4. Simple and easy implementation because significant features describe a case. Database Management Systems or DBMS could help to handle a large volume of information.

5. A CBR system can provide more than one alternative for a similar problem which is beneficial for the clinician.

6. CBR can help to reduce the recurrence of a wrong decision because the case library could contain both success and failure of cases.

7. Knowledge elicitation is most of the time a bottleneck in the health science domain since human behaviour is not always predictable. The CBR method can overcome this because prediction is based on the experience or old cases.

8. It is useful if the domain is not clear i.e. CBR does not depend on any rules or any models [40].

9. Systems using CBR can learn new knowledge by adding new solved cases into the case library, so domain knowledge is also updating in time.

A. CBR Approach Applied as a Core Technique

When the domain knowledge of any medical application is complex or not well defined such as stress management or post-operative pain treatment, it is very difficult to build a CDSS. Many of early CDSSs attempted to apply pure rule-based reasoning (i.e. IF-THEN rules), for example MYCIN [8] uses a knowledge base of ~600 rules. In order to define these 600 rules, one need to very detailed knowledge about the domain. The domain theory should be strong and well defined and this is complex and time consuming [40]. In the stress management domain, the knowledge is not well

defined and there is large variation within and between patients. There is no general straight forward rule for diagnosis and treatment of stress and sometimes it is very difficult even for an experienced clinician [45][46][6]. In these situations the CBR approach works well as a CDSS since it provides the clinician with past similar cases to help them make more informed solutions. According to our previous experience in [3] where a DSS was built in order to Duodopa dose tuning for Parkinson patient using the rules defined by the domain expert. During evaluation after building the whole system, it was observed that the system can only work well on on-going (stabilized) patients but bad for new patients since these new patients don't follow any rules. Also, the same problem has been announced in post-operative pain treatment that around 30% of whole population does not fit the standard protocol [48]. In our projects using CBR the systems can learn by acquiring new cases which can be done without modification to the system [40].

The CBR approach is much better compare to Neural Network (NN) when data source is multi-media, i.e. not purely a numerical data format rather a mixture of symbolic, textual and numeric data formats. At the same time, NN requires a large data set since it divides the whole data set into three parts, training, validation and testing. Whereas a CBR system can use its whole data set in order to build and evaluate. Thus, a CBR system can start its functionality with a few cases. In the stress management domain, the NN was not used due to too few cases (i.e. only 68) and the data format is not purely numeric. But the research could apply NN in the post-operative pain treatment domain since it has more than 1500 complete cases. However, a major disadvantage of NN is that it functions as a 'black box'. The output from an NN is a utility of the weighted vectors of its neurons [40]. It cannot give any explanation or justification about the output. Moreover, it is very difficult for clinician's to trust the system in this domain as clinicians are not likely to accept any solution without an explanation. In the CBR approach the most similar cases are retrieved and presented to the clinicians to enable them to make a more informed decision. This was one of the key reasons for the clinicians in the Pain-Out project to accept the CBR approach and this is why this research has applied the CBR approach for post-operative pain treatment [48].

The research could use other techniques such as machine learning or statistics but again they require a large volume of data. The data set should be well-understood, the knowledge/hypothesis should be well-defined, there should be generalizable rules and they should be actable by rule-trace [40]. The research applied CBR as the core technique for both the application domains since CBR has process similarity i.e. it is inspired by human reasoning [1, 40]. The reasoning process is also medically accepted since doctors quite often used previous experience to solve a problem. Using CBR, an expert can directly apply their knowledge by choosing related features and their importance, for example a patient's weight is more important than the shoe size. Moreover, they can also let the system know about the

similarity of two features, considering gender as a feature, a male and female may differ in similarity in e.g. choice of medication. Maintenance of a CBR system is much simpler since new knowledge can be inserted by adding new cases and the cases in case library can be used by trainee clinicians. Another interesting observation is that the CBR approach is compatible with other AI methods and thus the system can take advantage of other techniques in order to improve its performance [44] [47].

Nevertheless, some major problems that we have encountered while implementing the case-based systems are 1) Number of cases in the case library: In CBR, the case library should contain qualitative and representative cases. The problem that we have faced in the stress domain is that the number of cases especially for a particular class 'Very Relaxed' was not enough in the case library and this has reduced the performance of the system for diagnosing new patients of that particular class. However, we have taken advantage of fuzzy rule-based reasoning to generate artificial cases which is discussed in [47] [44]. 2) Automatic adaptation: automatic adaptation often requires clear domain knowledge. Therefore, in medical CBR systems, there is not much adaptation. The DSSs described here do not contain any automatic adaptation since in such systems where the best cases are proposed to the clinician as suggestions of solutions and when the domain knowledge is not clear enough automatic adaptation is difficult to develop or not advised [40]. However, in the presented CDSSs the solution of a past case often requires adaptation to find a suitable solution for the new case. This adaptation might often be a combination of two or more solutions of cases from the retrieved cases. Therefore, retrieving a single matching case as a proposed solution may not be sufficient for the DSSs. So, the systems retrieve a list of ranked cases to help in the adaptation process but finally the adaptation and validation of cases has been carried out by clinicians in the domains.

B. Others AI Techniques Applied as Tools

Besides the CBR approach, the research has investigated and applied several AI technologies and approaches. The other AI technologies have been used as tools help to fine tune the CBR approach in order to obtain the complete benefit of the CBR systems. The combination of several AI techniques depends on the nature of the domain, data format, complexity and performance. For both the application domains, fuzzy logic is applied in the similarity measurement of the CBR approach since it helps to accommodate uncertainty. Moreover, fuzzy similarity matching presented in [44][45][46] reduces the sharp distinction which is obtained in similarity matrix [6] formulated by an expert. In [44] section 3.1, comparisons of three local similarities are presented and it shows that when using fuzzy similarity the system can achieve a better performance. The information retrieval approach i.e. mainly vector space modeling (VSM) is applied together with a WordNet dictionary and domain specific ontology in order to retrieve textual cases presented in [45]. Here, the system did not combine textual cases and FT cases in order to provide a combined solution rather the

most similar textual cases are presented. These textual cases provide information regarding patients' contextual feelings, behaviors, social facts, working environments, lifestyle and other additional information which enhances the reliability of the CDSS. Thus, the CDSS for stress management provides support to clinicians in their decision making tasks by only retrieving the most similar cases (both textual cases and FT measurements cases simultaneously) rather than providing any combined direct solution.

To some extent, when the domain knowledge is well-defined the RBR can work, for example, when FT increases the patient is in a relaxed state and when FT is decreasing it is usually a sign of a stressed state. These simple rules can be used and in this research they are used only to create artificial cases [47]. So, in the stress management domain, fuzzy rule-based reasoning is used together with a CBR approach in order to improve the system's performance since there are very few reference cases in the case library. In [44] section 3.2, the result shows that the CDSS succeed to improve its performance by 22% by using a bigger case library initiated both by using reference cases and cases created by fuzzy rules. The details of the fuzzy rule-based reasoning scheme and related experimental works are presented in [47].

C. Future Direction and Application

CBR system can provide a case library which motivates a new direction of data mining and knowledge discovery and combination with CBR. For example in post-operative pain treatment domain, there were more than 1500 reference cases in the case library, so the clustering approach in terms of data mining and knowledge discovery could be used in order to identify unusual cases (outliers) from the regular ones[49]. Here, a novel combination of the FCM and Hierarchical clustering which was able to identify 18% of cases as rare cases. This group of unusual case together with regular one can be stored into the case library and the retrieval function of the CBR system could consider the most similar groups and present to a clinician accordingly. This could also help to reduce retrieval time in the CBR system.

Currently, the stress diagnosis system is expanded to use it in a professional driving situation [42]. The driver cases could lead to new research challenges in developing the CBR systems and meeting these challenges could positively impact on the advancement of CBR systems for health care in professional environment.

REFERENCES

[1] Aamodt A. and Plaza E., Case-based reasoning: Foundational issues, methodological variations, and system approaches, AICom - Artificial Intelligence Communications, IOS Press, Volume 7, Issue 1, pp 39-59, 1994.

[2] AAPB, The association for applied psychophysiology and biofeedback, http://www.aapb.org/, Last referred November 2011.

[3] Ahmed M. U., Westin J., Nyholm D., Dougherty M. and Groth T., A fuzzy rule-based decision support system for duodopa treatment in Parkinson, Proceedings of the 23rd annual workshop of the Swedish Artificial Intelligence Society, Umeå, May 10-12, Ed(s): Eklund P., Minock M. and Lindgren H., pp 45-50, 2006.

[4] Alayón S., Robertson R., Warfield S.K., and Ruiz-Alzola J., A fuzzy system for helping medical diagnosis of malformations of cortical development, Biomedical Informatics, Volume 40, Issue 3, pp 221-235, 2007.

[5] Begum S., Ahmed M.U., Funk P., Xiong N. and Scheele B. V., Using calibration and fuzzification of cases for improved diagnosis and treatment of stress, The Proceedings of the 8th European Workshop on Case-based Reasoning, pp 113-122, 2006.

[6] Begum S., Ahmed M.U., Funk P., Xiong N. and Schéele B.V, A case-based decision support system for individual stress diagnosis using fuzzy similarity matching, Computational Intelligence, Blackwell Publishing, Volume 25, Nr 3, pp 180-195, 2009.

[7] Bradburn C. and Zeleznikow J., The application of case-based reasoning to the tasks of health care planning. In proceedings of topics in case-based reasoning: 1st European workshop, EWCBR-93, Springer, Berlin, pp 365–378, 1994.

[8] Buchanan B.G. and Shortliffe E.H., Rule-based expert systems: The MYCIN experiments of the Stanford heuristic programming project, Reading Mass. : Addison-Wesley, 1984.

[9] Casas F., Orozco A., Smith W. A., De Abreu-García J. A. and Durkin J., A fuzzy system cardio pulmonary bypass rotary blood pump controller, Expert Systems with Applications, Volume 26, Issue 3, pp 357-361, 2004.

[10] Charles E. K, Linda M. R., Katherine A. S. and Peter H., Construction of a Bayesian network for mammographic diagnosis of breast cancer, Computers in Biology and Medicine, Volume 27, Issue 1, pp 19-29 January 1997.

[11] Charlton E., The management of postoperative pain, update in anaesthesia, World Federation of Societies of Anaesthesiologists, Issue 7, Ar. 2, 1997, http://www.nda.ox.ac.uk/wfsa/html/u07/u07_003.htm, Last referred November 2011.

[12] Clark W.C., Yang J.C., Tsui S.L., Ng K.F. and Clark S.B., Unidimensional pain rating scales: a multidimensional affect and pain survey (MAPS) analysis of what they really measure, Pain, Volume 98, Issue 3, pp 241-247, 2002.

[13] Cleeland C.S. and Ryan K.M., Pain assessment: Global use of the brief pain inventory, Annals of the Academy of Medicine Singapore, Volume 23, Issue 2, pp 129–138, 1994.

[14] Corchado J.M., Bajo J. and Abraham A., GERAmI: Improving healthcare delivery in geriatric residences, IEEE Intelligent Systems, Volume 23, Issue 2, pp 19-25. ISSN: 1541-1672, 2008.

[15] D'Aquin M., Lieber J. and Napoli A., Adaptation knowledge acquisition: A case study for case-based decision support in oncology, Computational Intelligence, Volume 22, Issue 3-4, pp 161 – 176, 2006.

[16] Demirali J., Reason: An introduction to critical thinking, 1st edition. ISSBN 978-1-4583-7749-4, Analogical Reasoning Institute, 2011.

[17] De Paz J.F., Rodriguez S., Bajo J. and Corchao J.M., Case-based reasoning as a decision support system for cancer diagnosis: A case study, International Journal of Hybrid Intelligent Systems (IJHIS), IOS press, Volume 6, Issue 2, pp 97-110, 2009.

[18] Díaz F., Fdez-Riverola F. and Corchado J.M., GENE-CBR: A case-based reasoning tool for cancer diagnosis using microarray data sets, Computational Intelligence, Volume 22, Issue 3-4, pp 254-268, 2006.

[19] Gardner R.M., Pryor T.A. and Warner H.R., The HELP hospital information system: update 1998, International Journal of Medical Informatics, Volume 54, Issue 3, pp 169-182, 1999.

[20] Glez-Peña D., Díaz F., Hernández J.M., Corchado J.M. and Fdez-Riverola F., geneCBR:A translational tool for multiple-microarray analysis and integrative information retrieval for aiding diagnosis in cancer research, BMC Bioinformatics, Volume 10, Issue 1, Publisher: BioMed Central, 2009.

[21] Hartrick C.T., Kovan J.P. and Shapiro S., The numeric rating scale for clinical pain measurement: a ratio measure?, Pain Pract, Volume 3, Issue 4, pp 310–316, 2003.

[22] Hawthorn J. and Redmond K., Pain: Causes and management, Journal of Psychiatric and Mental Health Nursing, Volume 6, Issue 5, pp 409–410, 1999.

[23] Huskisson E.C., Measurement of pain, The Lancet, Volume 304, Issue 7889, pp 1127-1131, 1974.

[24] Jose D.A., Fischer H.B.J., Ivani G., Mogensen T., Narchi P., Singelyn F.J., Stienstr R. and Wulf H., Postoperative pain management – good clinical practice, European Society of Regional Anaesthesia and Pain therapy,
http://www.esraeurope.org/PostoperativePainManagement.pdf, Last referred September, 2011.

[25] Kappes B., Biofeedback therapy: Training or treatment, Applied Psychophysiology and Biofeedback, Volume 33, pp 173-179, 2008.

[26] Kolodner J.L. and Leake D., A tutorial introduction to case-based reasoning, In Case-Based Reasoning: Experiences, Lessons and Future Directions, Leale D. (Ed.), Cambridge, MA: AAAI/MIT Press, pp 31-65, 1996.

[27] Koton P., Using experience in learning and problem solving, Massachusetts Institute of Technology, Laboratory of Computer Science, PhD Thesis MIT/LCS/TR-441, 1989.

[28] Kumar S., Tandon O.P. and Mathur R., Pain measurement: a formidable task, Indian Journal of Physiol Pharmacol, Volume 46, Issue 4, pp 396–406, 2002.

[29] Lehrer P., Smetankin A. and Potapova T., Respiratory Sinus Arrhythmia Biofeedback Therapy for Asthma: A Report of 20 Unmedicated Pediatric Cases Using the Smetankin Method, Applied Psychophysiology and Biofeedback, Volume 25, Issue 3, pp 193-200, 2000.

[30] Lindgaard G., Egan P., Jones C., Pyper C., Frize M., Walker R., Boutilier C., Hui B., Narasimhan S., Folkens J. and Winogron B., Intelligent decision support in medicine: back to Bayes?, Journal of Universal Computer Science, Volume. 14, Issue 16, pp 2720- 2736, 2008.

[31] Marling C. and Whitehouse P., Case-based reasoning in the care of Alzheimer's disease patients, 4th International Conference on Case-Based Reasoning, ICCBR 01, pp 702-715, 2001.

[32] Montani S., Portinale L., Leonardi G. and Bellazzi R., Case-based retrieval to support the treatment of end stage renal failure patients, Artificial Intelligence in Medicine, Volume 37, Issue 1, pp 31-42, 2006.

[33] Nilsson M., Funk P., Olsson E., Von Schéele B. H. C., and Xiong N., Clinical decision-support for diagnosing stress-related disorders by applying psychophysiological medical knowledge to an instance-based learning system, Artificial Intelligence in Medicine, Volume 36, Issue 2, pp 159-176, 2006.

[34] Noble R.E, Diagnosis of stress, Metabolism - Clinical and Experimental, Elsevier Science (USA),Volume 51, Issue 6, Part B, pp 37-39, 2002.

[35] Podgorelec V., Kokol P. and Zavrsnik J., Medical diagnosis prediction using genetic programming, 12th IEEE Symposium on Computer-Based Medical Systems, pp 202 - 207, 1999.

[36] Salton G., Wong A. and Yang C.S., A vector space model for automatic indexing, Communications of the ACM, Volume18, Issue11, pp 613–620, 1975.

[37] Salton G. and Buckley C., Term weighting approaches in automatic text retrieval, Information Processing and Management, Volume 24, Issue 5, p513-23, 1988.

[38] Schmidt R. and Vorobieva O., Case-based reasoning investigation of therapy inefficacy, Knowledge-Based Systems, Volume 19, Issue 5, pp 333–340, 2006.

[39] Selye H., The Stress of Life. New York: McGrawHill, 1956, Revised edition 1976.

[40] Watson I., Applying Case-Based Reasoning, Techniques for Enterprise Systems, Morgan Kaufmann Publishers Inc, 250 pages, ISBN 1-55860-462-6, 1997.

[41] Yang J.B., Xu D.L. and Kong G., Clinical decision support systems: a review on knowledge representation and inference under uncertainties, International Journal of Computational Intelligence Systems, Volume 1, Nr. 2, pp 159-167, 2008.

[42] Begum S., A Case-Based Driver's State Monitoring System Using Physiological Sensor Signals, 11th Industrial Conference, ICDM 2011, Advances in Data Mining, Workshop Proceedings on Case-Based Reasoning , p 42-54, Ibai Publishing, New York, USA, Editor(s):Petra Perner and Georg Rub, September, 2011.

[43] Begum S., Ahmed M.U., Funk P., Xiong N., Folke M., Case-Based Reasoning Systems in the Health Sciences: A Survey on Recent Trends and Developments, International journal of IEEE Transactions on Systems, Man, and Cybernetics-Part C: Applications and Reviews, vol 41, Issue 4, 2011, pp 421 - 434.

[44] Ahmed M.U., Begum S., Funk P., A Hybrid Case-Based System in Stress Diagnosis and Treatment, Accepted in the IEEEEMBS International Conference on Biomedical and Health Informatics (BHI2012), 2012.

[45] Ahmed M.U., Begum S., Funk P., Xiong N., von Schéele B, Case-based Reasoning for Diagnosis of Stress using Enhanced Cosine and Fuzzy Similarity. International journal of Transactions on Case-Based Reasoning on Multimedia Data, vol 1, Number 1, IBaI Publishing, ISSN: 1864-9734, 2008, pp 3-19.

[46] Ahmed M.U., Begum S., Funk P., Xiong N., von Schéele B, A Multi-Module Case Based Biofeedback System for Stress Treatment. International journal of Artificial Intelligence in Medicine, vol.51, Issue 2, Publisher: Elsevier B.V., 2010, pp 107-115.

[47] Ahmed M.U., Begum S., Funk P., Xiong N., Fuzzy Rule-Based Classification to Build Initial Case Library for Case-Based Stress Diagnosis. In the proceedings of 9th International Conference on Artificial Intelligence and Applications (AIA), 2009, pp 225-230.

[48] Ahmed M.U., Funk P., A Case-Based Retrieval System for Post-operative Pain Treatment, In the proceeding of International Workshop on Case-Based Reasoning CBR 2011, IBaI, Germany, New York/USA, Ed(s):Petra Perner and Georg Rub, September, 2011, pp 30-41.

[49] Ahmed M.U., Funk P., Mining Rare Cases in Post-Operative Pain by Means of Outlier Detection, Accepted in the IEEE International Symposium on Signal Processing and Information Technology, 2011.