Case-based systems in health sciences - a case study in the field of stress management

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Abstract: - Now-a-days medical domain is a popular area for the artificial intelligence (AI) research. Many of the early AI systems were attempted to apply rule-based reasoning in developing computer-based diagnosis system in medical domain. However, for a broad and complex medical domain the effort of applying rule-based system has encountered several problems. Today many systems are serving multi-purpose i.e. tend to support not only in diagnosis but also in number of other complex tasks and combining more than one AI techniques in the health care domain. In this paper, we will investigate the state-of-the art of case-based reasoning (CBR), a recent AI method in the medical domain. A case study in the stress medicine domain is presented here. Today stress has become a major concern in our society. The demand of the decision support system (DSS) in stress domain is increasing rapidly. However, the application of DSS in this domain is limited so far due to the weak domain theory. In our on going research, we have proposed a solution analyzing the relation between stress and finger temperature using case-based reasoning and other AI techniques namely case-based reasoning, textual CBR, rule-based reasoning, and fuzzy logic to support classification and diagnosis in stress management.

Key-Words: - Case-based reasoning, Medical domain, Stress, Fuzzy logic, Classification and Diagnosis.

1 Introduction

In the medical domain, diagnostic, classification and treatment are the main tasks for a physician. The multi-faced and complex nature of the medical domain such as the psychophysiological domain often requires the development of a system applying several artificial Intelligence techniques for instance CBR, textual CBR, rule-based reasoning (RBR), and fuzzy logic and so on. Some of the computer-aided systems in the health sciences using different AI techniques are: a computer based diagnosis system for retinal diseases in [38] in which artificial neural network is used to train for diagnosing new disease in medical images. Park et al. [39] address a system for the improvement of skin cancer diagnosis by the fuzzy algorithm. A contrast enhancement of diabetic retinal images via a hybrid neurofuzzy system is demonstrated in [41]. Bulucea et al. [40] has presented a real time medical telemonitoring of sustainable health care measuring devices using AI techniques.

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

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

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

1. CBR [1, 46] method can work in a way close to human reasoning e.g. solves a new problem

applying previous experiences. This reasoning process is also medically accepted.

2. Knowledge elicitation is another problem in some medical domain, as human behaviour is not always predictable. Even for an experienced clinician might have difficulty to articulate their knowledge explicitly. Sometimes they make assumptions and predictions based on experiences or old cases. Using CBR this knowledge elicitation bottleneck can be overcome.
3. CBR can be used when there are no sets of rules or a model [47].
4. Sometimes it is possible to identify features for the success or failure of a case. This would help to reduce the repetition of mistakes in future.
5. The knowledge in medical domain is growing with time so it is important the system can learn new knowledge. Many of the AI systems failed to continue because of the lack of this type of maintenance. CBR system can learn by adding new cases into the case base.
6. The cases in the case base can be used for the follow up of the treatment and also for training purposes of the less experience clinicians.

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

- Feature extraction- desire to let medical CBR systems handle increasingly complex data format, such as image, sensor signals etc.
- Limited number of available cases- in the initial phase of a medical CBR system there are often a limited number of cases available which. This may reduces the performance of the system. If past cases are missing or very sparse in some areas the accuracy is reduced.
- Adaptation- medical domains are often complex, knowledge and recommendation change in medical knowledge; cases often have large number of features; risk analysis for an automatic adaptation strategy [48].

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

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

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

1.1 Case-based Reasoning Cycle

A case represents a piece of knowledge as experience and plays an important role in the reasoning process. Cases can be presented in different ways [46]. To provide solution of a new case, the cases can be represented as problem and solution structure. For the evaluation of the current cases, cases can also contain outcome/result [Fig 1].

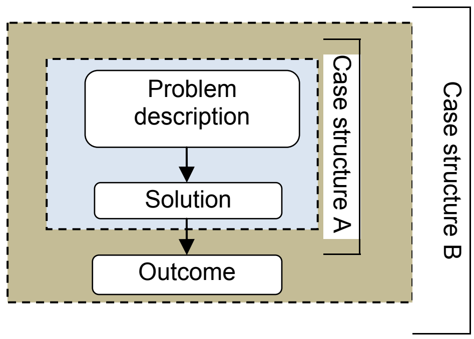

Fig 1. Case representation: cases can contain problem description and solution only or may include the result/outcome into the case structure in medical domain. [45]

Aamodt and Plaza have introduced a life cycle of CBR [1] which is a four-step model with four RE-s, as shown in Fig 2. Retrieve, Reuse, Revise and Retain present the key tasks to implement such kind of cognitive model. In the retrieve step, the system tries to retrieve the most similar case(s) by matching previous cases from a case base. If it finds any suitable case that is close to a current problem then the solution is reused (after some adaptation and revision, if necessary). A clinician may revise the selected case with solution and retain this solution along with the new problem into the case base. In many medical CBR systems feature extraction is a relative large issue due to complexity of the data. In medical CBR systems, the use of complete CBR cycle is still rare.

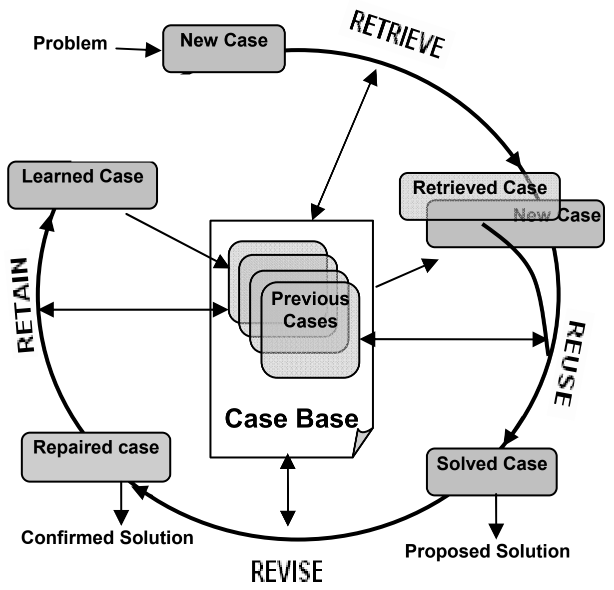

Fig 2. CBR cycle. The figure is introduced by Aamodt and Plaza [1]

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

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

2 Medical CBR systems

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

2.1 Overall trends

Table 1 presents CBR systems with their purpose-oriented properties and application domain.

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

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

According to table 1, the majority of the recent CBR systems address more than one purpose-oriented category. In 2004, only 2 of the evaluated systems were multipurpose- systems while today most of the systems have two or more purposes [28]. Note that, Nilsson et al. [28] investigated 15 CBR systems yet did not explicitly mention overlapping among their purpose-oriented properties. So the systems today are not only concentrating on the diagnostics and treatment tasks as the early CBR systems.

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

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

Recent CBR systems tend to support in other complex tasks in the health care domain. In particular, we can observe the use of CBR systems in Knowledge acquisition/management has attained increasing attention in recent years. Also planning in the medical domain offers interesting challenges to case-based reasoning researcher and/or being an application where the CBR methodology may offer valuable progress and commercial applications.

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

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

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

3 IPOS: a CBR system in stress

The goal of the IPOS [7, 2, 3] project is to develop personalized and adaptive methods, techniques and tools that improve the user's health. An important focus of the project is to develop tool based methods reducing stress to levels that are safe in the long term and thus improving health of an individual. Moreover, diagnostic methods and techniques are important in order to adapt and personalize any health improving recommendations and exercises. The research interest of this part of the project lies in employing AI techniques and methods in physiological time-series data in diagnosing psychophysiological disorder i.e. stress.

Psycho-physiology addresses the relation between psychology and physiology. Stress medicine is a branch of Psycho-physiology where the treatment of stress-related dysfunctions is studied. In psychology stress is defined as a condition caused by different factors in which human beings are inclining to change the existing normal stable state. When we react to certain events or facts it may produce stress. Stress may in worst case cause severe mental and physical problems that are often related to psychosomatic disorders, coronary heart disease etc. [42]. Stress can lead to different problems like fluctuation in body temperature, fluctuation in body sugar etc. But these symptoms of stress are very individual, so it's difficult to diagnose stress. There are many techniques and exercises available to diminish the aftereffects of stress.

Since one of the effects of stress is that the awareness of the body decreases, it is easy to miss signals such as high tension in muscles, unnatural breathing, blood-sugar fluctuations and cardiovascular functionality. It may take many weeks or months to become aware (perhaps first when symptoms reach a handicapping or dramatic level) of how high the stress has been, and once notified, the effects and unaligned processes, e.g. metabolic processes, may need long and active behavioural treatment to revert to a normal state [43]. For patients with high blood pressure and heart problems high stress levels may be directly life endangering. A system that notifies when stress levels are rising or too high is valuable in many situations.

A procedure for diagnosing stress-related disorders using CBR has been put forward by Nilsson et al. [44] under the Artificial Intelligence in Medical Applications (AIM) project at Mälardalen University, Sweden. According to which stress-related disorders are diagnosed by classifying the heart rate patterns analyzing both cardio and pulmonary signals, i.e., physiological time series and used as a research tool in psycho-physiological medicine. This was an initial attempt to use a decision support system (DSS) in a previously unexplored domain e.g. psycho-physiological medicine. This tool is more suitable to use in clinical environment.

The construction of multi-purposed and multi-modal medical systems is becoming a hot topic in current applied CBR research as discussed in section 2. The research efforts in this direction can be well demonstrated by the IPOS. Our aim is to develop tool based methods to diagnose and monitor stress levels and thereby improving health of an individual. Fig. 3 presents the steps to develop a hybrid multi-purpose CBR system to support in diagnosis and treatment of stress-related disorder based on finger temperature measurements.

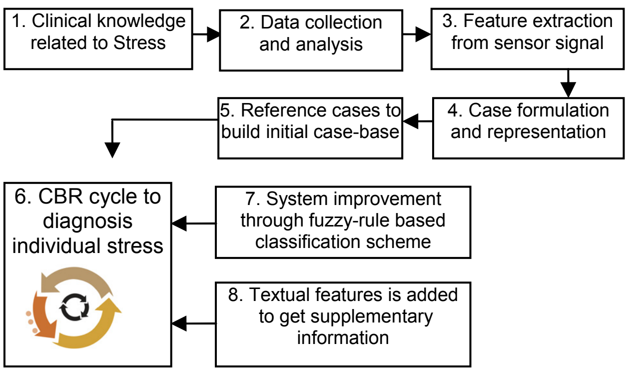

Fig 3. Schematic diagram of developing the CBR system

Stage 1: The signal employed in IPOS is finger temperature (FT) which generally decreases with stress as shown in clinical studies. This is one of the psychophysiological parameter that is clinically used to quantify the stress-related dysfunctions. But, interpreting a particular FT measurement and diagnosing stress level is difficult even for experts in the domain due to the large individual variations and absence of general rules. Clinicians normally observe the FT signal in a computer screen and analyze this signal manually, which is very tedious task and often requires time and experience. Fig 4 shows that the finger temperature is rising after lunch and falling before lunch. The finger temperature is different for different individuals due to health factor, metabolic activity etc.

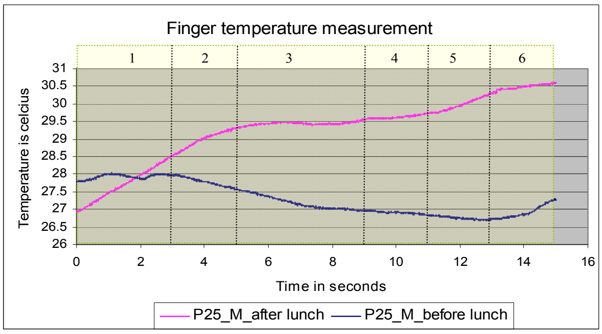

Fig 4. Variations on finger temperature measurement with stress

Stage 2: The FT measurement is taken using a temperature sensor in six steps (i.e. Baseline, Deep-breath, Verbal-stress, Relax with positive thinking, Math-stress and Relax) in the calibration phase [8].

Test step	Observation time	Conditions Finger temp.Notes
1.	3 min	Base Line
2.	2 min	Deep Breath
3.	2+2 min	Verbal Stress
4.	2 min	Relax
5.	2 min	Math stress
6.	2 min	Relax

Table 3: Measurement procedure used to create an individual stress profile.

Table 3 demonstrates these conditions with the observation time for each step. In this phase a number of individual parameters are identified to establish an individual stress profile.

Baseline may be seen as indicating the representative level for the individual when he/she is neither under strong stress nor in a relax state. Clinicians let the person to read a neutral text during this step. A clinician not only identifies an individual's basic finger temperature, but also notes fluctuations and other effects, e.g. disturbances in the environment or observes person's behaviour.

In *Deep-breath* the person breaths deeply which under guidance normally causes a relax state. Also how quickly the changes occur during this step is relevant and recorded together with observed fluctuations.

Verbal-stress is initiated with letting a person tell about some stressful events they experienced in life. During the second half of the step a person thinks about some negative stressful events in his/her life. In *Relax*, the person may be instructed to think of something positive, either a moment in life when he was very happy or a future event he looks forward to experiencing. *Math-stress*; it tests the person's reaction to directly induced stress by the clinician where the person is requested to count backwards. Finally, the *relaxation* step tests if and how quickly the person recovers from stress.

Stage 3: According to the clinical experts *Verbal stress* and *Relax* (table 3) are the most significant steps to classify a person's sensitivity to stress. Verbal stress is defined as reactions during lab stress conditions and relaxation step is to see how quickly a person recover or cope with stress. We find that different persons behave differently in this phase, (talking about and thinking about a negative event) some have a very sharp drop in finger temperature, others a slow drop, a few have no drop in temperature (i.e. after lunch). Also some persons quickly recover in step 4 (thinking positive event) others have slow increase in temperature, a few just continue dropping. According to the clinicians the later may be an indication of being more sensitive to stress, but in some cases there are normal explanations for these cases (i.e. a person having an exam after the test or being very hungry) and they are probably not needing treatment, but if this pattern is repeatedly consistent, then there may be a problem that need some treatment. Also a stressed person may not reach a stable or relaxed state if the body is misadjusted. This can be caused by different illnesses or by long periods of increased stress. One indication of such an increased stress level may be that the difference between a stressed state (*Verbal stress*) and a relaxed state (*Relax*) is small. The time it takes for a person to switch from one state to another state is relevant information for a clinician, e.g. a person who still has a finger temperature level that corresponds to stressed state after spending time on relaxation exercises may need a different treatment than a person quickly reaching a finger temperature corresponding to a relaxed state. This kind of reasoning is what clinicians often doing, weighting different information. Therefore, the shape or 'behaviour' in these steps i.e. 3 and 4 (*Verbal stress* and *Relax*) is significant to classify a person's sensitivity to stress.

We propose to introduce "degree of change" as a measurement for finger temperature change. A low value, e.g. zero or close to zero is no change or stable in finger temperature. A high value indicating a steep slope upwards indicates a fast increase in finger temperature, while a negative angle, e.g. -20° indicates a steep decline. Together with clinicians we have agreed on a standardisation of the slope to make changes visible and patients and situations easier to compare. The proposal is that the X axis in minutes and the Y axis in degrees Celsius, hence a change during 1 minute of 1 degree gives a "degree of change" of 45° see Fig 5.

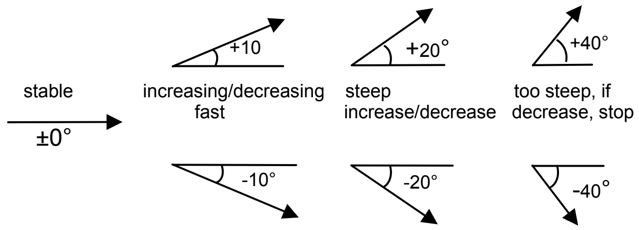

Fig 5. Example of visualisations of temperature change, X axis minutes, Y axis 0.5 degree Celsius and clinicians response.

Decrease of temperature may be an indication of stress and how steep the change is also of importance for the clinicians. Using negative angles make this more obvious and give the clinician a terminology to reason about change. This is shown in Fig 5 as text under the arrows. If a clinician classifies temperature change we have to be aware that this also is context dependent, e.g. -17° decline may be classified "decreasing fast" for one patient and "steep decrease" for another. This is important e.g. when explaining a case to a clinician or explaining the differences and similarities between two cases.

This notation makes it also easier to compare different person's differences and similarities during the test cycle, despite that their finger temperature differs widely [7]. List of the features those are extracted from the finger temperature are presented in table 4.

Total signal from step2 to step6 is divided into 12 parts with one minute time interval and 12 features (i.e. *Step2_Part1*, *Step2_Part2*, *Step3_Part1*, ………, *Step6_Part1*, *Step6_Part2*) are extracted. Five other features *start temperature* and *end temperature* from step2 to step6, *minimum temperature* of step3 and step5, *maximum temperature* of step4 and step6, and *difference between ceiling and floor* are also been extracted from the sensor signal. Finally, 17 (12+5) features are extracted automatically (See table 4) from the fifteen minutes (1800 samples) FT measurements signal data.

No	Feature
1	Step2_part1
2	Step2_part2
3	Step3_part1
4	Step3_part2
5	Step3_part3
6	Step3_part4
7	Step4_part1
8	Step4_part2
9	Step5_part1
10	Step5_part2
11	Step6_part1
12	Step6_part2
13	Start_temperature
14	End_temperature
15	Maximum_ temperature
16	Minimum_ temperature
17	Diff_ceiling/floor

Table 4: List of features extracted from the FT sensor signal.

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

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

Stage 6: To diagnosis individual stress level new FT measurement (formulated as a problem case) is inputted into the CBR cycle. The new problem case is then matched using different matching algorithms including modified distance function; similarity matrix and fuzzy similarity match [7].

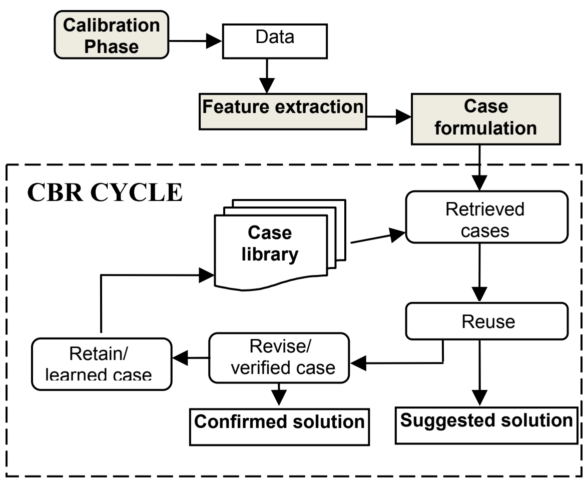

Fig 6. General overview of a decision support system for stress diagnosis

Fig 6 illustrates CBR system for diagnosis of stress, where data were collected through the calibration phase and after the feature extraction new problem case is introduced into the CBR cycle. The system can provide matching outcome in a sorted list of best matching cases according to their similarity values in three circumstances: when a new problem case is matched with all the solved cases in a case base (between subject and class), within a class where the class information is provided by the user and also within a subject [7].

Stage 7: The cases stored in the case library should be both representative and comprehensive to cover a wide spectrum of possible situations. The composition of the case library is one of the key factors that decide the ultimate performance of a CBR system. As presented above, in the initial condition this CBR system has a limited number of cases available (only 39 cases) which reduces the performance of the system. Therefore Ahmed et al presents a fuzzy rule-based classification scheme which is introduced into the CBR system to initiate the case library, providing improved performance in the stress diagnosis task [2]. A single-input single-output Mamdani fuzzy model is implemented where the calculated *percentage of negative slope* is taken as the input variable and the corresponding *stress class* as output.

Stage 8: Moreover, clinicians are also considering other factors such as patients feelings, behaviours, social facts, working environments, lifestyle and so on in diagnosing individual stress levels. Such information can be presented by a patient using natural text format and visual analogue scale. Textual data of patients captures important indication not contained in measurements and also provides useful supplementary information. Therefore system added textual features in the case vector which helps to better interpret and understand sensor readings and transferring valuable experience between clinicians [4].

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

3.1 Result

In CBR systems, 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. Specially, in medical domains the domain knowledge is often not well understood as in circumstances of diagnosing stress related to psycho-physiological issues. Therefore, retrieving a single matching case as a proposed solution may not be sufficient for the DSS in this domain. So, the proposed system retrieved a list of ranked cases in three matching circumstances. The three yielded matching circumstances are: 1) a ranked list by the system for a current/new case matching with all the other cases in a case base is shown Fig 7. 2) a sorted list of matched cases that matches a current/new case with the same subjects'/patients' cases and 3) presented best matched cases when a new problem case is matched with the solved cases in the same class where case-class is given by the user. In all the circumstances ranked list of cases are presented on the basis of their similarity value and the identified class. The solution for a retrieved old case that is diagnosis and treatment suggestions, are also presented in the system. There is also option to see a comparison of FT measurement between a new case and old case plotted through line chart using the signals. The user can use different matching algorithms by selecting a specific method. Details of the matching information for a new case with an old case is also provided as a result by which clinicians/users get an opportunity to see more details of the matching cases which may assists to determine if the solution is reusable or require an adaptation for a new problem.

Cases matching with current case
karoline_magnusson_2008-12-05_15-05-40.xls

<< Previous Next >>

Case	Percent	Evaluation	Times reviewed	Score
Case 24	60.1	stressed	0	0
Case 39	55.6	normal	2	0
Case 17	51.6	stressed	0	0
Case 37	51.1	relaxed	0	0
Case 9	50.9	very_stressed	0	0
Case 19	50.7	relaxed	0	0
Case 25	50.7	very_relaxed	0	0
Case 32	50.2	stressed	0	0
Case 21	50.2	normal	0	0
Case 15	49.7	very_stressed	0	0
Case 13	48.9	normal	0	0
Case 22	48.5	stressed	0	0
Case 23	48.2	very_stressed	0	0
Case 11	48.1	normal	0	2
Case 4	48.1	very_stressed	0	0

Fig 7. Similarity matching of a current case with the previous cases presented in a ranked list of cases as solution.

Users can adapt solutions i.e. it could be a combination of two solutions from the list of retrieved and ranked cases in order to develop a solution to the problem in the new case. Then clinician/expert determines if it is plausible solution to the problem and he/she could modify the solution before approved. Then the case is sent to the revision step where the solution is verified manually for the correctness and presented as a confirmed solution to the new problem case. In the retention step, this new case with its verified solution can be added to the case base as a new knowledge. An example is illustrated in Fig 7 which shows similarity matching of a current case with the previous cases in a ranked list. For the current case the system establishes with 60.1% of reliability that the patient is under state stressed as shown in Fig 7.

4 Conclusion

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

In the system the integration of CBR with fuzzy set theory enables to handle impreciseness existed in the domain knowledge in a way understood and accepted by the clinicians. The calibration phase also assists to individualize the system. The system extracts key features from the finger temperature signal and classifies individual sensitivity to stress. This provides important information to the clinician to make a decision about individual treatment plan. The problem with the insufficient number of initial cases into the case library, one of the recent challenges of medical CBR systems is also overcome introducing the fuzzy rules into the system. One of the strengths of the method is that it bears similarities with how the clinicians work manually and when clinicians are confronted with the concepts and functionality of the decision support system it is readily accepted by them. This support is valuable since clinicians are willing to participate actively in the project and validate the results.

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