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A CASE-BASED MULTI-MODAL CLINICAL SYSTEM FOR STRESS MANAGEMENT

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Abstract

A difficult issue in stress management is to use biomedical sensor signals in the diagnosis and treatment of stress. Clinicians often make their diagnosis and decision based on manual inspection of physiological signals such as, ECG, heart rate, finger temperature etc. However, the complexity associated with manual analysis and interpretation of the signals makes it difficult even for experienced clinicians. Today the diagnosis and decision is largely dependent on how experienced the clinician is interpreting the measurements. A computer-aided decision support system for diagnosis and treatment of stress would enable a more objective and consistent diagnosis and decisions.

A challenge in the field of medicine is the accuracy of the system, it is essential that the clinician is able to judge the accuracy of the suggested solutions. Case-based reasoning systems for medical applications are increasingly multi-purpose and multi-modal, using a variety of different methods and techniques to meet the challenges of the medical domain. This research work covers the development of an intelligent clinical decision support system for diagnosis, classification and treatment in stress management. The system uses a finger temperature sensor and the variation in the finger temperature is one of the key features in the system. Several artificial intelligence techniques have been investigated to enable a more reliable and efficient diagnosis and treatment of stress such as case-based reasoning, textual information retrieval, rule-based reasoning, and fuzzy logic. Functionalities and the performance of the system have been validated by implementing a research prototype based on close collaboration with an expert in stress. The case base of the implemented system has been initiated with 53 reference cases classified by an experienced clinician. A case study also shows that the system provides results close to a human expert. The experimental results suggest that such a system is valuable both for less experienced clinicians and for experts where the system may function as a second option.

Sammanfattning

Användandet av biomedicinska sensorsignaler för stresshantering och stressbehandling ger upphov till många svårlösta problem. Kliniker ställer ofta sin egen diagnos baserad på manuell inspektion av fysiologiska signaler såsom ECG, hjärtrytm, fingertemperatur etc. Men komplexiteten associerad med denna form av analys och tolkning av signaler gör den ofta svår att utföra, även för en erfaren kliniker. Idag är ställandet av en korrekt diagnos ofta direkt avhängig klinikerns erfarenhet av att tolka mätdata. I detta fall skulle ett datorbaserat beslutstödssystemmöjliggöra ett mer objektivt och konsekvent tillvägagångssätt av diagnos och behandling av stress.

Det är en medicinsk utmaning att åstadkomma ett tillräckligt noggrant system och det är essentiellt att klinikern själv kan bedöma noggrannheten hos systemets föreslagna lösningar. Fallbaserade system för medicinska applikationer blir mer och mer multi-ändamålsinriktade och mer och mer multimodala genom att utnyttja sig av en mångfald av olika metoder och tekniker för att möta de medicinska utmaningar som de ställs inför. Detta forskningsarbete beskriver utvecklingen av ett intelligent kliniskt beslutstödssystem för diagnos, klassificering och behandling av stress. Systemets grundläggande egenskap är dess användande av signalvariationer från en fingertemperatursensor. Flera metoder från disciplinen artificiell intelligens såsom fallbaserat resonerande, textuell informationsåtkomst, regelbaserat resonerande och fuzzy logik har utvärderats för att möjliggöra en mer effektiv och pålitlig diagnostisering och behandling av stress. Systemets funktion och prestanda har utvärderats genom att det implementerats som en forskningsprototyp i nära samarbete med stressexperter. Systemets falldatabas har fyllts på med 53 referensfall som är klassificerade av en klinisk expert. En fallstudie visar att systemet presterar i närheten av en klinisk expert. Resultaten från dessa experiment visar att detta system är värdefullt både för oerfarna kliniker och för experter där systemet kan fungera som kompletterande information.

To the memory of my Father
and
Grandfather

Preface

I would like to thank all the people who helped me making this thesis a fact. First of all I would like to express my sincere gratitude to Peter Funk at Mälardalen University, Västerås who has contributed with lots of ideas and valuable discussions; grateful to my assistant supervisor Ning Xiong, without them this thesis work would have been impossible. Secondly, I am thankful to my wife and colleague Shahina Begum for her support to my work. A special thanks to Professor Bo von Schéele at PBM Stress Medicine AB who helped me to congregate domain knowledge. I would also like to express my thankfulness to my room colleague Erik Olsson and all the members of the School of Innovation, Design and Engineering, Mälardalen University, for always being helpful.

Finally, I would like to thank all of my family members for making my life and work bearable!

Mobyen Uddin Ahmed
Västerås, April 15, 2010

Publications by the Author

The following articles are included in this thesis:

A. Case-based Reasoning for Diagnosis of Stress using Enhanced Cosine and Fuzzy Similarity. Mobyen Uddin Ahmed, Shahina Begum, Peter Funk, Ning Xiong, Bo von Schéele (PBMStressMedicine AB). International Journal Transactions on Case-Based Reasoning on Multimedia Data, vol 1, Number 1, IBaI Publishing, ISSN: 1864-9734, October, 2008.

B. Fuzzy Rule-Based Classification to Build Initial Case Library for Case-Based Stress Diagnosis. Mobyen Uddin Ahmed, Shahina Begum, Peter Funk, Ning Xiong. In the proceedings of the 9^{th} international conference on Artificial Intelligence and Applications (AIA) 2009.

C. A Multi-Module Case Based Biofeedback System for Stress Treatment. Mobyen Uddin Ahmed, Shahina Begum, Peter Funk, Ning Xiong, Bo von Schéele (PBMStressMedicine AB). Accepted in the international journal on Artificial Intelligence in Medicine, 2010.

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Publications not included in the thesis:

Stress domain:

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List of Figures

List of Abbreviations

ABS	Absolute
AI	Artificial Intelligence
AIM	Artificial Intelligence in Medicine
CBR	Case-Based Reasoning
CDSS	Clinical Decision Support System
DSS	Decision Support System
EEG	Electroencephalography
ECG	Electrocardiography
EMG	Electromyography
ETCO2	End-Tidal Carbon dioxide
FT	Finger Temperature
FL	Fuzzy Logic
FIS	Fuzzy Inference System
FRBR	Fuzzy Rule-Based Reasoning
HR	Heart Rate
HRV	Heart Rate Variability
IPOS	Integrated Personal Health Optimizing System
IR	Information Retrieval
MFs	Membership Functions
NN	Nearest Neighbour
RBR	Rule-Based Reasoning
RSA	Respiratory Sinus Arrhythmia
tf-idf	term frequency – inverse document frequency
VSM	Vector Space Model
VAS	Visual Analogue Scale

Table of Content

PART 1

Thesis

Chapter 1.

Introduction

This chapter presents an introduction of the thesis report, the motivation of the research, research questions, research contributions and an outline of the report.

Medical knowledge is today expanding rapidly to the extent that even experts have difficulties to follow all new results, changes and new treatments. Computers surpass humans in the ability to remember and such property is very valuable for a computer-aided system that enables improvements in both diagnosis and treatment. There is an increasing interest for decision support in the medical domain. Early approaches in decision support in the medical domain never got full clinical acceptance due to their less intuitive reasoning and explanation capability [12]. Decision support systems (DSS) that bear more similarities with human reasoning have benefits and are often easily accepted by physicians in the medical domain [6]. Hence, DSS systems that are able to reason and explain in an acceptable and understandable style are more and more in demand and will play an increasing roll in tomorrow's health care. DSS or computer-aided systems that can simulate expert human reasoning or serve as an assistant of a physician in the medical domain are increasingly important. In the medical domain, diagnostics, classification and treatment are the main tasks for a physician. These applications are also increasingly popular research areas for artificial intelligence (AI) research. Today many clinical decision support systems are developed to be multi-purposed and often combined more than one AI method and technique. In fact, the multi-faceted and complex nature of the medical domain motivates to design such multi-modal systems [43, 45]. Many of the early AI systems attempted to apply pure rule-based reasoning for the decision support in the area. However, for broad and complex domains, pure rule-based systems encountered several problems such as the knowledge acquisition bottleneck (medical knowledge evolves rapidly, updating the large rule based systems and proving their consistency is expensive), transparency (rules become increasingly complex in medical applications) and reliability (one faulty rule makes the whole system unreliable) [12]. A promising AI method for implementing decision support systems for the medical domain is case-based reasoning (CBR). CBR is especially suitable for domains with a weak domain theory, e.g. when the domain is difficult to formalize and is empirical. Clinicians often reason with cases by referring and comparing the cases. This makes a CBR approach intuitive for the clinicians. A case may be a patient record structured by symptoms, diagnosis, treatment and outcome. Some applications have explored the integration of CBR and rule-based reasoning (RBR) , e.g. in systems like CASEY [35] and FLORENCE [11].

This thesis focuses on the application of artificial intelligence techniques for a diagnosis, classification and treatment planning in the domain of psychophysiology. This research work proposes a multi-modal and multipurpose-oriented clinical decision support system for the stress management. The stress management system is based on the finger temperature (FT) sensor data and also it considers contextual information i.e. human perception and feelings in textual format. The system applies CBR as a core technique to facilitate experience reuse and decision explanation by retrieving the previous “similar” profiles. Reliability of the performance for the diagnosis and decision making tasks into the system is further improved through textual information retrieval (IR) with ontology [PAPER A]. An effort has also been made to improve the performance of the stress diagnosis task when there are a limited number of initial cases, by introducing a fuzzy rule-based classification scheme into the CBR system [PAPER B]. Another important goal is to assist in the treatment procedure. A three phase computer-assisted sensor-based DSS for treatment i.e. biofeedback training in stress management is proposed here in [PAPER C]. The system incorporates fuzzy techniques with CBR to handle vagueness, uncertainty inherently existing in clinicians reasoning.

1.1 Motivation

Diagnosis and treatment of stress is an example of a complex application domain. It is well known that an increased stress level can lead to serious health problems. Medical investigations have showed that the finger temperature (FT) has a correlation with stress for most people [64]. During stress, the sympathetic nervous system of our body is activated, causing a decrease in the peripheral circulation which in turn decreases the skin temperature. During relaxation, reverse effect occurs (i.e. parasympathetic nervous systems activates) and increases the finger temperature. Thus the finger skin temperature responds to stress. In clinical practice, the balances between the sympathetic and parasympathetic nervous systems are monitored as a part of diagnosis and treatment of psychophysiological dysfunctions. Hence, the rise (increase) and fall (decrease) of the finger temperature (FT) can help to diagnose stress-related dysfunctions. However, the behaviour of the FT is individual for each individual due to health factors, metabolic activity etc. Interpreting/analyzing the FT and understanding large variations of measurements from diverse patients require knowledge and experience. Without having adequate support, erroneous judgment could be made by a less experienced staff. Since there are large individual variations when looking at FT, it is a worthy challenge to find a computational solution to apply it in a computer-based system. The demand of a computer-aided system in the stress domain is increasing day-by-day in our present world. However, the application of such systems in this domain is limited so far due to the weak domain theory. So, the overall goal of this research work is to propose methods or techniques for a multipurpose-oriented clinical decision support system for stress management. Moreover, reliability and performance in the diagnosis and decision making tasks are the two important issues of clinical DSS which are also addressed here.

1.2 Research Questions

Clinical studies show that FT, in general, decreases with stress; however this effect of change is very individual. Clinicians are also considering other factors such as a patients feelings, behaviour, social facts, working environments, lifestyle and so on in diagnosing individual stress levels. Such information can be presented using a natural text format and a visual analogue scale (VAS). VAS is a measurement instrument (a scale in range between 0 and 10) which can be use to measure subjective characteristics or attitudes. Textual data of patients capture important information not contained in measurements and it also provides useful supplementary knowledge to better interpret and understand sensor readings. It also allows transferring valuable experience between clinicians which is important for diagnosis and treatment planning. Controlling stress is a more complex area for the use of biofeedback as treatment and different patients have different physical reactions to stress and relaxation. A clinician is commonly supervising patients in biofeedback in the stress area and makes together with the patient individual adjustments. The results are largely experience based and a more experienced clinician often achieves better results.

RQ 1. How can a computer-based stress diagnosis system provide more reliable solutions in the stress classification task? Could the framework be capable to coping textual information i.e. human perceptions and feelings with biomedical signals i.e. FT measurements?

RQ 2. How can the proposed system function if the core technology not succeeds to provide solution and also how to improve the system performance especially in the areas where zero or limited number of initial cases exists?

RQ 3. What methods and/or techniques can be used to design a system to assist in treatment i.e. bio-feedback training in stress management?

RQ 4. What methods and/or techniques can be used to design a multi-modal and multi-purpose system in stress management?

In this research, CBR have chosen as a core technique which works well when the domain knowledge is not clear enough, as in the psycho-physiological domain where even an experienced clinician might have difficulty expressing his knowledge explicitly. Textual information retrieval (IR) is added to the CBR system to make a more reliable diagnosis and decision making task. Fuzzy rule-based reasoning (RBR) is incorporated to support the system in its initial condition to classify patients. Fuzzy set theory is also used to compose an efficient matching method for finding the most relevant cases by calculating similarities between cases. Thus the combinations of all such AI techniques are applied to build a multi-modal computer-aided DSS for a multi-purpose task i.e. diagnosis, classification and treatment of stress-related disorders.

1.3 Research Contributions

A brief description of the contributions of this research work is presented in part 2 in the included papers. A short summary of each paper also presented in chapter 5. The main contributions of this thesis can be summarized as follows:

RC 1. The textual data (i.e. human perceptions and feelings) of a patient capture important information which may not be available in the sensor measurements. So, a hybrid system is required to address this issue. The research addresses the design and evaluation of such hybrid diagnosis system capable of handling multimedia data. By using both of the medium (sensor signal and textual information) the clinician can be offered more relevant previous cases. Thus it enables enhanced and more reliable diagnosis and treatment planning [PAPER A].

RC 2. A CBR system could diminish its performance if a case library doesn't contain enough cases similar to the current patient's case. In this research, methods are explored to overcome this problem. A set of rules is used to generate hypothetical cases in regions where limited number of cases are available. The method has also been evaluated and showed better performance in the task of diagnosing the stress [PAPER B].

RC 3. A multi-module computer assisted sensor-based biofeedback decision support system assisting a clinician as a second option to classify patient, estimate initial parameters and to make recommendations for biofeedback training. The intention of the system is to enable a patient to train himself/herself without particular supervision [PAPER C].

RC 4. Literature review in the research area of CBR in health sciences has provided recent advancements and trends, pros and cons of CBR methods in the medical domain. [PAPER D].

1.4 Outline of thesis

The thesis report is divided into two parts; the first part is organized as: an introduction chapter which presents the motivation of the research work, research questions and research contributions. Chapter 2 provides a theoretical background to the methods and techniques applied in this research. Chapter 3 presents information of the proposed clinical decision support system for stress management. Chapter 4 contains experimental work that has been carried out in this research. Chapter 5 provides the research contributions along with a summary of the included papers. Chapter 6 considers related work in the area of CBR in the health sciences. Chapter 7 concludes the first part of the thesis and presents the limitation and future work. The second part of the thesis contains four chapters with the completed version of the four included papers.

Chapter 2.

Background and Methods

This chapter presents a short description of the problem in terms of domain knowledge and related methods investigated into this research work. It starts with information about human stress and then describes several artificial intelligence techniques such as case-based reasoning, textual case retrieval, fuzzy logic, fuzzy rule-based reasoning.

In our daily life we are subjected to deal with a wide range of pressures. When the pressures exceed the extent that we are able to deal with then stress is trigged. Severe stress during long period is highly risky or even life-endangering for patients with e.g. heart disease or high blood pressure. Stress has a side effect of reducing awareness of bodily symptoms and people on a heightened level of stress often may not be aware of it and one may notice it weeks or months later when the stress has already caused more serious effects in the body [65]. A computer-aided system that helps early detection of potential stress problems would bring essential benefits for the treatment and recovery of stress in both clinical and home environment.

2.1 Stress

According to Hans Selye, stress can be defined as “the rate of wear and tear within the body” [40]. He first introduced the term ‘stress’ in the 1950s when he noticed that patient suffering physically without having only a disease or a medical condition. He defined stress as "non-specific response of the body to any demand" [60]. We people have an inborn reaction to stressful situations called the “fight or flight” response. That means we can react to certain events or facts that may produce stress and our body's nervous system activates and then stress hormones are released to protect ourselves. The wear and tear is a physiological reaction such as blood pressure rises, heart rate rises, increase respiration rate and muscles get ready for action.

The human nervous system is divided into two main parts, the voluntary system and autonomic system. The automatic nervous system is further divided into sympathetic and parasympathetic nervous system. Walter Cannon described in [13], that the Sympathetic Nervous System (SNS) activates the body for the "fight or flight" response to perceived threats to physical or emotional security. Thus the SNS works to protect our body against threats by stimulating the necessary glands (i.e. thyroid and adrenal glands) and organs. It decreases the blood flow to the digestive and eliminative organs (i.e. the intestine, liver, kidney etc.) and enhances the flow of blood to the brain and muscles. The thyroid and adrenal glands also supply extra energy. As a result it speeds up the heart rate, increases blood pressure, decreases digestion and constricts the blood vessels i.e. vasoconstriction which slows down the flow of blood etc. The SNS thus activates the body for the fight-or-flight response to stress. The parasympathetic nervous system counteracts the fight-or-flight response to return the body to its normal state. It stimulates digestion, the immune system and eliminative organs etc. to rebuild the body [36].

2.1.1 Good Vs bad stress

Stress is not always bad. It is almost impossible to live without some stress because it gives life some spice and excitement. A moderate amount of stress is often positive because it helps our bodies and minds to work well and to contribute to our mental health. Thus, good performance can be achieved but high level of stress reduces our performance that may harm in personal relationships, and enjoyment of life. A relationship curve between performance and stress is shown in Fig. 1. The explanation of the traditional performance-stress relationship curve can be: at zero or low level stress, a person has low performance means that the person is either sleeping or meditating. At a high level stress the person also have zero performance i.e. the person may injure by panic.

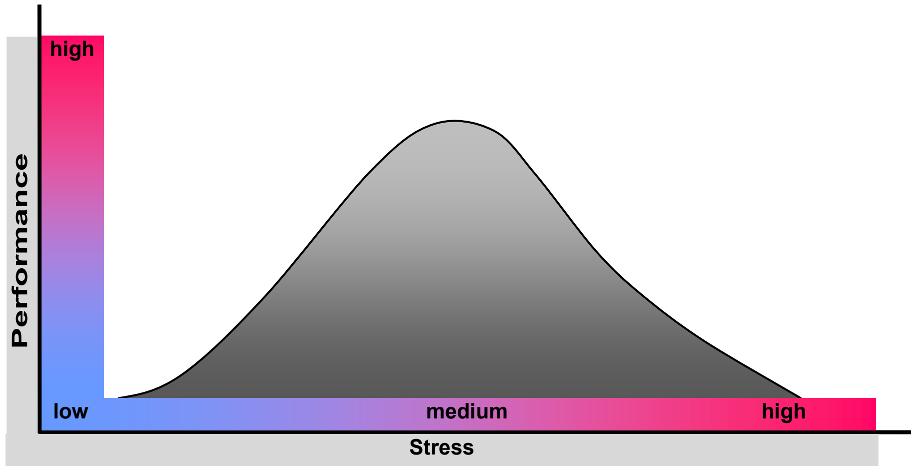

Figure 1: Stress versus performance relationship curve [3].

So, to achieve a good performance it is better to have a moderate amount of stress. This means if any person can accomplish any activity such as driving a car with a moderate level of stress, he/she could do it with good performance. Such kind of stress experiences can be treated as good or short-term stress. But long-term stress, for example constant worry about work or family is bad for health because it may drain energy and decries the ability to perform well. So, if suffering from extreme stress or long-term stress, the body will eventually wear itself down.

2.1.2 Stress diagnosis and treatment

The diagnosis of stress is often multi-factorial, complex and uncertain due to large variations and personalization. According to [55], 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 quit traditional way to diagnose stress. Rudolf E. Noble in [55], mentioned various biochemical parameters e.g., corticosteroid hormone which can be measured from the body fluids, blood, saliva and urine. Since the autonomic nervous system is activated with 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. In this research, stress diagnosis has been conducted using the skin temperature i.e. finger temperature (FT).

There are several methods to control or manage stress e.g. exercise or training. In our everyday life we need to control our stress often in many situations for instance, when we are sitting at our desk or behind the wheel getting stuck in traffic. In such a situation 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, 37]. Experienced clinicians often achieved good results in these areas and their success largely based on many years of experiences and often thousands of treated patients. The basis of biofeedback therapy is to support a patient in realizing their self ability to control specific psychophysiological processes [31]. The general strategy is that, patients get a feedback in a clear way (e.g. the patient observes some measurements visualizing some physical processes in their body) and behaviorally train the body and/or mind to change the biological responses to improve the condition. Sensor-based biofeedback is drawing increasing attention and one reason is the development of sensors able to measure processes in the body previously not able to be measured.

An area where biofeedback has proven to give results is the area of practicing relaxation. 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. This increase in the peripheral blood vessels in turn results in an increased blood flow and skin temperature. Therefore, FT measurement is an effective biofeedback parameter [27, 42] for self regulation training and has a clinical consensus as an important parameter in stress treatment. This research also investigates biofeedback training by employing FT measurements for stress control.

2.2 Case-based reasoning (CBR)

Case-based reasoning (CBR) is a problem solving method that gives priority to the past experiences for solving current problems (solutions for current problems can be found by reusing or adaptating the solutions to problems which had been solved in the past). Riesbeck & Schank presented CBR as, “A case-based reasoner solves new problems by adapting solutions that were used to solve old problems" [54]. The CBR method in a problem solving context can be described as follows: 1) given a particular problem case, the similarity of a particular problem with the stored problems in a case library (or memory) is calculated 2) retrieve one or more most similar matching cases according to their similarity values 3) attempt to reuse the solution of one of the retrieved problems by doing revision or possible adaptation (if needed i.e. due to differences in problem descriptions) 4) finally, the current problem case and its corresponding solution can be retained as a new solved case for further use [53].

CBR is not only a powerful method for computer reasoning, but also a common human problem solving behavior in everyday life; that is reasoning is based on the past personally experienced cases. CBR is inspired by a cognitive model on a way how humans solves certain class of problems e.g. solve a new problem by applying previous experience adapted to the current situation. Watson and Marir have reported in [68] that CBR is attracting attention because:

- It does not require explicit domain knowledge but gathering of cases.
- Simple and easy implementation because significant features describe a case.
- Database management system or DBMS could help to handle a large volume of information.
- Systems can easily learn by obtaining new knowledge as cases.

The root of CBR can be traced from the work of Schank and his student at Yale University in the early 1980s but Watson presented in [68] that the origin of CBR is found in 1977. CYRUS [32, 33] developed by Janet Colodner, is the basic and earliest CBR system. She employed knowledge as cases and used an indexed memory structure. Other early CBR systems such as CASEY [35] and MEDIATOR [63] have implemented based on CYRUS. In the medical domain around 1980s, early CBR systems have taken place by Konton[35], and Braeiss[5, 4].

The medical domain is suitable and at the same time challenging for a CBR application. Doctors often recall similar cases that he/she has learned and adapt them to the current situation. A clinician may start his/her practice with some initial past experiences (own or learned solved cases), and attempt to utilize this past experience to solve a new problem which simultaneously increase his/her experience. One main reason that CBR is suitable for the medical domain is its adequate cognitive model and cases may be extracted from the patient's records

[24]. Several research works i.e. in [24, 9, and 43] have investigated the key advantages of CBR in the medical domain. The motivations to apply CBR method in the above domain are listed below:

1. The CBR [1, 67] method can solve a problem in a way similar to the normal behavior of human problem solving e.g. it solves a problem using experience.
2. 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 his/her practice with a few cases and gradually increases the experiences.
4. A CBR system can provide more than one alternative for a similar problem which is beneficial for the clinician.
5. CBR can help to reduce the recurrence of a wrong decision because the case library could contain both success and failure of cases.
6. Knowledge elicitation is most of the time a bottleneck in the health science domain since human behavior is not always predictable. The CBR method can overcome this because prediction is based on the experience or old cases.
7. It is useful if the domain is not clear enough i.e. CBR does not depend on any rules or any models [28].
8. Systems using CBR can learn new knowledge by adding new solved cases into the case library, so domain knowledge is also updating in time.

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

1. *A limited number of reference cases* – even though a CBR system can work with a few number of reference cases, the performance might be reduced due to a limited number of available cases.
2. *Feature extraction* – cases are formulated with number of features or a feature vector, so the big issue is to dig out features from the complex data format (i.e. images, sensor signals etc).

3. *Adaptation* – the medical domain is often complex knowledge and recommendation in the medical domain evolving with time, cases often consist of large number of features, and therefore it is a real challenge to apply automatic adaptation strategy in this area. [22].

2.2.1 The CBR cycle

According to Kolodner in [34] a case is a “contextualized piece of knowledge representing experience that teaches a lesson fundamental to achieving the goals of the reasoner”. Representation of a case structure can be done in various ways. The most common and well known way is to present a case only with a problem and a solution description. The *problem* part describes the condition of a case and the *solution* part presents advice or recommendation to solve a problem. Some systems could also add an outcome besides the solution to evaluate a new state. The outcome describes the state after the case had been taken place [68]. A comprehensive case structure has been proposed by Kolodner in [34] as follows: 1) a state with goal, 2) the solution 3) the outcome 4) explanations of results and 5) lessons learned. Further ahead, Bergmann et al classified case representation in the following three categories: a) feature vector representations or propositional cases b) structured representations or relational cases, and c) textual representations or semi-structure cases [8].

A schematic or a life cycle that presents the key processes involved in the CBR method is shown in Fig 2. Aamodt and Plaza [1] have introduced a four-step model of CBR in a cyclical process comprising the four REs: Retrieve, Reuse, Revise and Retain. Fig 2 illustrates these four steps that present the key tasks to implement such kind of cognitive model. The current situation is formulated as a new problem case and matched against all the cases in a library, depending on the similarity value of the cases one or more of the most similar cases are retrieved. Matching cases are presented with their corresponding solutions and a solution is then proposed to be reused and tested for success. If the retrieved case is not close enough to the new problem case, the solution will probably be revised and/or adapted. Finally, the new solved case is retained into the case library. The steps are described below with the aspect of CBR in the health science.

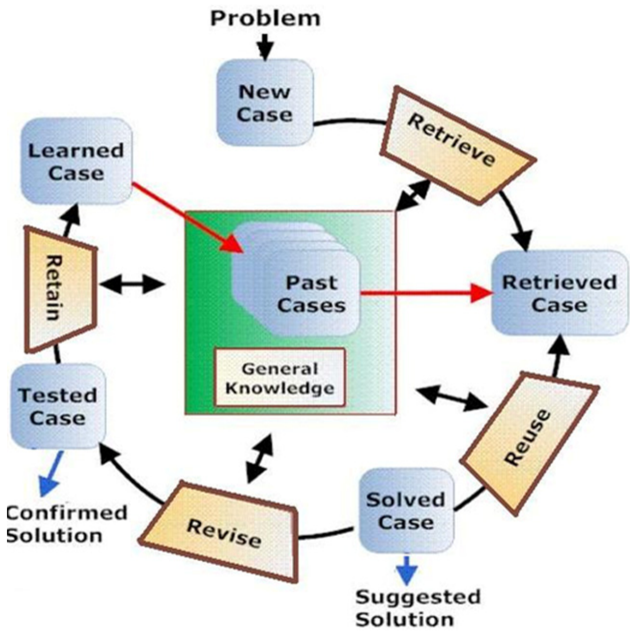

Figure 2: CBR cycle. The figure is introduced by Aamodt and Plaza [1].

The *Retrieval* step is the major part of a CBR cycle and it is the most common for many CBR systems. Retrieval is essential since it plays a vital role for calculating the similarity of two cases. Given a description of a current situation, the retrieval algorithm computes the similarity value for all the cases in a case library and retrieves the most similar cases against a current problem. The similarity value between cases is usually represented as 0 to 1 or 0 to 100, where "0" means no matching and "1 or 100" means perfect matching. One of the most common and well known retrieval methods is the *nearest neighbour* (or kNN) [67, 61] which *is* based on the matching of a weighted sum of the features. For a feature vector, local similarity is computed by comparing each feature value and a global similarity value is obtained as a weighted calculation of the local similarities. A standard equation for the nearest-neighbor calculation is illustrated in Eq 1.

$$\mathit{Similarity}\ (T,S) = \frac{\sum_{i=1}^{n} f(T_i, S_i) \times w_i}{\sum_{i=1}^{n} wi} \tag{1}$$

In equation 1:

T is the target case

S is the source case

n is the number of attributes in each case

i is an individual attribute from *1 to n*

f is a similarity function for attribute *i* in cases *T* and *S*

w is the importance for weighing of attribute *i*. The weights allocated to each feature/attribute provide them a range of importance. But determining the weight for a feature value is a problem and the easy way is to calibrate this weight by an expert or user in terms of the domain knowledge. However, it may also be determined by an adaptive learning process i.e. learning or optimizing weights from the case library as information source.

Looking from the classical CBR cycle in Fig 2, the *Reuse* step comes just after the retrieve. This step is reusing one of the retrieved cases from the case library and returning it as the proposed solution for a current case. But in some cases, this phase can become more difficult, especially when there are notorious differences between the current case and the closest one retrieved. An adaptation of the obtained solution is required in order to provide a solution for the current problem. For adaptation, it could calculate the differences between the retrieved case and the current case. Then it is possible to apply algorithms or rules that take the differences into account to suggest a solution. This adaptation could be done by an expert/user in the domain. The expert determines if it is a reasonable solution to the problem and he/she can modify the solution before approved. After that the case is sent to the *Revise* step where the solution is verified and evaluated for the correctness and presented as a confirmed solution to the new problem case [67].

The term *Retain* becomes the final stage which is functioning as a learning process in the CBR cycle, and it incorporating the new solved case into the case library for future use. The most common way to retain a case is to simply record the information concerning the target problem specification and its final solution (assuming that the solution given was accurate and correct) [53]. If the solution retrieved is not as reliable as it should be additional information might be stored into the case library such as the changes made to the retrieved solution. So, the information to be saved has to be considered carefully [46].

2.3 Textual case retrieval

As we mentioned above, Bergmann et al [8] have proposed that a case could be represented as a textual or semi-structural format. Textual case retrieval could be defined as matching a user query against a bunch of free-text cases. Text retrieval is a branch of information retrieval (IR) if the information is stored in the form of text. IR is a science used for searching documents and/or for information within a document or metadata about the document. In this research the knowledge of IR is applied where the term "document" is converted as a "case". The idea of this process begins when a query is entered by a user into the system through a user interface. Then the system extracts information from the query. The extracted features may match with several objects (cases) in the collection (case library) with different degree of relevance. The degree of relevance can be computed by the system as a numerical value that shows how well each case is matched with the query. Finally, according to this numerical value, all the cases will be sorted and the top ranked cases will be presented to the user [72]. According to wiki, there are several ways to find a match between a user query and the stored cases, such as Boolean model, fuzzy retrieval, vector space model, binary retrieval etc [72]. The vector space model (VSM) [56] is the most common and well know method that has been using in information retrieval.

VSM or term vector model is an algebraic model that represents textual cases in a vector of terms. It identifies similarity between a query case Q and the stored cases C_i. One of the best known schemes is the *tf-idf* (term frequency – inverse document frequency) [57] weighting used together with cosine similarity [69] in the vector space model [56] where the word "document" is treated as a case. The *tf-idf* is a traditional weighting algorithm and often used in information and/or textual retrieval. The similarity/relevancy is measured from the cosine angle between a query case Q and the stored cases C_i inside a vector i.e. a deviation of angles between the case vectors. "$\cos\theta = \frac{Q.C_i}{\|Q\|\|C_i\|}$" is a general equation to calculate the cosine similarity where $Q.C_i$ is the dot product and $\|Q\|\|C_i\|$ is the magnitude of the vectors (a query and the stored case), i is the index of the cases in the case library. The value of the similarity lies in the range of -1 to +1, where -1 means no matching and +1 means exactly the same. In terms of IR, the cosine similarity of two cases will range from 0 to 1, since the *tf-idf* weights cannot be negative. The final result 1 is a full match and 0 means no words match between Q and C_i. To measure the similarity we need two things, the weight of each term in each case and the cosine similarity between the cases inside a vector space.

The terms are words, keywords, or long phrases in a case and the dimension of the vector is the number or frequency of each term in the vocabulary of cases. If a term occurs in a case the value will be non-zero in the vector. Each word *tf* is the relative frequency of the word in a specific case (document represent as a case) and it presents the importance of the word inside the case. *idf* is the inverse proportion of the word over the whole case corpus which presents the importance of the word over the entire case pool. The weight vector for a case c is $V_c = [w_{1,c}, w_{2,c}, \ldots, w_{N,c}]^T$ and $w_{t,c} = tf_t \,.\, \log \frac{|C|}{|\{t \in c\}|}$ where tf_t is the term frequency or the number of times a term/word t occurs in a case c and $\log \frac{|C|}{|\{t \in c\}|}$ is the inverse case frequency. The symbol "$|C|$" is the total number of cases in the case library and $|\{t \in c\}|$ is the number of the cases containing the term t i.e. case frequency.

2.3.1 Advantages, limitations and improvements

The number of advantages of this model that attracts to use it in textual retrieval is summarized below:

1. VSM represents both the query and the stored cases in a weight vector where weights are non-binary and terms are weighted by importance.
2. Stored cases can be ranked according to their similarity value.
3. Retrieval can be done with partial matching that is cases can be retrieved even if they don't contain a query keyword.
4. It is simple to compute

Even though VSM is an easy and well known method in text retrieval, there are a number of limitations. According to Wikipedia the limitations are as below:

1. When the information in a document or case is very long, a similarity measure is difficult or poor because of a high dimensional vector with small dot product.
2. Keywords from the user query must exactly be matched with the keywords from the stored documents/cases, so prefix/suffix word or parsing can affect the similarity results.
3. A similar information/context can contain both in a query and the stored cases using different words (for example synonym of words) may result in poor dot product.

4. The order of each word/term that appears in the document/case is lost in the vector during the representation.

In terms of time complexity VSM also has couple of limitations, they are as follows:

1. From the computational point of view it requires a lot of processing time.
2. During adding a new case or a new term into the case library or term space, all vectors need to be recalculated.

Most of the limitations discussed above have been overcome by improving the model presented in this research (contribution PAPER A). A short summary is as follows:

1. Stored cases are formulated and retained by a human expert; only essential information is used and the cases are not very large.
2. Extracted number of significant keywords represented a stored case, so the cases are not containing high dimensional term vectors.
3. Removal of all the less significant and common words such as "a", “an”, “the”, "in", "of", etc named as stopwords.
4. Stemmed necessary terms to their root or basic form i.e. suffix/prefix the words such as "stemmer", "stemming", "stemmed" as based on "stem".
5. Added a dictionary such as “WorldNet” to get semantic relation among the words that is synonyms of the words.
6. Altered the term vector using expert defined domain specific ontology. The domain specific ontology provides relational strength among the special words in the domain to identify similarity between cases in similar context.
7. Used a user defined similarity threshold or select a number of retrieved cases, so that the only relevant cases can be retrieved.
8. The implemented system uses several services to update the case library in time such as during adding a case and/or altering the ontology. All the calculations i.e. weighting and re-weighting terms are performed offline and stored into the case library. As a result less computational time is required.

2.4 Fuzzy logic (FL)

Information can be incomplete, inconsistent, uncertain, or all of these three and it is often unsuitable for solving a problem. For example," The motor is running *really hot*. Or Tom is a *very tall* guy." Experts rely on *common sense* when they solve problems. To deal with such vague and uncertain information exact mathematical techniques are not sufficient, we need a technique that use a much closer concept of human thinking. Fuzzy logic is specifically designed to mathematically represent this uncertainty and vagueness. So, fuzzy logic is not a logic that is fuzzy, but a logic that is used to describe fuzziness. It is the theory of fuzzy sets, sets that calibrate vagueness. Moreover, it is a form of multi-valued logic with more than two truth values to deal with reasoning i.e. an approximate value rather than exact value. Just opposite to the binary or crisp logic it handles the concept of 'Partially Truth' i.e. the values between completely 'true' and completely 'false'. The degree of truth of a statement can range between false (0) and true (1) and considers more than two truth values.

Aristotle was the first to realize that logic based on "True" or "False" alone was not sufficient. Plato laid the foundation indicating that there was a third region (beyond True and False) [71]. Multi-valued logic was introduced by a Polish philosopher Jan Lukasiewicz in the 1930s. He introduced logic that extended the range of truth values to all real numbers in the interval between 0 and 1 [39, 38]. In 1965 Lotfi Zadeh a professor in the University of California at Berkley, published his famous paper "Fuzzy sets". He extended the work on possibility theory into a formal system of mathematical logic, and introduced a new concept for applying natural language terms. This new logic for representing and manipulating fuzzy terms was called fuzzy logic [23, 75]. The term "Fuzzy logic" derives from the fuzzy set theory or the theory of fuzzy sets. The fuzzy set theory has successfully been applied in handling uncertainties in various application domains [30] including the medical domain. The use of fuzzy logic in medical informatics has begun in the early 1970s.

Fig. 3 represents binary logic with a crisp boundary of 4 different seasons in Sweden; where the X-axis corresponds to days according to the months of the year and the Y-axis represents the probability between zero and one. In binary logic the function that relates to the value of a variable with the probability of a judged statement is a 'rectangular' one. The output probability for any input will always be 'one' i.e. only one season and 'zero' for the rest of the seasons. The crisp boundary of the season winter drawn at 31st March and 20th March is winter with the probability of one.

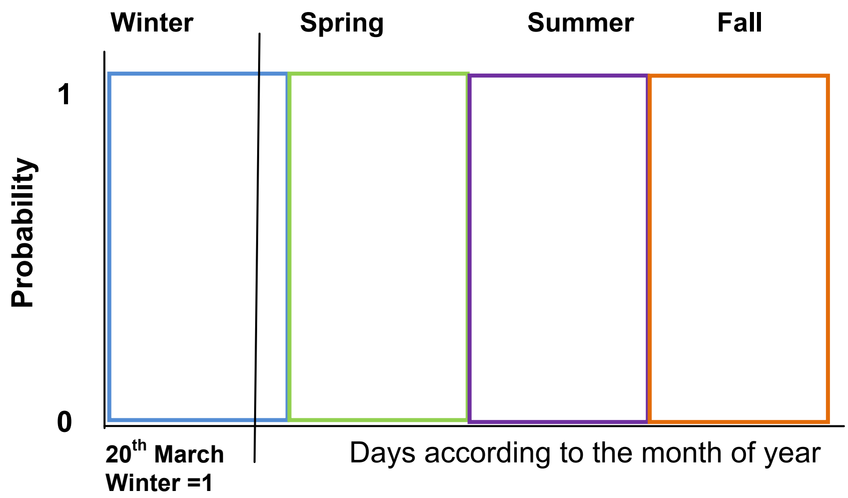

Figure 3. Binary or crisp logic representation for the season statement.

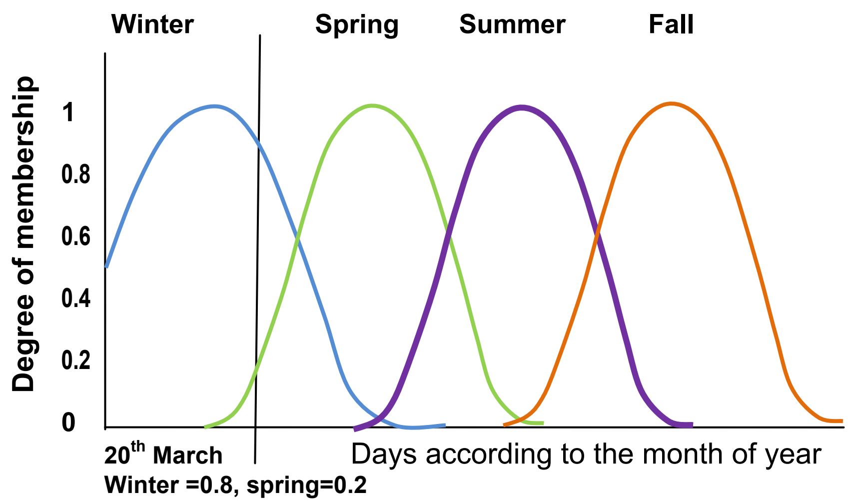

Figure 4. Fuzzy logic representation of the season statement.

In fuzzy logic the function can take any shape, as the season example illustrated with the Gaussian curve in Fig 4, here, X-axis is the universe of discourse which shows the range of all possible days for each month in a year for an input and Y-axis represents the degree of the membership function i.e. the fuzzy set of each season maps day values into a corresponding membership degree. In fuzzy logic, the truth of any statement becomes a matter of degree. Considering the 20th March as an input in the fuzzy system, it is winter with the degree of truth 0.78 and at the same time spring with the degree of membership 0.22. So, according to Zadeh "*Fuzzy logic is determined as a set of mathematical principles for knowledge representation based on degrees of membership rather than on crisp membership of classical binary logic*".

2.5 Fuzzy rule-based reasoning

Fuzzy rule-based reasoning is a combination of fuzzy logic approach with traditional rule-based reasoning (RBR) which also called as fuzzy inference system (FIS). Fuzzy inference is a computer paradigm based on fuzzy set theory, fuzzy if-then-rules and fuzzy reasoning. A traditional RBR system contains a bunch of if-then rules in crisp format. A general form of a rule is "If <antecedent> then <consequence> "and in term of crisp example "If speed is > 100 then stopping distance is 100 meter". In 1973, Lotfi Zadeh outlined a new approach to analyse the complex systems, in which he suggests to capture human knowledge in fuzzy rules [74]. A fuzzy rule is a linguistic expression of causal dependencies between linguistic variables in form of if-then conditional statement, considering the previous example in fuzzy format "If *speed* is ***fast*** then stopping *distance* is ***long***". Here the term '*speed*' and '*distance*' are linguistic variables, '***fast***' and '***long***' are linguistic values determined by fuzzy sets, '*speed* is ***fast***' is antecedent and 'stopping *distance* is ***long***' is consequent.

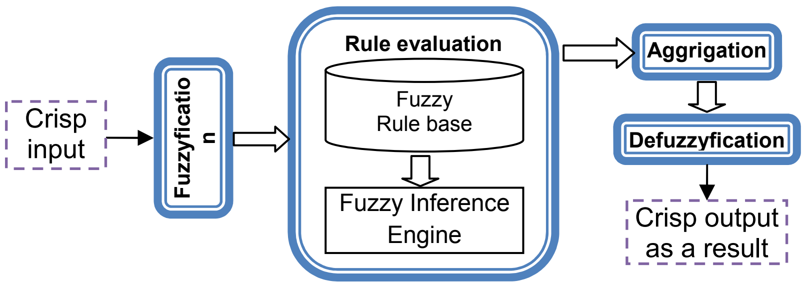

Figure 5. Steps in a fuzzy inference system.

Fuzzy decision making or inference system can be defined as a process of mapping a given input to an output with the help of the fuzzy set theory i.e.

fuzzyfication → fuzzy reasoning → defuzzification [30]. Well known inference systems are the Mamdani-style and Sugeno-style but both of them perform the 4 steps process as described in Fig 5. It illustrates the steps of a fuzzy inference system for the Mamdani-style. As can be seen from Fig 5, the first step is the fuzzification of an input variable i.e. crisp input is fuzzified against appropriate fuzzy sets. Given an input in crisp format, *step1* computes the membership degree with respect to its linguistic terms. Consequently, each input variable is fuzzified over all the membership functions (MFs) used by the fuzzy rules. In traditional rule-based system, if the antecedent part of a rule is true then the consequent part is also true. But in a fuzzy system, the rules fire to some extent. If the antecedent is true to some degree of membership then the consequent is also true to that degree.

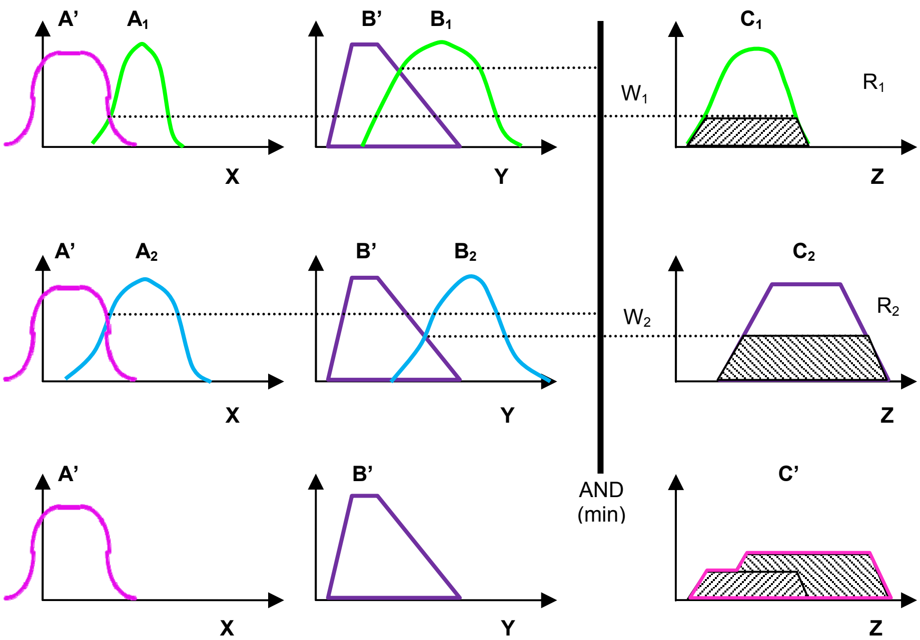

Figure 6. Graphical representation of an example of fuzzy inference.

Step2 is the rule evaluation where it takes fuzzyfied inputs and applies them to the antecedent part of the fuzzy rules. So it compares facts with the antecedents of the fuzzy rules to find degrees of compatibility. The value or firing strength is a single number from each rules represented in the result of the antecedent evaluation. This number is then applied to generate consequent MFs. Aggregation in *step3* is the process that merges all the output MFs for all the rules i.e. all outputs are combined into a single fuzzy set. The last and final phase (*step4*) in the inference process is the defuzzification that determines a crisp value from the output membership function as a solution. The input for the defuzzification is the aggregate fuzzy set and the output is a single number.

A simple example of fuzzy inference with multiple rules and multiple antecedents is illustrated in Fig 6, the rules and inputs are as follows: Rule 1: if x is A_1 and y is B_1 then z is C_1 and Rule 2: if x is A_2 and y is B_2 then z is C_2; Inputs: x is A and y is B then z is C (?). First the inputted crisp values (A and B) are converted into the fuzzy sets A' and B'. Then for the rule R_1 and R_2, A' and B' are fuzzified with the fuzzy sets A_1, B_1 and A_2, B_2. The dotted line in Fig. 6 presents the clipped area of the membership functions in the antecedent part of the rules. As the rules contain multiple antecedents with AND operators, fuzzy intersection used to obtain a single number that represent the evaluation result of the antecedents. W_1 and W_2 are the evaluation result those applied to the MFs in the consequent part of the rules. Upward and downward diagonal patterns in the fuzzy sets C_1 and C_2 show the firing strengths for the rules evaluation. After aggregation, the clipped fuzzy set C_1 and C_2, and the new fuzzy set C' are obtained. A defuzzification algorithm could convert this fuzzy set into a crisp value which is a single number that represents the final output.

Chapter 3.

Case-Based Multi-Modal System

This chapter provides information about the methods and framework of a multi-modal and multipurpose-oriented clinical decision support system in stress management. It describes how the system is performing complex tasks such as diagnosis, classification and treatment by combining more than one artificial intelligence technique and finger temperature (FT).

Human experience is a valuable asset and could be even more valuable if stored and reused in an efficient way. Clinicians/doctors have experience which may have been collected during many years of successful diagnosis and treatment. As an example, when a less experienced clinician/doctor is confronted with a new problem (for example symptoms that are not familiar) she/he might start to analyze the whole situation and try to make a diagnosis by using his/her education and experience (with some solved cases). This may be a very time-consuming task and may sometimes result in not finding a proper diagnosis. In that case she/he needs to find other sources for help and a very common way is to ask his/her seniors who have more experience. A professional (more experienced clinician) might start to think himself: "Have I ever faced any similar problem and in that case, what was that solution?" and refer the problem with her/his past solution to the less-experienced clinician. The less-experienced clinician then solves the problem and learns the new experience and save it in her/his own 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. Cases may also be hypothetical, e.g., hypothetical cases containing some rare/unusual symptoms and tests which could result in a wrong treatment with severe consequences. Similarity, for such "negative" cases, it is essential to alert a clinical staff. Therefore, a computer-based system for such experience reuse in health care would be valuable both for junior clinicians and as a second opinion for professionals.

A difficult issue in stress management is to use a biomedical sensor signal in the diagnosis and treatment of stress. Clinicians often base their diagnosis and decision on manual inspection of signals such as, ECG, heart rate, finger temperature (FT) etc. However, the complexity associated with a manual analysis and interpretation of the signals makes it difficult even for experienced clinicians. A computer system, classifying the sensor signals is a valuable property to assist a clinician. Diagnosis and treatment of stress is such an example of a complex application domain. An important focus of this research 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 e.g. biofeedback treatment. The research interest of this part lies in employing several AI techniques and methods in physiological time-series data for diagnosis, classification and treatment of stress. Case-based reasoning (CBR) is especially suitable for domains with a weak domain theory, i.e. when the domain is difficult to formalize and is empirical. The advantages of CBR in the medical domain have been identified in several other research works i.e. in [29, 24, 9, 44, and 48]. For some applications the integration of CBR and rule-based reasoning have been explored, e.g. in systems like [11, 41]. Cases comprising textual features or textual cases and introducing ontology into the CBR system, to get the advantages, are also implemented in systems such as in [47, 73]. The use of fuzzy logic in medical informatics has begun in the early 1970s. In fuzzy CBR, fuzzy sets are used in similarity measurement e.g. [10, 21, and 66].

The construction of multi-purposed and multi-modal medical systems is also becoming a hot topic in the current applied CBR research, using a variety of different methods and techniques to meet the challenges from the medical domain. The research contribution through PAPER-D presents some of the recent medical case-based reasoning systems alone with their classifications according to their functionality and development properties. It shows how a particular multi-purpose and multi-modal case-based reasoning system solves certain challenges in the medical domain. The research efforts in this direction can be demonstrated by Fig. 7 where it presents the steps to develop a hybrid multi-purpose CBR system to support in diagnosis and treatment of stress-related disorders.

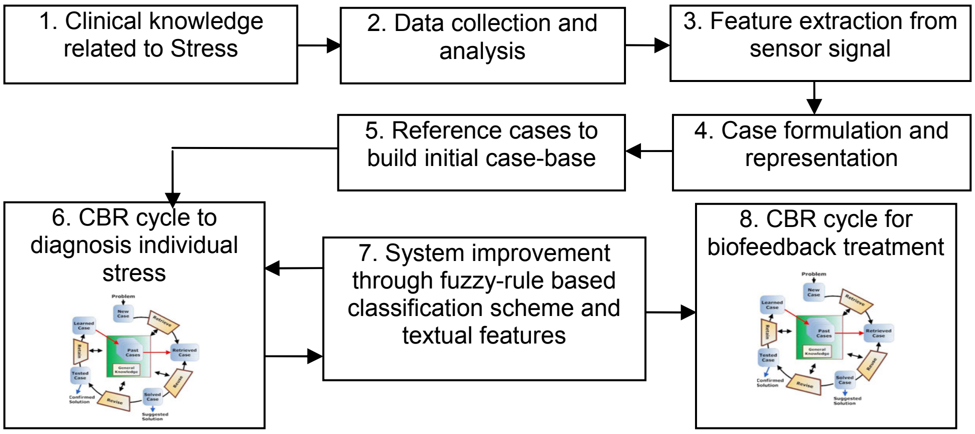

Figure 7. Schematic diagram of the stress management system.

Step 1: The signal employed in this research is finger temperature (FT) and clinical studies shows that the FT is decreases with stress in general. This is one of the psychophysiological parameters clinically used to determine stress-related disorders [64]. Analyzing/interpreting finger temperature and understanding large variations of measurements from diverse patients requires knowledge and experience and, without adequate support, erroneous judgment could be made by less experienced staff.

Step 2 and 3: The measurement is collected from 31 subjects 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 [7]. Eight women and twenty three men within the age range of 24 to 51 are participating in this study. The number of individual parameters identified and features extracted from the complex data format are briefly presented in section 3.1.1

Step 4 and 5: A new problem case is formulated by the 19 features (17 extracted features from the signal and 2 other features) in total. The problem description part of a case contains a vector of the features extracted from the FT measurements and the solution part provides a level of stress. The levels of stress are denoted as Very Relaxed, Relaxed, Normal/Stable, Stressed and Very Stressed and the initial case base, with 53 reference cases from 31 subjects, is classified by a domain expert.

Step 6: To diagnose individual stress level [6], a new FT measurement (formulated as a problem case) is inputted into the CBR cycle. The new problem case is then matched using three different matching algorithms: 1) *modified distance* function, 2) *similarity matrix* and 3) *fuzzy similarity*. The nearest neighbour (NN) algorithm is applied for the retrieval of similar cases. Finally, the top most case or the case selected by a clinician will provide a classification of the FT measurement as output. A detailed description about the diagnosis of stress is presented in section 3.1.

Step 7: A fuzzy rule-based classification scheme [PAPER B] and textual information retrieval [PAPER A] are introduced to provide an improved performance and increased reliability in diagnosing the individual stress. Section 3.2 and 3.3 provide a detailed discussion about the fuzzy rule-based classification and textual information retrieval.

Step 8: The last step in Fig 7 focuses on the CBR system in biofeedback treatment. A three phase CBR framework [PAPER C] is deployed to classify a patient, estimate initial parameters and to make recommendations for biofeedback training. A detailed description on the three phases is given in section 3.4.

3.1 Diagnosis of stress levels with FT sensor signal

Stress influences the sympathetic nervous system (SNS). In general, the temperature of the finger decreases when a person is stressed and increases during relaxation or in a non-stressed situation.

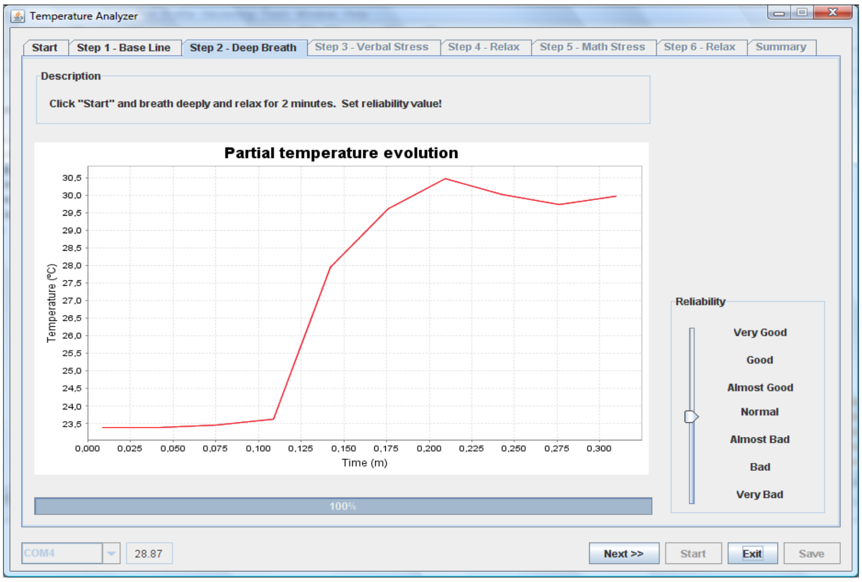

Figure 8. User interface to measure FT through the calibration phase.

A calibration phase [7] helps to establish an individual stress profile and is used as a standard protocol in the clinical environment. The protocol comprises with different conditions in 6 steps, they are as follows: baseline, deep breath, verbal stress, relax, math stress, and relax. Fig. 8 demonstrates the user interface used to collect FT measurements with the conditions of each step. In this phase a number of individual parameters are identified to establish an individual stress profile. The *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 read a neutral text during this step. In the step *Deep-breath*, the person breaths deeply which under guidance normally causes a relax state. The step *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 the *Relax* step, the person is instructed to think of something positive, either a moment in life when he was very happy or of a future event that he looks forward to experiencing. The *Math-stress* step 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.

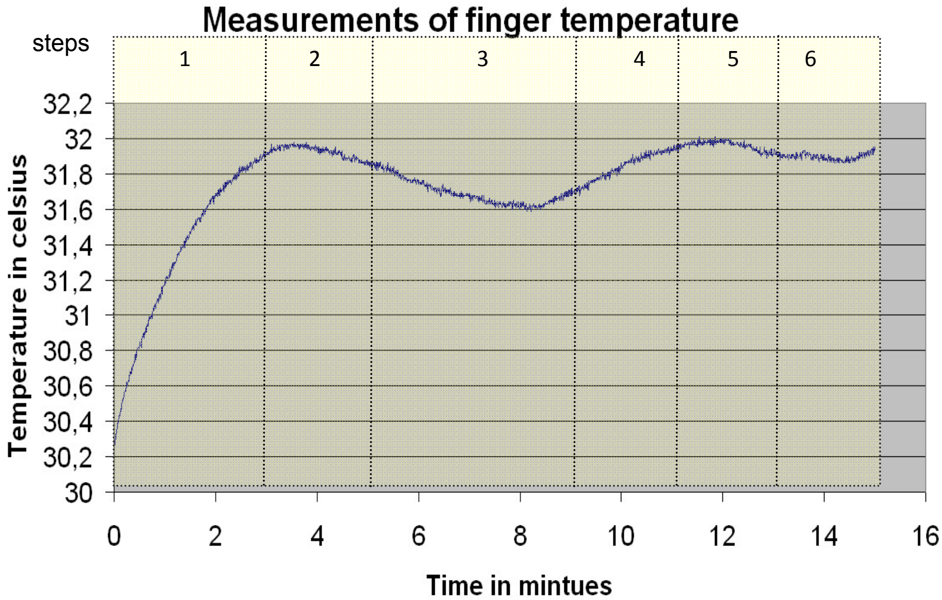

Figure 9. An example of a finger temperature measurement during the six different steps of a calibration phase. Y-axis: temperature in degree Celsius and X-axis: time in minutes. 1, 2, ..6 are six differences steps.

An example of the changes in finger temperature during the calibration phase is illustrated in Fig. 9. As mentioned earlier in this section, it can be observed from the figure that during step 3 in the *Verbal-stress* condition finger temperature decreases, and it increases during step 4 i.e. in the *Relax* condition.

The proposed computer-based stress diagnosis system uses CBR and fuzzy logic to assist in the diagnostic and/or classification tasks. It performs several steps to diagnose individual sensitivity to stress as shown in Fig. 8. The system consists of a thermistor, sensing the finger temperature [17]. The sensor is attached to a finger on the patient/subject and connected to an electronic circuit that is connected to a USB-port on a computer. The system takes the finger temperature measurement as an input and identifies essential features and formulates a new problem case with the extracted features in a vector. The feature extraction technique from the biomedical sensor signal is illustrated in the following subsection 3.1.1.

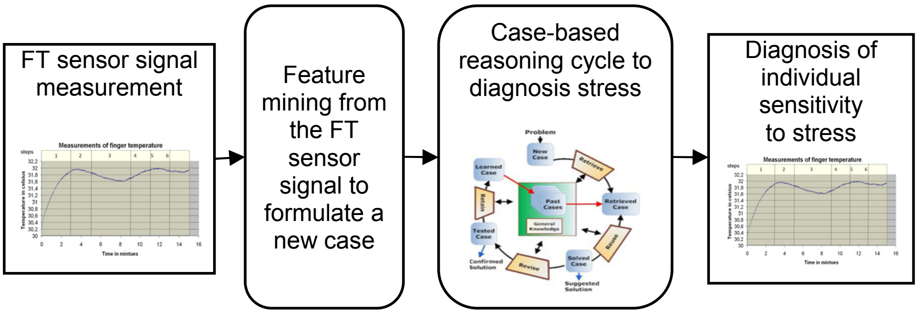

Figure 10. Schematic diagram of the steps in stress diagnosis.

CBR solves a new problem by applying previous experience adapted to the current situation [67]. Most of the CBR systems follow the reasoning cycle discussed in the earlier chapter with Retrieve, Reuse, Revise and Retain as shown in Fig. 2. A case represents a piece of knowledge and plays an important role in the reasoning process. This 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 matching algorithms. 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, a similarity between the same gender 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.

$$sim(C_f, S_f) = s_f(m1, m2) = \max(om/m1, om/m2) \qquad (2)$$

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 could be found through the research contributions in PAPER-A.

Cases matching with current case **2008-11-12_11-12-45_erikO.xml**

<< Previous Next >>

Case	Percent	Evaluation	Times reviewed	Score
Case 15	71.8	very_stressed	0	0
Case 23	70.8	very_stressed	0	0
Case 9	70.4	very_stressed	0	0
Case 24	69.6	stressed	0	0
Case 4	65.8	very_stressed	0	0
Case 31	65.5	stressed	0	0
Case 35	62.8	normal	0	0
Case 27	57.5	very_stressed	0	0
Case 5	57	normal	4	3
Case 28	56.8	stressed	0	0
Case 7	56.7	normal	3	2
Case 32	56.3	stressed	0	0
Case 18	56	stressed	0	0
Case 13	53.5	normal	0	0
Case 17	52.2	stressed	0	0

Figure 11. The most similar cases presented in a ranked list with their solutions.

A similarity measurement is taken to assess the degree of matching and create a ranked list containing the most similar cases retrieved according to equation 3.

$$Similarity\ (C, S) = \sum_{f=1}^{n} w_f * sim\ (C_f, S_f) \tag{3}$$

Where *C* is a current/target case, *S* is a stored case in the case base, *w* is a normalized weight defined by equation 4, *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*.

$$w_f = \frac{lw_f}{\sum_{f=1}^{n} lw_f} \tag{4}$$

Here, a *Local weight (lw)* is defined by experts, assumed to be a quantity reflecting importance of the corresponding feature, *Normalized weight (w)* is calculated by equation 4.

The system provides a matching outcome in a sorted list of the best matching cases i.e. a ranked list by the system for a current/new case matching with all the other cases in a case base as shown in Fig 11. A ranked list of cases is presented on the basis of their similarity value and identified classes. The solution for a retrieved old case that is diagnosis and treatment recommendations, are also displayed by the system. It also show the number of times each case is reviewed by an expert as well as the number of times each case solution is used to solve a new problem as a score of the case. Moreover, by clicking a case id, the user can see detailed information of that case and a comparison between the new problem case and the selected case. A screen shot of such information is presented in Fig 12. It also provides a better visualization of the comparison of FT measurement between a new case and an old case through plotted line chart using the signals (see Fig 13). The user can apply different matching algorithms by selecting a specific method. Details matching information provides t an opportunity to see more clearly the matching between the cases (a current case and old cases) which may assist clinicians/users to determine if a solution is reusable or requires an adaptation for the new situation/problem. An example described in Fig 10, 11 and 12 show the similarity matching of a current case (Case Id 43) with the previous cases (Case Id 15 and 23) in a ranked list. For the current case, the system establishes with 71.8% of reliability that the patient is under the *Very stressed* condition. Finally, as output, the top matching case is displayed which provides the classification of the individual stress level for the diagnosis of individual sensitivity to stress.

Similarity matchings with current case **2008-11-12_11-12-45_erikO.xml**									
Attributes	Local weight	Normalized weight	Current case 43	Stored case 15	Similarity function	Weighted similarity	Stored case 23	Similarity function	Weighted similarity
Gender	5	0.03	F	M	0.5	0.01	M	0.5	0.01
Maximum temperature	10	0.06	23.99	24.61	0.987	0.06	24.84	0.983	0.06
Minimum temperature	10	0.06	23.18	24.24	0.978	0.06	24.58	0.971	0.06
Difference	10	0.06	0.81	0.37	0.627	0.04	0.26	0.486	0.03
Start temperature	10	0.06	24.98	25.24	0.995	0.06	25.49	0.99	0.06
End temperature	9	0.05	23.23	24.1	0.982	0.05	24.5	0.973	0.05
Hours since last meal	10	0.06	0	4	0	0	3	0.4	0.02
Before_after meal	0	0	unknown	unknown	1	0	unknown	1	0
Room temperature	0	0	0	0	1	0	0	1	0
Step1_part1	4	0.02	-9.858	-13.281	0.852	0.02	-16.843	0.738	0.02
Step1_part2	4	0.02	-7.704	-7.714	0.999	0.02	-13.823	0.716	0.02
Step1_part3	4	0.02	-4.101	-6.266	0.791	0.02	-9.112	0.621	0.01
Step1_reliability	0	0	8	5	0.769	0	5	0.769	0
Step2_part1	10	0.06	-9.786	-5.96	0.757	0.05	-8.936	0.955	0.06
Step2_part2	10	0.06	-8.825	-5.956	0.806	0.05	-8.04	0.953	0.06
Step2_reliability	0	0	6	5	0.909	0	5	0.909	0
Step3_part1	6	0.04	-5.804	-6.484	0.945	0.03	-6.228	0.965	0.03
Step3_part2	6	0.04	-6.553	-6.818	0.98	0.03	-5.898	0.947	0.03
Step3_part3	6	0.04	-8.102	-6.268	0.872	0.03	-6.2	0.867	0.03
Step3_part4	6	0.04	-5	-4.666	0.965	0.03	-5.43	0.959	0.03
Step3_reliability	0	0	5	5	1	0	5	1	0
Step4_part1	9	0.05	0.22	-3.961	0	0	-5.574	0	0
Step4_part2	9	0.05	-7.216	-4.591	0.778	0.04	-4.95	0.814	0.04
Step4_reliability	0	0	7	5	0.833	0	5	0.833	0
Step5_part1	6	0.04	-7.392	-5.901	0.888	0.03	9.369	0	0
Step5_part2	6	0.04	-6.427	-5.072	0.882	0.03	-4.41	0.814	0.03
Step5_reliability	0	0	8	5	0.769	0	5	0.769	0
Step6_part1	9	0.05	14.764	-4.816	0	0	-7.548	0	0
Step6_part2	9	0.05	-6.416	-4.037	0.772	0.04	-4.412	0.815	0.04
Step6_reliability	0	0	7	5	0.833	0	5	0.833	0
	Update				Global similarity case 15	**71.755**		Global similarity case 23	**70.78**

Figure 12. Comparison between a new problem case and most similar cases.

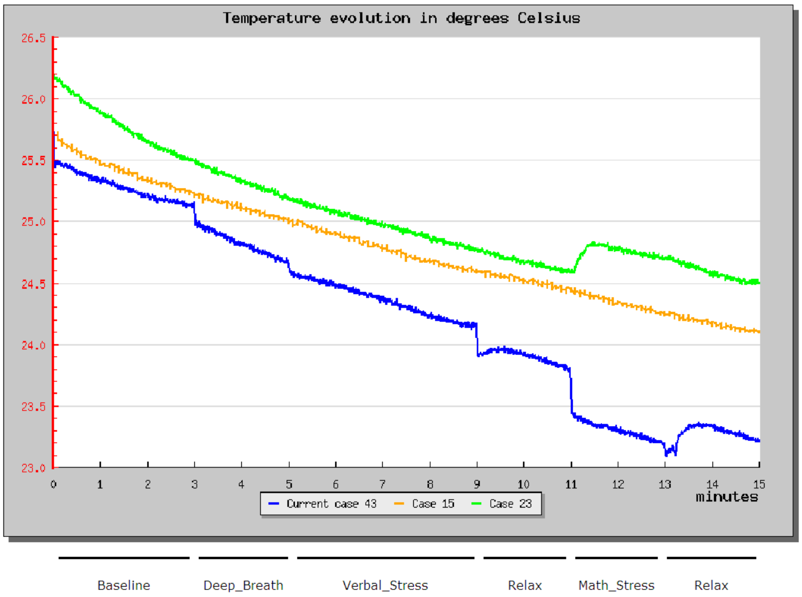

Figure 13. Comparison in FT measurements between a new problem case and old cases.

Users can adapt solutions i.e. it could be a combination of two solutions from the list of the retrieved and ranked cases in order to adjust a solution to the current problem case. Then clinician/expert determines if it is a plausible solution to the problem and he/she can 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.

3.1.1 Feature extraction from the biomedical sensor signal

Clinician normally observes the FT signal on a computer screen and analyzes this signal manually, which is a very tedious task and often requires time and experience. After analyzing a number of finger temperature signals, a large individual variations was found, but also a similarity in the pattern that the temperature decreases during stress and increases during relaxation for most people. That is an important feature which needs to be identified by an automatic classification algorithm searching for “similar” patients.

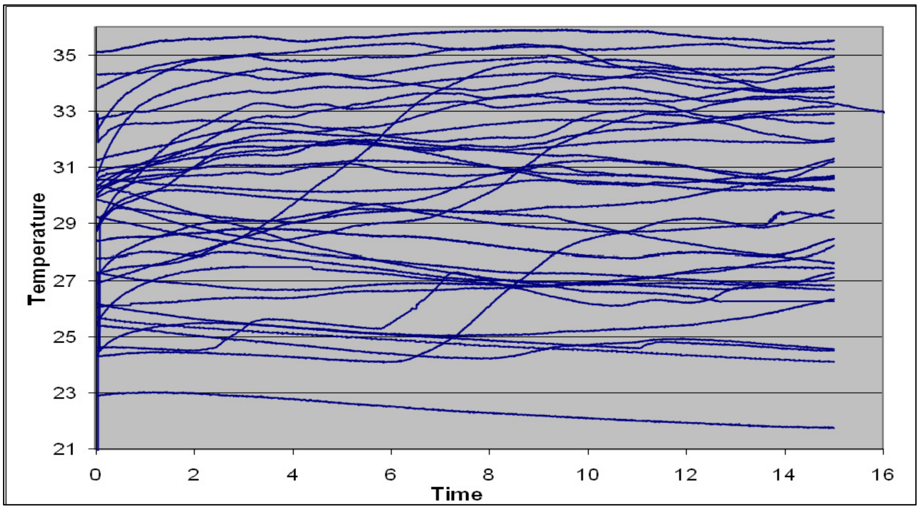

Figure 14. FT sensor signals measurement samples are plotted.

The variation of FT can be seen in Fig. 14 where 39 measurements are plotted in one chart. The indication of a person's stress might be found both from the low or high temperature signals. The different techniques applied to investigate similarity between the signals are discussed below.

We have applied *point-to-point* matching between two signals. But it shows some disadvantages to identify similarity/difference for such kind of signals:

i) It needs to calculate each and every point i.e. difference between two cases can be achieved by calculating the difference for 1800 samples in our case. So the computational time is an important issue here.

ii) It does not calculate similarity in pattern for two cases. Let's consider this example, one case with 15 minutes of sample data where finger temperature lies with 33^0 C to 35^0 C, with the same pattern considering another case where finger temperature lies within 24^0 C to 28^0 C is not similar according to their different temperature values. But they are similar in pattern.

iii) If the finger temperature for a new problem case lies in higher level (like as 35^0 C) then the system will never consider any cases where finger temperature lies in lower level (like as 23^0 C) and vice versa.

iv) This similarity method is not considering any variation in FT when calculating the difference between two cases, whereas the change in finger temperature is an important factor for classifying stress.

Besides, either mean value or standard deviation of the FT measurement might not be an indicative for stress. For instance, consider two signals one is increasing from 20^0 C to 30^0 C, and the other is decreasing from 30^0 C to 20^0 C, and both have the same mean/standard deviation value in the duration, but indicate opposite stress levels. As an alternative way, we guess that the mean of the slope value might be a feasible feature to convey a relation with stress. If the mean slope is sufficiently positive, it will be an indication of relax, otherwise an indication of stress. But if the mean slope is around zero, it shows a situation with high uncertainty for decision or a weak decision.

We have applied case-based reasoning where two cases (i.e. signals) are matched depending on the feature values that define a case. An experienced clinician often classify a FT signal manually without being pointed out intentionally all the features he/she uses in the classification. However, extracting appropriate features is of great importance when performing accurate classification in a CBR system. To determine important features the system uses 15 minutes measurements (time, temperature) in 1800 samples, together with other numeric (age, room-temperature, hours since meal, etc) and symbolic (gender, food and drink taken, sleep at night, etc) parameters. 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 stable in finger temperature. A high positive angle value indicates rising FT, while a negative angle, e.g. -20° indicates falling FT. The total signal, except the baseline, is divided into 12 parts with one minute time interval. A case is formulated with 19 features in total in which17 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 in a CBR cycle and assist to the diagnosis and treatment plan of stress.

3.2 Fuzzy rule-based reasoning for artificial cases

The composition of a case library is one of the key factors that decide the ultimate performance of a CBR system. The cases stored in the case library should be both representative and comprehensive to cover a wide spectrum of possible situations. One of the limitations in CBR is that it depends on the case library; enough cases in a case library gives better result (with the purpose of accuracy) otherwise it may reduce the performance due to the lack of knowledge. Initially, when a system starts only with a small number of cases the performance could be reduced so an algorithm that automatically classifies new cases would be valuable. A fuzzy rule-based reasoning is introduced into the CBR system to initiate the case library with artificial cases providing an improved performance in the stress diagnosis task. The details research effort is presented in PAPER B. In this research, the rules used in the classification process limit the number of cases in the matching procedure. Furthermore, a sharp distinction in the classification of individual sensitivity to stress may lead to misclassification. The system overcomes the problem by introducing fuzzy rules in the classification scheme. Instead of sharp distinction everything in fuzzy logic appears as a matter of some degrees or degrees of truth.

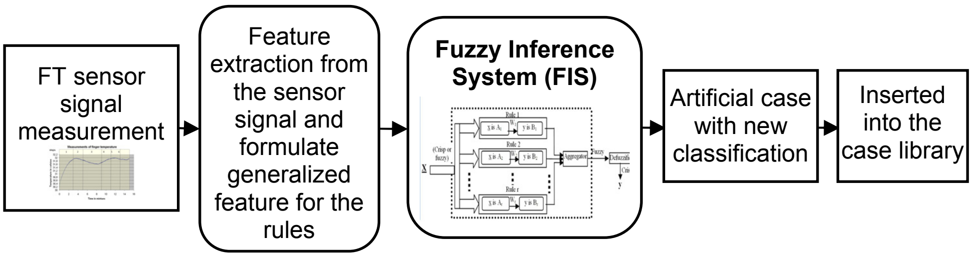

Figure 15. Steps to create artificial cases in a stress diagnosis system.

Fuzzy rule-based reasoning to create artificial cases function as follows: 1) A FT sensor signal is measured through the calibration phase presented in the earlier section, 2) Features are extracted from the sensor reading and formulated them into a generalized feature, 3) The generalized feature is then supplied into the fuzzy inference system (FIS) to classify a new case, 4) The output from the FIS is the new classification defined in a feature vector and, 5) Finally, this case is saved into the case library as an artificial case (See Fig. 15). The rules used in this classification process are defined by a domain expert and formulated with a generalized feature allowing the sensor signal abstraction. A detailed description of these steps is presented as a research contribution in PAPER B.

A single-input single-output Mamdani fuzzy model is implemented in which the percentage of a negative slope (feature) is considered as the input variable and the corresponding stress class as the output. The parameters of the IF–THEN rules (known as antecedents or premise in fuzzy modeling) define a fuzzy region of the input space, and the output parameters (known as consequent in fuzzy modeling) specify a corresponding output as shown in Table 1. The crisp rules of these fuzzy rules are available in the included article PAPER B.

Table 1. Rules for the fuzzy inference system.

Fuzzy rules for classification
1. if **X** is *VeryHigh* then **Y** is *VeryStress* 2. if **X** is *High* then **Y** is *Stress* 3. if **X** is *Medium* then **Y** is *Normal/Stable* 4. if **X** is *Low* then **Y** is *Relax* 5. if **X** is *VeryLow* then **Y** is *VeryRelax*
X= Percentage_Negative_Slope, and Y= Stress_Condition

Percentage_Negative_Slope and Stress_Condition are the linguistic variables with the universe of discourse {0, 100} and {1, 5} respectively. *VeryHigh*, *High*, *Medium*, *Low* and *VeryLow* are the linguistic values determined by the fuzzy sets "TriangleFuzzySet" on the universe of discourse of Percentage_Negative_slope. *VeryStress*, *Stress*, *Normal/Stable*, *Relax* and *VeryRelax* are the linguistic values determined by the fuzzy sets "SingletonFuzzySet" on the universe of discourse of Stress_Condition class. The basic structure of fuzzy logic expert systems, commonly known as a fuzzy inference system (FIS) is shown in Fig. 16.

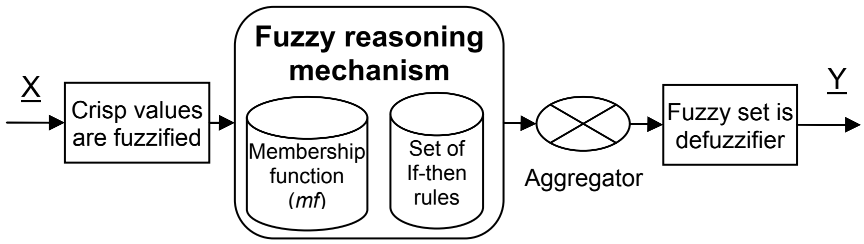

Figure 16. A block diagram of a fuzzy inference system [30].

A rule-based system consisting of three conceptual components: a rule base that consists of a collection of fuzzy IF–THEN rules; a database that defines the membership functions (*mf*) used in the fuzzy rules; and a reasoning mechanism that combines these rules into a mapping routine from the inputs to the outputs of a system to derive a reasonable conclusion as output. X is the crisp value inputted for fuzzificaiton. The fuzzy reasoning mechanism takes the fuzzyfied inputs and applies them to the antecedent part of the fuzzy rules. The value or firing strength from each rule represents the result of the antecedent's evaluation. After that this number is applied to generate consequent MFs. All the output MFs are combined into a single fuzzy set through the aggregator. Finally, defuzzification determines a crisp value from the output membership function as the solution which is Y.

3.3 Textual information retrieval

Unlike measurement-based experience, human perceptions are usually expressed in an informal and natural language format, but they are proved important information for diagnosis. Furthermore, contextual awareness is essential for decision support in diagnostics and treatment plans in the medical domain which is often conveyed in relevant notes or reports. Therefore, capturing perception-based experience coming from human observations and feelings and utilizing contextual awareness in a medical CBR system can provide more reliable and effective experience reuse.

In fact, when diagnosing an individual stress level, clinicians also consider other factors such as a patient feelings, behavior, social facts, 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 [PAPER A]. To enable similarity matching on less structured cases containing text, this research contributes with a proposal which combines cosine similarity with synonyms and ontology. PAPER A presents a hybrid model that considers textual information besides FT sensor signal reading. For textual cases, the *tf-idf* (term frequency–inverse document frequency) [57] weighting scheme is used in a vector space model [56] 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 relation between words. The different steps in retrieval of similar case(s) in the system are described in Fig. 17.

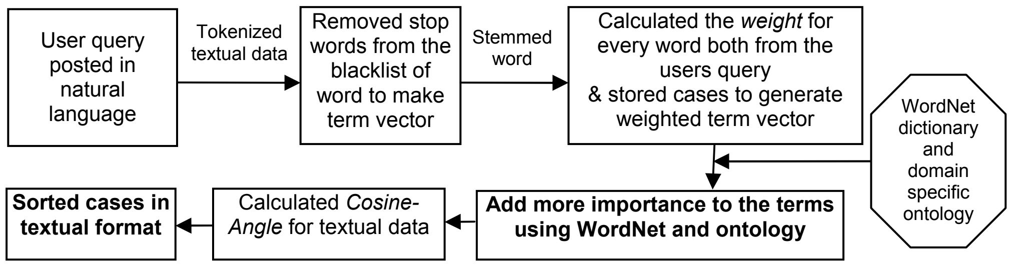

Figure 17. The different steps for case retrieval.

The text tokenize algorithm decomposes the textual information into sentences, and then into individual words. Due to a huge amount of words a filtering step is required to improve the retrieval efficiency. . The following three steps are applied to extract important textual features:

1. Remove the stop-words and special characters, blacklist from both the users' query and patients' record.
2. A list of synonyms of words is used to reduce the number of terms. The Porter stemming algorithm helps to stem the words and provide ways of finding morphological variants of a search term. After calculating a weight for each word, these words are represented as terms in a vector space.
3. Improve the importance assessments for candidate terms before measuring the cosine similarity value for the textual information between the stored case and user's query case by using domain specific ontology.

The *tf-idf* [57] weighting scheme is used for this system where the word "document" is treated as a case. The weight of a term is computed as a function $W_{i,j}$, that calculates the weight of each term or word in the stored cases and in the query case as illustrated in Equation 5. Here, $W_{i,j}$ is the weight of a term T_j in a case C_i, $tf_{i,j}$ is the frequency of a term T_j in a case C_i and idf_j is the inverse case frequency where N is the number of cases in a case library and df_j is the number of cases where term T_j occurs at least once.

$$W_{i,j} = tf_{i,j} * idf_j = tf_{i,j} * \log_2\left(\frac{N}{df_j}\right) \qquad \textbf{(5)}$$

Equation 5 is modified slightly to give more emphasis on the terms, an adaptation of $tf_{i,j}$ based on the frequency of occurrence of the instances in each case is computed in Equation 6 where $max_k(tf_{j,k})$ is the frequency of the most repeated instance tf_k in C.

$$tf_{i,j} = \frac{tf_{i,j}}{\max_k (tf_{j,k})} \quad \textbf{(6)}$$

In a traditional VSM model, term vectors are generated by ordering terms in a case vector according to their occurrence in the case i.e. by a normalized *tf-idf* score where synonyms or relation of words are not used. However, the implemented system uses a WordNet dictionary to provide the necessary information about the relation by employing synonyms, hyponym and hypernyms of words. Therefore, it is necessary to alter a term vector to a new vector, in this term vector previous terms are re-weighted and/or new terms are added on the basis of different conditions. The function for re-weighting a term is shown in Equation 7.

$$W'_{i,j} = W_{i,j} + \sum_{sim(j,k) \geq T}^{j \neq k} W_{i,j}\, sim(j,k) \quad \textbf{(7)}$$

Where $W'_{i,j}$ is the new weighting function for a term j of a case vector i, adjusted by similar terms k within the same vector. T is a user defined threshold, we use T=0.8; that means each term in a vector will match with other terms in the same vector and the terms who have a similarity value more than 0.8 will be added by multiplying their original weight. The source term can obtain several related terms employing synonyms, hyponyms and hypernyms which means a term can be related with other terms that already exist in the case term vector. Now all the terms with a similarity value greater than a threshold value ($T=0.9$) will be considered as new terms and are added to the case term vector. These new terms are then weighted according to the similarity values of the terms in the case vector. If a related term already exists in the vector then only the similarity value of that term will be added with the original weight of the source term. Thus, the system identifies and gives higher preferences to these key terms compared to other terms in order to match a source case with query cases.

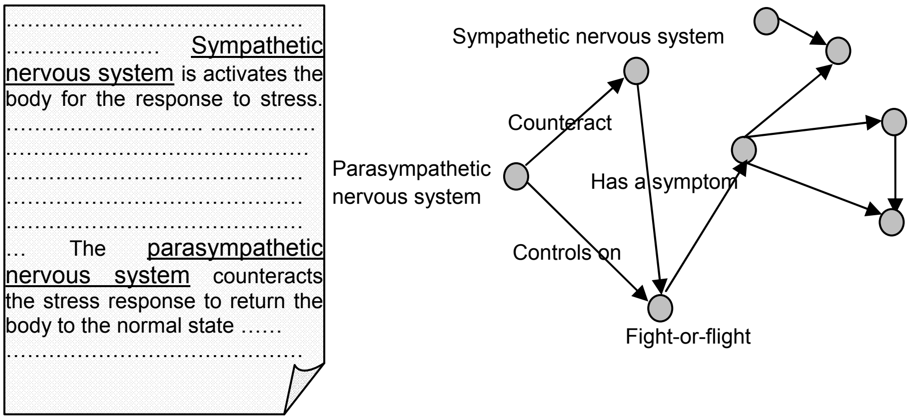

Figure 18. Weighting the term vector using ontology.

A domain specific ontology or user defined ontology represents specific domain knowledge, i.e., the relation between words. The terms of a case can be compared with other cases by exact matching or a synonym matching or using a co-occurrence. However, some words or terms can have a complex relationship (for example, the term "sympathetic nervous system" and "parasympathetic nervous system"), the weight of such terms can be increased automatically using a domain specific ontology defined by an expert. An example is shown in Fig. 18 on how the ontology helps to improve the weight vector.

From Fig. 18 "sympathetic nervous system" is a term that appears both in the case text and in ontology, it also has a relation with another term "fight-or-flight" in the ontology but the term does not exist in the case text, so the term "fight-or-flight" is important for this case. Again the term "parasympathetic nervous system" and "sympathetic nervous system" both already exist in the case text and as well as has a relation in the ontology so the value of the strength of their relationship for those two terms will increase the weights for their importance. The terms "parasympathetic nervous system" and "sympathetic nervous system" are related with another term "fight-or-flight" in the ontology so the term "fight-or-flight" will get more importance.

The similarity between a stored case vector C_i and a new case as a query vector Q is calculated using a cosine similarity function [56] [26] [70] where the cases deal with textual information. This ratio is defined as the cosine of the angle between the vectors, within the values between 0 and 1 and can be calculated by Equation 8.

$$Cos\theta_{C_i} = Sim(Q, C_i) = \frac{Q \bullet C_i}{\|Q\| \|C_i\|} = \frac{\sum_j w_{q,j} w_{i,j}}{\sqrt{\sum_j w_{q,j}^2} \sqrt{\sum_j w_{i,j}^2}} \tag{8}$$

Where $Cos\theta_{C_i}$ is the *cosine of the angle* between a stored case and query case which is defined as the similarity function $Sim(Q, C_i)$. The dot product of a stored case and a query case is $Q^\bullet C_i$ where the zero products is ignored; and $w_{i,j}$ and $w_{q,j}$ are the weight of vector length.

3.4 Biofeedback treatment

The basic of biofeedback system is that a patient gets feedback in a clear way (a patient observes the graph and knows from preceding education how it should change). The feedback can behaviorally train the body and mind in a better way against with biological respond. After discussions with clinicians it has been figured out that most of the sensor based biofeedback applications comprise of three phases, 1) analyze 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. PAPER C, addresses this issue through the research contribution added in part 2 (included paper section) of this thesis.

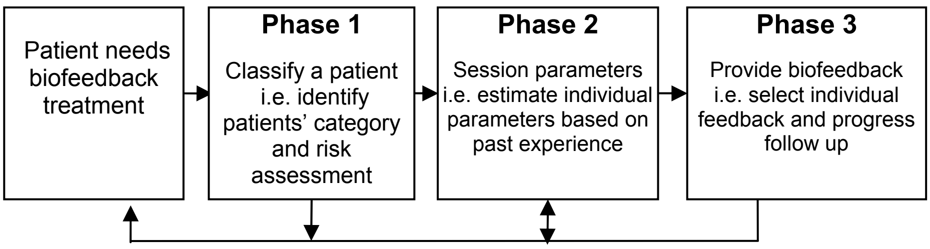

Figure 19. General architecture of a three-phase biofeedback system.

In the first phase as shown in Fig 19, a clinician normally asks a number of questions and makes a number of more or less systematic measurements, and then he classifies a patient depends on the risk and risk-reduction of stress (e.g. stress reactivity and recovery/capacity). In the second phase, a number of measurements have been done to find out parameters such as, baseline, ceiling, floor temperature etc. needed to tailor the biofeedback session to a patient in order to achieve as good results as possible. Finally, the third phase generates recommendations for a biofeedback training session. In Fig. 19 a complete biofeedback system is outlined and the arrows from the individual phases are continuous input to the monitoring computer system and clinician, if present. When a biofeedback session does not follow the expected route, reclassification of the patient may be necessary or adjustment of the biofeedback parameters. In each phase, the CBR approach is applied to predict solutions of a new problem referring to the solution of similar and useful problems where the matching between the attribute values of two cases are performed employing the fuzzy similarity matching algorithm. This biofeedback system can either be a decision support system for a clinician, or be a second opinion for an expert, used with on-line supervision.

Biofeedback often focus on relaxation and how the patient can practice relaxation whilst observing, e.g. the changes in skin temperature. The intention of the system is to enable a patient to train himself/herself without particular supervision. For the biofeedback treatment [27, 42] procedure a cycle with several steps is considered. An illustration of this biofeedback cycle is shown in Fig. 20.

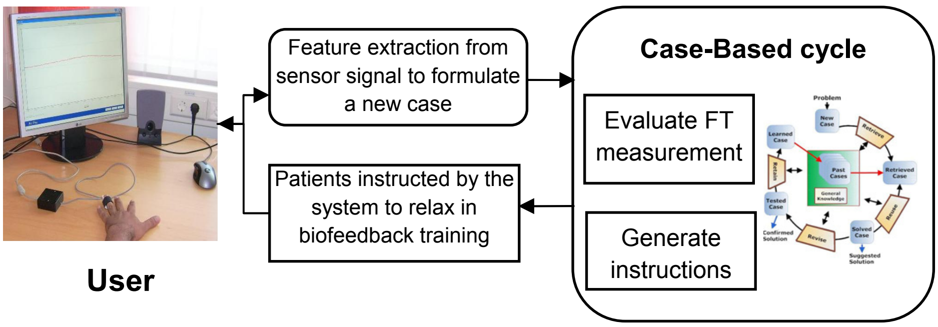

Figure 20. A schematic diagram of the steps in the biofeedback treatment cycle.

In this cycle, a user (patient/subject) connects a sensor with his/her finger and can see the changes of FT during several instructions in relaxation training. The FT measurements are preformed 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 his/her training between 6 minutes (as minimum) to 20 minutes (as maximum). Nevertheless, the system generates feedback with appropriate suggestions in 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.

Chapter 4.

Experimental Work

This chapter presents the experimental work that has been carried out in this research. The included papers also contain their corresponding evaluations however this chapter contains the summary of the evaluation and some extended experimental works.

To evaluate the different approaches and methods addressed in this research, the framework of the computer based system has been implemented and primarily validated in a prototypical system. The performance of the system in terms of accuracy has been compared with experts in the domain where the main goal is to see how close the system can perform compared to an expert. The accuracy of the system is computed using a statistics *square of the correlation coefficient* or *Goodness-of-fit* (R^2) [14], *absolute mean difference* and *percentage of the correctly classified cases*. The initial case base comprises of 53 FT measurements as reference cases from 31 subjects in total. Eight (8) woman and twenty-three (23) men with the age range of 24 to 54 are participating in the study. The cases, in their conditional or problem description part, contain a vector with the extracted features and a solution part comprised of an expert's defined classification as a diagnosis. The level of stress is classified by the expert into five classes ranging from 1 to 5 where 1=VeryStressed, 2=Stressed, 3=Normal/Stable, 4=Relaxed and 5=VeryRelaxed.

4.1 Similarity matching in CBR

In the previous chapter in section 3.1 we have discussed the three local similarity matching algorithms for the CBR system. These algorithms are implemented in the prototypical system to evaluate the system performance. The main goal of this experiment is to investigate the best similarity matching algorithm for the CBR system compared to the expert's opinion. In PAPER A the experiment has been conducted considering 39 cases within the 24 subjects, which is further extended in this thesis by considering 53 cases from 31 subjects. Moreover, more test data sets i.e. 7 test sets is considered along with the previously used three test subsets Set A, Set B and Set C. The seven subsets of cases and the seven query cases are: Set A: {7 cases} with query case id 4, Set B: {11 cases} with query case id 16, Set C: {10 cases} with query case id 28, and so on are chosen randomly. Table 2 presents Set C with case id 28 as an example for the comparison of the three similarity matching algorithms against an expert.

Table 2. Similarity matching for the Set C with case id 28 in comparison with a clinical expert.

Matching (Query, Set C)	Expert Ranking	Expert Similarity (%)	Using Distance Ranking	Using Distance Similarity (%)	Using Matrix Ranking	Using Matrix Similarity (%)	Using Fuzzy-logic Ranking	Using Fuzzy-logic Similarity (%)
28, 12	1	90	1	92	1	80	1	70
28, 35	2	85	2	91	3	72	2	69
28, 31	3	82	4	89	4	69	3	68
28, 24	4	80	5	87	5	68	4	65
28, 8	5	70	6	86	2	78	5	66
28, 13	6	65	3	90	6	67	6	60
R^2 in Ranking & similarity			0.44	0.27	0.43	0.13	0.89	0.80
ABS Mean Difference in Ranking & Similarity			1.00	11	1.00	10	0.33	12

In the table above, the 1st column describes the identification of the two matching cases (Query and Set C). The gray coloured columns represent the position of each case ranked by an expert and the three algorithms. The rest of the columns display the similarity value of each case defined by both the expert and system using the three algorithms. The last two rows show the value of goodness-of-fit (R^2) and the absolute (ABS) mean difference, calculated on the basis of the ranking and similarity values identified by the expert and the system. Likewise, all the test sets have been sorted according to the similarity with a query case decided by a domain expert (human reasoning). The sorted cases are then converted to rank numbers, i.e., the position of a case in the ranking. The top six cases from each set according to the expert's ranking are used as standard for the evaluation process where both the similarity values and the ranking numbers are considered.

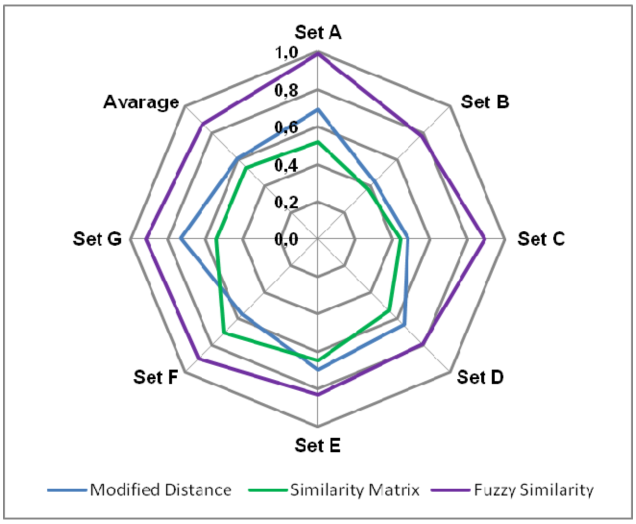

Figure 21. Goodness-of-fit in ranking to compare the three algorithms.

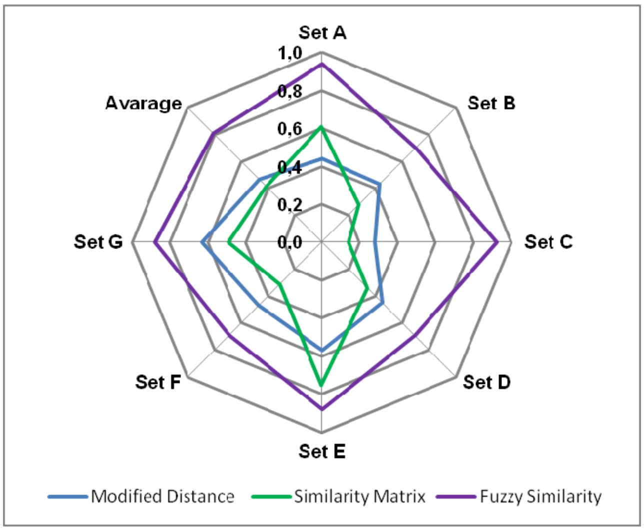

Figure 22. Goodness-of-fit similarity to compare the three algorithms.

As can be seen from Fig. 21 and Fig. 22, both in the "ranking number" and "similarity value" criteria, the fuzzy similarity algorithm is more reliable than the other algorithms. The fuzzy similarity algorithm performs better in all the seven test subsets. Table 4 shows the average outcome across the seven subsets (from Set A to Set G) in terms of the goodness-of-fit (R^2), evaluating the three algorithms comparing the expert's in two aspects: cases ranked by the system as well by the expert and similarity values given by the expert and the system. As can be seen from Table 4, the similarity matching algorithm using fuzzy logic seems to be reliable both in its similarity and ranking value and it outperforms the other two matching algorithms.

Table 3. Average Goodness-of-fit for the three matching algorithms.

Similarity Algorithms in Average of all the subsets	Goodness-of-fit	
	Ranking	Similarity (%)
Modified Distance	0.61	0.47
Similarity Matrix	0.54	0.42
Fuzzy Similarity	0.87	0.81

4.2 CBR supports in stress diagnosing

The goal of this experimental work is to see how CBR classification supports in the stress diagnosis i.e. the performance of the system's diagnosis task compare to an expert. In the case library, 20 cases are classified as a stress-related disorder, among them 8 are classified as *VeryStressed* and 12 are as *Stressed*. For the evaluation, one case is taken out from the case library at a time and is matched against the remaining cases. Then, the classification of the cases by the system is compared with the expert's classification. The comparison result is presented in Table 4 and Table 5.

Table 4. Comparison between the expert's & system's classification in *VeryStressed* class.

CaseID	**Expert's classification**	**System's classification using Fuzzy Similarity**
Case_001_009	VeryStressed	VeryStressed
Case_004_015	VeryStressed	VeryStressed
Case_004_023	VeryStressed	VeryStressed
Case_039_027	VeryStressed	Stressed
Case_039_004	VeryStressed	VeryStressed
Case_501_040	VeryStressed	VeryStressed
Case_101_042	VeryStressed	VeryStressed
Case_634_043	VeryStressed	VeryStressed
Correctly Classified Cases in **VeryStressed class**		88%

Table 5. Comparison between the expert's and system's classification in *Stressed* class

CaseID	Expert's classification	System's classification using Fuzzy Similarity
Case_789_017	Stressed	Normal/Stable
Case_008_018	Stressed	Stressed
Case_007_022	Stressed	Stressed
Case_103_024	Stressed	Stressed
Case_873_028	Stressed	Relaxed
Case_763_031	Stressed	Stressed
Case_876_032	Stressed	VeryStressed
Case_245_038	Stressed	Stressed
Case_345_046	Stressed	Stressed
Case_823_047	Stressed	Stressed
Case_780_053	Stressed	Stressed
Case_101_052	Stressed	Stressed
Correctly Classified Cases in **Stressed class**		75%

As can be seen in Table 4 and Table 5, the 2nd column presents the expert's classification and the 3rd column presents the classification of the cases by the system. Here, the system uses a fuzzy similarity matching function as local similarity and kNN (k=1) is used to retrieve the similar cases. For evaluation purpose, the top most similar case is considered. For the group *VeryStressed*, the system classifies 88% correctly and 75% correctly for the *Stressed* group in comparison with the expert's classification. Only one case (Case_039_027) is misclassified by the system among the 8 *VeryStressed* cases and three out of the twelve classes are misclassified in *Stressed* class. In total, 80% stress-related cases are correctly classified by the system compared to the expert.

Table 6. The total distribution of correctly classified cases.

Classification criteria	Values
Correctly classified cases in **Total**	80%
Low false positive	5%
Low false negative	10%
Serious false negative	5%

Table 6 illustrates the total distribution of the classified cases, where 80% of the cases are classified correctly by the system. Among the 20% misclassified cases there are 5% low false positive i.e. cases are one step over classified; 10% are low false negative i.e. cases that are one step over misclassified and 5% are serious false negative i.e. cases that are two step more misclassified. One example of a serious false negative can be seen in Table 5, case id Case_873_028, which is misclassified as *Relaxed* whereas the expert has classified it as *Stressed.* Similarly, an example of a low false positive case is id Case_876_032 which is misclassified as *VeryStressed* and the expert has classified the case as *Stressed*.

4.3 Fuzzy rule-based classification into the CBR

As mentioned earlier that the performance of a CBR system depends on the number of available cases in a case library. Fuzzy rule-based classification helps to generate artificial cases in this system. So, the goal of this evaluation is to see an improvement of the CBR system adding these artificial cases into the CBR library. PAPER B addresses this excremental work in detail, only the summary of the evaluation is presented in this chapter.

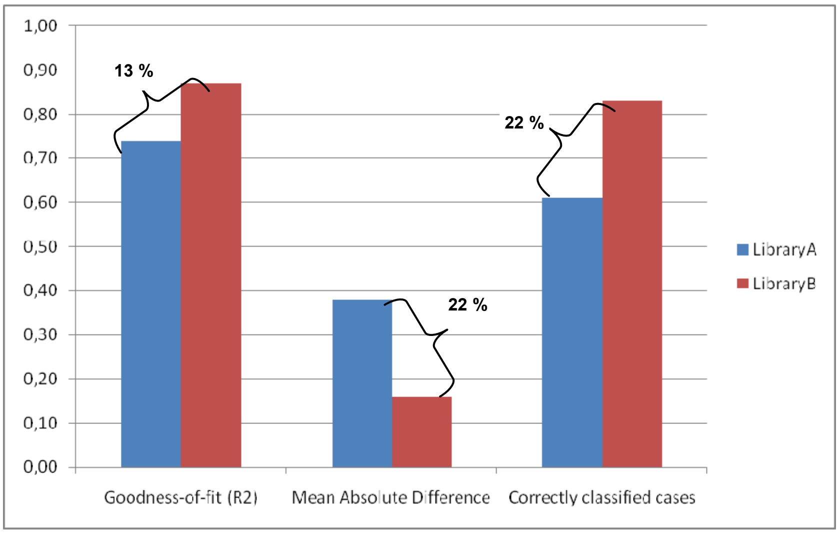

Figure 23. Comparison results between the case libraries A and B.

The experiment has been done by defining two different case libraries as: LibraryA, with real cases only, classified by the expert and LibraryB being twice as big as LibraryA with hybrid cases, classified by the expert and fuzzy rule-based classification. As shown in Fig 24, for the two tests (test1 and test2) on an average LibraryB indicates classification accuracy of 87% while LibraryA reaches 74% of fitness compare to the expert's classification. So, there is a 13% increase in the R^2

value and 22% (Mean absolute difference) decrease in the error rate when the system uses LibraryB (hybrid cases) i.e. the case library contains enough cases. For the two tests (using two case libraries) the number of correctly classified cases on average is presented in percentage. Here, the CBR system can correctly classify 83% of the cases using LibraryB whereas using LibaryA the system can only correctly classify 61% of the cases. So, system improves by 22% in the criteria of correctly classified cases.

4.4 System performance vs. trainee clinicians

This experiment is designed to investigate how good the system can classify compared to the trainee clinicians. For testing purpose an experienced clinician and two trainee clinicians (*TC1* and *TC2*) are involved, 2 subsets of cases (*setA* and *setB*) are created randomly with 11 and 14 expert approved cases. Cases for both the subsets are classified by two trainee clinicians who have less experience in this domain. The main goal is to see how good the system can classify compared to the trainee clinicians i.e. whether the system can be useful to assist a trainee clinician in the classification task.

Table 7. Comparison results between the system and trainee clinicians.

Evaluation Method	Test setA			Test setB		
	TC1	*TC2*	*The System*	*TC1*	*TC2*	*The System*
Correctly Classified Cases	64%	55%	81%	57%	57%	79%
Goodness-of-fit (R^2)	0.86	0.88	0.92	0.80	0.81	0.83
Absolute Mean Difference	0.36	0.45	0.18	0.43	0.43	0.28

From Table 7 it can be seen that the system using the fuzzy similarity matching algorithm can classify correctly better than all the trainee clinicians. For the test group setA with 11 cases, the system classifies correctly 81% and the trainee clinicians classify correctly 64% and 55% respectively. The number of the correctly classified cases for setB with 14 cases in percentage is 79 by the system whereas the trainee clinicians have succeeded to classify correctly as 57 in percentage. For both the test groups (setA and setB), when comparing the system against a senior clinician, the obtained Goodness-of-fit (R^2) values are 92% (setA) and 83% (setB). It shows that the R^2 values are almost the same or little better than the junior clinicians which are (86% and 88% for setA, 80% and 81% for setB. The absolute mean difference or error rates in classification for both the test groups are comparatively lower (0.18 and 0.28) than the junior clinicians. Table 7 shows that in both the test data sets and all the evaluation criteria the system can perform better than the less experienced/trainee clinicians. A detailed evaluation result using only one subset of case in another study presented in PAPER C.

Chapter 5.

Research Contributions

This chapter presents the research contributions through the included papers. A short summary of each paper and the contribution of the author are also presented.

To answer the research questions presented in the introduction chapter, the research contributions of this licentiate thesis includes 3 journals and 1 international conference papers. The *first* included journal paper proposes methods to design a hybrid diagnosis system that is capable of handling multimedia data i.e. a combination of time series measurements as well as unstructured textual information. The goal of this proposed system is to provide a more reliable functionality in diagnosis and decision making tasks. The *second* paper introduces a supplementary supporting technique/method to the CBR system that provides an improved performance to stress diagnosis task. Another journal paper (*third*) proposes a computer assisted sensor-based biofeedback decision support system assisting a clinician as a second option to classify a patient, estimate initial parameters and to make recommendations for biofeedback training. The *fourth* included journal paper presents a survey in "CBR in the medical domain" which investigates the current trends and developments of CBR systems in medicine. The following sub-chapters point-out the summary of each included papers.

5.1 Paper A: Case-based reasoning for diagnosis of stress using enhanced cosine and fuzzy similarity

The paper is published in the international journal "Transactions on Case-Based Reasoning on Multimedia Data" by the IBaI Publishing on October, 2008; ISSN no is 1864-9734.

As the main author of this journal paper Mobyen Uddin Ahmed contributed in writing a system overview, a method for extracting features from textual information, a matching algorithm for textual case retrieval, evaluation and related work. In addition, a prototypal system was developed by Mobyen Uddin Ahmed to evaluate the model of the system framework and its functionality.

This paper proposes a method for a hybrid case-based reasoning system to diagnose stress which is capable of coping with both numerical signals and textual data at the same time. The total case index consists of two sub-parts corresponding to signal and textual data respectively. For matching of cases on the signal aspect we present a fuzzy similarity matching metric to accommodate and tackle the imprecision and uncertainty in sensor measurements. A preliminary evaluation has revealed that the fuzzy matching algorithm leads to a more accurate similarity estimate for improved case ranking and retrieval compared with a traditional distance-based matching criterion. For evaluation of similarity on the textual dimension we propose an enhanced cosine matching function augmented with related domain knowledge. This is implemented by incorporating Wordnet and domain specific ontology into the textual case-based reasoning process for refining weights of terms according to available knowledge encoded therein. Such knowledge-based reasoning for matching of textual cases has empirically shown its merit in improving both precision and recall of retrieved cases with our initial medical databases.

5.2 Paper B: Fuzzy rule-based classification to build an initial case library for case-based stress diagnosis

This is a conference paper published in the proceedings of the 9th international conference on Artificial Intelligence and Applications (AIA) 2009. The Editor(s) of the proceedings is M.H. Hamza, Austria February, 2009.

Mobyen Uddin Ahmed has contributed as the main author of this paper and the idea of the proposed method was introduced by him. He has contributed in writing related work, fuzzy rule-based classification, rule induction with a generalized feature and experimental results. He was responsible for the evaluation part of the paper.

This paper proposes a fuzzy rule-based classification scheme which is introduced into to the existing CBR system to improve performance to the stress diagnosis task. In the initial phase of a CBR system there are often a limited number of cases available which reduces the performance of the system. If past cases are missing or are very sparse in some areas the accuracy is reduced. Experimental results show that the CBR system using the enhanced case library can correctly classify 83% of the cases, whereas previously the correctness of the classification was 61%. Consequently the proposed system has an improved performance with 22% in terms of accuracy. In terms of the discrepancy in classification compared to an expert, the goodness-of-fit value of the test results is on average 87%. Thus by employing fuzzy rule-based classification, the new hybrid system can generate artificial cases to enhance the case library. Furthermore, it can classify new problem cases previously not classified by the system.

5.3 Paper C: A multi-module case based biofeedback system for stress treatment

This paper is accepted in the international journal "Artificial Intelligence in Medicine", printed by ELSEVIER. The current status of the paper is now in printing.

This is the 2nd journal paper included in the thesis where Mobyen Uddin Ahmed was the main author. The basic idea of the designed framework is introduced by him. He has contributed in writing introduction, related work, biofeedback system for stress treatment, and experimental results and discussion chapters. He was also responsible for the evaluation part of the paper.

This paper presents a computer-based decision support system for biofeedback training in health care. The system aims to facilitate experience sharing and reuse among clinicians by utilizing the CBR methodology from artificial intelligence. The main contribution of this research is a three-module system architecture enabling decision support to clinicians carrying out biofeedback. Classification, parameter estimation as well as biofeedback training are dealt with. The approaches have been validated in a case study related to stress diagnosis and treatment. The results of the case study reveal that our case-based system for biofeedback training outperforms novice clinicians in patient diagnosis by making judgments even closer to senior experts in the underlying domain. We believe that our developed system will be valuable to help less experienced clinicians making more accurate and prompt decisions as well as to offer useful second opinions for experts in dealing with complex and controversial situations. Our future work will focus on the interaction among the three modules in the existing system and also investigate ways to further improve the overall performance of the system using delayed reports of treatment effects of patients.

5.4 Paper D: Case-Based Reasoning Systems in the Health Sciences: A Survey on Recent Trends and Developments

This paper is accepted with minor revision to the international journal on IEEE Transactions on Systems, Man, and Cybernetics-Part C: Applications and Reviews.

Another journal paper is included in the thesis and Mobyen Uddin Ahmed was one of the co-author. He was involved in 50% of the whole work, in systems studies, literature reviews, analysis of the systems properties and email questionnaires.

In this paper, 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, investigating the current trends and developments. The effort makes an in-depth study of the issues and challenges of applied CBR researches in the 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 underlying complexity in medical domains. It shows how a particular multi-purpose and multi-modal case-based reasoning system solves these challenges.

Chapter 6.

Related Work

This chapter presents a short summary of the related systems in the medical domain where CBR is used as a core technique.

CBR has been demonstrated as an increasingly useful methodology widely applied in medical scenarios for decision support. The contribution of an in-depth literature study in CBR research in medical domains outlined that the recent CBR systems are increasingly multi-modal and multi-purpose to tackle the high complexity in the area. Such study and analysis compares to the proposed system addressed in PAPER D.

6.1 Projects or systems descriptions

This section narrates a short description of some CBR system in the health sciences. The systems those are considered here are created or reported after about the year 2003, earlier medical CBR systems can be found in [24] and [45].

ExpressionCBR [19] (the purpose of this system are *diagnosis* and *classification*), the system provides decision support system for cancer diagnosis. It uses Exon array data and classifies the Leukemia patients automatically to help in the diagnosis of various cancer patients. A data filtering algorithm is introduced to overcome the dimensionality problem in data sets. Besides, a clustering algorithm helps to speeds up the classification approach in the system.

Fungi-PAD [51, 49] (*classification*, *knowledge acquisition/ management* are the purpose of the system) applies image processing technique and CBR approach to detect biomedical objects i.e. airborne fungal spores in a digital microscopic images. Due to the large biological variation the appearance of fungal spores cannot be generalized. The system uses a set of cases to explain the appearance of each object. It compares an object in the image to the original object. This original object is generated using a template which is a prototypical case produced by a semi-automatic process.

FrakaS [15] (purpose: *diagnosis*, *knowledge acquisition/ management*) is a prototype build in the domain of oncology using CBR. The paper emphasizes on proper management of domain knowledge to avoid wrong decisions in medical decision support system. Evolution of domain knowledge is highlighted in the paper in a way when inconsistency between the domain and the expert knowledge is added as a new knowledge. The authors propose a conservative adaptation strategy for knowledge acquisition from experts.

GerAmi [16] (the purpose are *planning* and *knowledge acquisition/ management*) '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. This helps to optimize work schedules and provide up-to-date patient data. The prototype system has been implemented at a care facility for Alzheimer patients in geriatric residences.

geneCBR [20, 25] (*diagnosis* and *classification* are the purpose of the system) is focusing on classification of cancer, based on a gene expression profile of microarray data. Each case contains 22,283 features. 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. Several AI techniques are combined to optimize the classification accuracy. Cases are represented using fuzzy sets, and fuzzy-prototype based retrieval is applied in the case retrieval. A set of rules helps to a present an explanation of the provided solution. The patients are clustered into group of genetically similar patients using neural networks.

HEp2-PAD [50, 49, and 52] (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 low level unit. CBR performs the segmentation parameter selection mechanism based on current image characteristics. Cases are represented with image and non-image information. A similarity value is calculated from both image and non-image information. This provides an image interpretation close to a human expert.

In ISOR [59] (purpose: *diagnosis, planning*), the authors address particularly the endocrine domain. The system identifies the causes of ineffective therapies and advises better recommendations to avoid inefficacy to support in long-term therapies. The system is exemplified in diagnosis and therapy recommendations of Hypothyroidism patients treated with hormonal therapy. The system is not only based on a case base but also on other knowledge components such as a knowledge base that represents the domain theory in a tree structure, prototypes i.e. generalized cases and medical histories of a patient. Information of these containers worked in a form of dialogue and key words are used for the case retrieval.

The IPOS [6] (the purpose of the system is *diagnosis*) project aims at proving a case-based decision support system to assist clinicians in diagnosing individual stress condition based on finger temperature measurements. The system uses a calibration phase to generate an individual stress profile. Case-based reasoning is applied as the key methodology to facilitate experience reuse and decision explanation by retrieving previous similar temperature profiles. Further, a fuzzy technique is incorporated into the CBR system to handle vagueness, uncertainty inherently existing in clinicians reasoning as well as imprecision of feature values.

The KASIMIR project [18] (purpose: *diagnosis*, *classification* and *knowledge acquisition/management*), 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. The system [15] stresses particularly on the importance of a proper management of domain knowledge to avoid wrong decisions. The analysis of failure adds as a new dimension of knowledge into the domain knowledge enabling automatic evolution of this knowledge. Conservative protocol adaptation to a new case, depending on a revision the operator provides a consistency between the domain knowledge and the target case.

Song et al. (the purpose of the system is *planning*), proposes a system in radiotherapy for dose planning in prostate cancer [62]. Their system is able to adjust appropriate radiotherapy doses for an individual while, at the same time, it reduces the risks of possible side effects of the treatment. The system is implemented in cooperation with the City Hospital at the Nottingham University Hospital. Matching between cases applies a fuzzy similarity measurement to incorporate the experts' knowledge in retrieving past similar experience. Dempster-Shafer theory is introduced to fuse multiple cases to recommend a dose plan for a case, when in a real-world situation several retrieved similar cases provide different treatment solutions.

Wu et al. [73] (purpose: *knowledge acquisition/management*, *planning*), present a CBR framework based on NutriGenomics knowledge considering a person's genetic variation i.e. the individual gene expression to provide a personalized dietary counseling. The genetic variation of a person has an impact on the person's response to a diet. The system proposes a dietary strategy that influences the individual gene expression and, as a consequence, facilitates to maintain health and prevent disease. The NutriGenomics knowledge is collected applying a data mining technique and represented in form of ontologies. A distributed case base allows the system to save this knowledge, and generates new cases automatically if necessary, using a Case Builder based on stored knowledge.

Chapter 7.

Conclusions

Conclusions drawn from the research work are presented in this chapter. The limitations and future works of this research are also discussed here.

Clinical systems have proven to be able to extend the capability of clinicians in their decision making task. But reliability is often a concern in clinical applications. The research presented in this thesis report, explores an approach for a clinician to support diagnosis, classification and treatment task in stress management. The approach is basically based on sensor signal measurements and textual information. Moreover, the approach combines more than one artificial intelligence techniques where CBR is applied as the core technique. Reliability of clinical systems based on sensor readings could certainly be increased by providing contextual information supporting the reasoning tasks. Therefore, the system considers additional information in textual format applying textual information retrieval with ontology. Here, it is also illustrated that it is possible to increased accuracy in the classification task, by extending the case library with artificial cases. A case study also shows that the system provides results close to a human expert and the system could be useful both for trainee and senior clinicians.

Although the experimental work shows promising results, there are still some limitations. First of all, the reference cases used here collected neither from a hospital nor from any real patient. They are from voluntary participants; however, some of them were really stressed during the measurement was taken. The measurement of a student before his M.Sc thesis presentation is one example. For the textual feature, the experiment has been conducted with the artificial cases and very limited ontology. The number of the reference cases is still limited even though the research contributions included a supplementary method to address this issue. Moreover, today the system is based on one physiological parameter i.e. finger temperature sensor signal. In future, several other parameters such as heart rate variability, breathing rate etc. could be investigated. Also, the system needs to be tested with the real patient's cases from the clinical environment. With the intention to deploy it in day-to-day clinical practice the evaluation process needs to be done in a large scale.

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PART 2

Included Papers

Chapter 8.

Paper A: Case-based Reasoning for Diagnosis of Stress using Enhanced Cosine and Fuzzy Similarity

Mobyen Uddin Ahmed, Shahina Begum, Peter Funk, Ning Xiong Bo von Schéele (PBMStressMedicine AB). In press of the International Journal Transactions on Case-Based Reasoning on Multimedia Data, vol 1, Number 1, IBaI Publishing, ISSN: 1864-9734, October, 2008

Abstract

Intelligent analysis of heterogeneous data and information sources for efficient decision support presents an interesting yet challenging task in clinical environments. This is particularly the case in stress medicine where digital patient records are becoming popular which contain not only lengthy time series measurements but also unstructured textual documents expressed in form of natural languages. This paper develops a hybrid case-based reasoning system for stress diagnosis which is capable of coping with both numerical signals and textual data at the same time. The total case index consists of two sub-parts corresponding to signal and textual data respectively. For matching of cases on the signal aspect we present a fuzzy similarity matching metric to accommodate and tackle the imprecision and uncertainty in sensor measurements. Preliminary evaluations have revealed that this fuzzy matching algorithm leads to more accurate similarity estimates for improved case ranking and retrieval compared with traditional distance-based matching criteria. For evaluation of similarity on the textual dimension we propose an enhanced cosine matching function augmented with related domain knowledge. This is implemented by incorporating Wordnet and domain specific ontology into the textual case-based reasoning process for refining weights of terms according to available knowledge encoded therein. Such knowledge-based reasoning for matching of textual cases has empirically shown its merit in improving both precision and recall of retrieved cases with our initial medical databases. Experts in the domain are very positive to our system and they deem that it will be a valuable tool to foster widespread experience reuse and transfer in the area of stress diagnosis and treatment.

8.1 Introduction

In our daily life we are subjected to a wide range of pressures. When the pressures exceed the extent that we are able to deal with then stress is trigged. Moderate amount of pressures can be a great motivator that helps our bodies and minds work well and contribute to our mental health. But it is also well known that increased stress level can lead to serious health problems. Stress has a side effect of reducing awareness of bodily symptoms and people on a heightened level of stress often may not be aware of it and first notice it weeks or months later when the stress is causing more serious effects in the body and health [29]. Severe stress during long periods is highly risky or even life-endangering for patients with e.g. heart disease or high blood pressure. A computer-aided system that helps early detection of potential stress problems would bring vital benefits for treatment and recovery in both clinical and home environments.

Medical investigations have identified that finger temperature (FT) has a strong correlation with stress status for most people. Although interpreting and analyzing finger temperature profiles for diagnosing severity of stress and other related dysfunctions is receiving increasing significance within the psychophysiological domain, 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. Furthermore, FT measurement requires a sensor and special software which may not be available or possible to use in some environment such as in some working places. Textual data of patients captures important data not contained in measurements and also provides useful supplementary information to better interpret and understand sensor readings and transferring valuable experience between clinicians important for diagnosis and treatment planning.

Clinicians are required to carefully inspect lengthy streams of measurements for capturing indicative characteristics from FT signal and recognizing any possible disorders. Diagnosing individual stress condition based on finger temperature measurements is not easy and understanding large variations of measurements from diverse patients requires knowledge and experience and, without adequate support, erroneous judgment could be made by a less experienced staff. It is also time-consuming and tedious task for humans to diagnose stress-related disorders from a semi or even unstructured text format. Therefore a system that can manage multimedia data e.g. signals from FT sensor as well as textual information is essential in this domain. This paper presents a case-based reasoning system using fuzzy and cosine similarity to cater decision support for clinicians with emphasis on hybridization of textual data with time series measurements as case representation. We use Case-based Reasoning (CBR) as it works well in such domain where the domain knowledge is not clear enough as in interpreting FT signal data [18] in the psycho-physiological domain where even an experienced clinician might have difficulty expressing his knowledge explicitly.

The proposed system considers textual information as of the one components of the case index and the degree of matching of textual information is treated as a partial similarity evaluation. This partial similarity on the textual dimension is then combined with other partial similarities on signal measurement to reach a global similarity between cases of mixed data formats. The matching between textual information is implemented with the cosine similarity function and term vectors are enhanced by the background knowledge expressed in WordNet and a domain specific ontology.

8.2 Overview of the system

A system for diagnosing individual stress level based on finger temperature measurements or textual descriptions works in several stages as illustrated in Figure 1. The first stage is the Calibration phase [3] where the finger temperature measurement is taken using a temperature sensor to establish an individual stress profile. Some extension has been done in this phase by adding a reliability test using a visual analog scale (VAS) after completing each step where a subject can describe his/her feelings about the test of each step by VAS. From the calibration phase 15 minutes finger temperature measurements and reliability test input are stored into an xml file to the local device. The system provides a user interface that receives either a signal data or textual information or combination of them. Features are extracted both from the signal and textual data before making a new problem case; several techniques have been applied for the feature extraction and are shown along with case representation in chapters 3 and 4. As a result of the extracted features when a problem case has been formulated, CBR cycle is introduced to solve this new problem case. Then the new problem case is matched with each of the solved cases within the case-base to retrieve the best matched cases; matching algorithms are described in case retrievals and matching chapter. A sorted list of best matched cases along with their solutions has been proposed and presented to the user (i.e. clinician) for revision. A clinician thereafter revises the best matching cases and approves a case to solve the new problem case by using the solution of this old case;

this confirmed solution is then prescribed to the patient. However, often an adjustment to the solution of the old case may require since a new problem case may not always be as same as an old retrieved case. However, there is no adaptation of the cases in the proposed system. This adaptation could be done by clinicians in the domain.

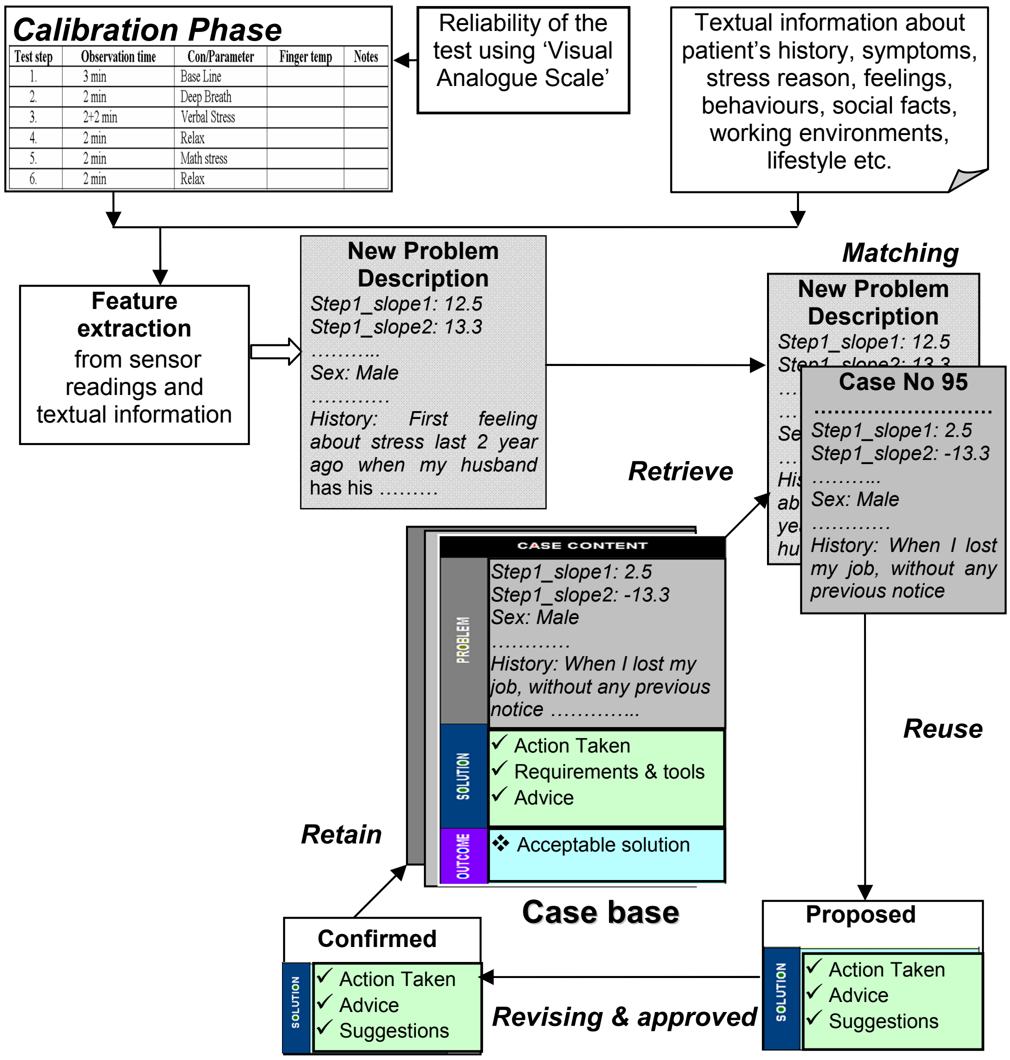


Figure 1. Overview of the stress diagnosis system

Finally, this new solved case is added to the case base functioning as a learning process in the CBR cycle and allows the user to solve a future problem by using this solved case, which is commonly termed as case retain.

8.3 Feature extraction from time series signal data

Appropriate features are extracted to abstract a sensor signal and help to represent rules for the system. A standard procedure followed by clinicians to establish a person's stress profile has already been discussed concerning the calibration phase [3][4]. An experienced clinician manually evaluates the FT measurements during different stress conditions as well as in non-stressed (relaxed) conditions to make an initial diagnosis. In this phase, the finger temperature is measured using a temperature sensor connected to a computer and the temperature is observed in 6 steps [3][4] (Baseline, Deep-breath, Verbal-stress, Relax with positive thinking, Math-stress and Relax). The FT sensor measurements are recorded using software which provides filtered data to the system. The signal data are then stored in a file in the local device and exported to the system. From these exported files, it retrieves 15 minutes temperature measurements (time, temperature) in 1800 samples. After analyzing a number of finger temperature signals, it has been found that the temperature rises or falls against time. According to a closer discussion with clinicians, standardization of the slope i.e. negative and positive angles makes a better visualization and provides a terminology to a clinician for reasoning. Therefore, we calculate the derivative of each phase [5] to introduce "degree of changes" as a measurement of the finger temperature changes. A low angle value, e.g. zero or close to zero indicates no change or stability in finger temperature. Total signal from step2 to step6 is divided into 12 parts with one minute time interval. Step1 (baseline) is used normally to stabilize the finger temperature before starting the test hence this step does not need to be considered and the clinician also agreed on this point. Each step is divided into one minute time intervals (4 minutes step3 is extracted as 4 features) and each feature abstracts 120 sample data (time, temperature)[5].

8.4 Feature extraction from textual data

For the textual feature the *tf-idf* (term frequency–inverse document frequency) [24] weighting scheme was used in the vector space model [25] together with cosine similarity to determine the similarity between two textual cases [30].

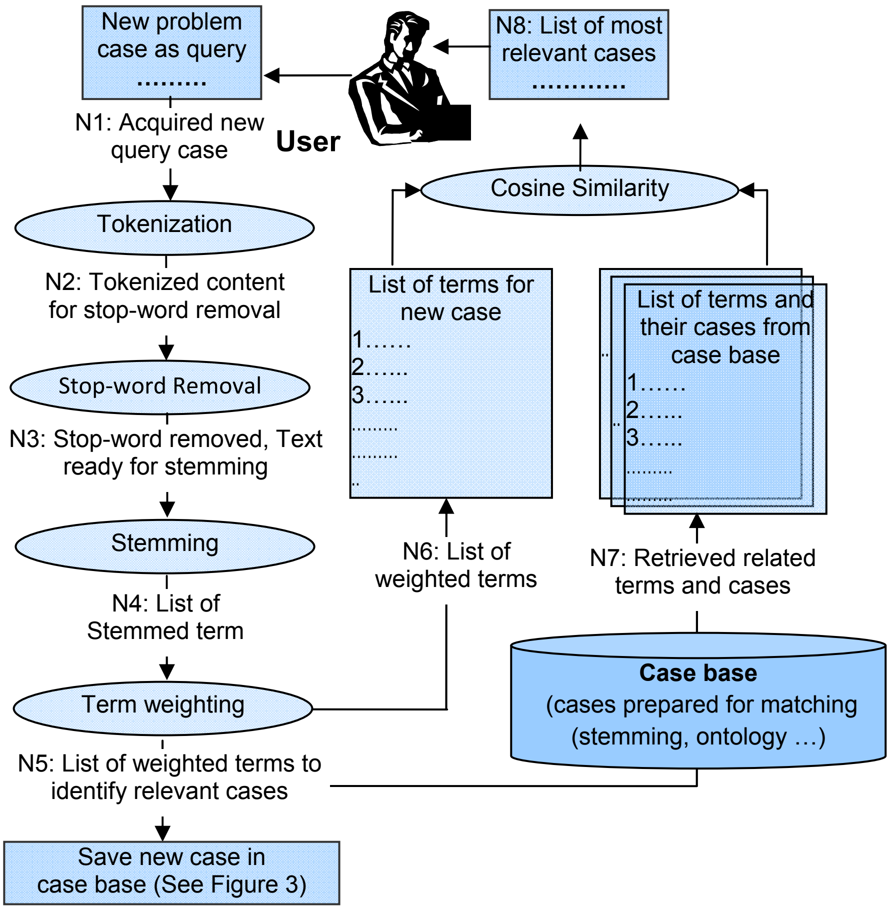


Figure 2. Work flow diagram of the retrieval process for textual cases

In our system, the procedure to calculate similarity is functioning in two different point-of-views; 1) when a new problem case is entered by a user to the system in order to retrieve most relevant cases and 2) when a user has to check if a case in consideration is novel enough for being retained into the case base. The work flow diagram shown in Figure 2 describes the retrieval process of relevant cases when a new case is entered into the system as a query case. In Figure 2 the prefix *N* is used as a new problem case (as a query case), by acquiring a new case content (i.e. *N1*) the system initiates the process. The text tokenizer algorithm then decomposes the whole textual information into sentences, and then into individual words to reduce textual cases into term (noun) vectors (i.e *N2*). Due to huge amount of words a filtering process is required to improve the effectiveness of the retrieval. Therefore, very infrequent or very frequent terms are eliminated as a list of stop-words and special characters (i.e. *N3*). After that stop-words are removed and the text is ready for stemming. Porter stemming algorithm [25] helps stemming the words providing the ways of finding morphological variants of searched term (i.e N4). Each term (stemmed non-stop word) in a vector is then assigned by its weight where the weight is computed as a function of its (term) frequency of occurrence in the case base (i.e *N5*); details will be described in "Term frequency and weighting" section. These terms are afterward used to identify relevant terms (using synonyms and ontology) from the case base and ready for matching process between a new case and old solved cases (i.e *N6* and *N7*). Finally, the cosine similarity function is applied to provide a list of relevant cases to the user (i.e *N8*).

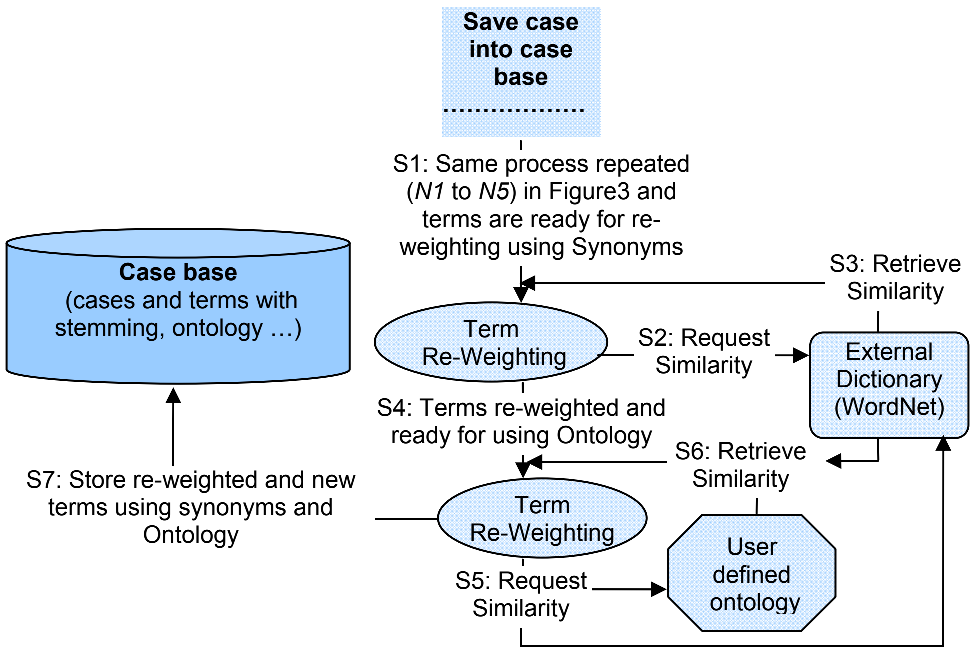


Figure. 3. Work-flow diagram to add a case into the case base

In order to retain a case the same steps as described in Figure 2 (*N1* to *N5*) are repeated, also other processes such as term re-weighting using synonyms and ontology are applied as shown in Figure 3. The prefix *S* is used to describe work flows for saving a case (i.e. retain case). After initial weighting for each term (i.e

S1) completing N1 to N5 in Figure 3, these terms are forward ahead to re-weight using synonyms. First, the system is requested to retrieve similar terms (i.e *S2*) using synonyms of word, if found, then system retrieve similarity value (i.e *S3*) and re-weigh the source terms using several conditions, see more details in "Altering term vector using WordNet" section. Additional domain information often improves results, e.g. a list of words and their synonyms or dictionaries that provide comparable words [26] [22] and relationships within the words using class and subclass. Our proposed system uses domain specific ontology that represents specific knowledge i.e. relation between words. After finishing the re-weighting step using synonyms it starts to look for similar terms using ontology. This ontology could be defined both as a relation of general/common words found in a dictionary (i.e WordNet) and/or as a relational words defined by a human expert (i.e in medical domain relation of medical words). System thereafter, requested to retrieve similar terms both from a dictionary as well a user defined ontology (i.e *S5*) and if found the system then retrieves similarity value (i.e *S6*) to re-weight the source terms, details condition and steps will be presented in section "Enhanced term vector using ontology". Finally, the weighted terms using synonyms and ontology along with their original case are retained into the case base (i.e *S7*).

In the system, the re-weighting process is functioning only during the case retention however the weighting method is functioning when a user enters a new case as a query. The reason behind that is to produce less computational time in query prospect, so that query result could be retrieved straightaway and presented to a user (clinician). Our proposed model allows for non-binary weights in stored cases and in query case initial weights are computed using the standard $tf_{i,j}* \ idf_j$ formula. The implemented system uses several services to update the case base in time such as during adding a case and/or altering ontology. All the calculations i.e. weighting and re-weighting terms are performed in offline and stored into the case base.

8.4.1 Term Frequency and Weighting

The *tf-idf* (term frequency–inverse document frequency) [24] weighting scheme is used for this system where the word "document" is treated as a case. The weight of a term computed as a function $W_{i,j}$, calculates the weight of each term or word of stored cases and a new case given in a user's query to perform further matching. The general equation for $W_{i,j}$ is shown in equation 1. There, $W_{i,j}$ is the weight of a term T_j in a case C_i, $tf_{i,j}$ is the frequency of a term T_j in a case C_i and idf_j is the inverse case frequency where N is the number of cases in a case base and df_j is the number of cases where term T_j occurs at least once.

$$W_{i,j} = tf_{i,j} * idf_j = tf_{i,j} * \log_2(\frac{N}{df_j}) \quad \textbf{(1)}$$

The cases are processed according to the vector space model and stored separately. First, from these collection of the cases an index of the terms is constructed and then the frequency of each term ($tf_{i,j}$) appearing in a case (C_i) and a new query case (Q) is counted. The case frequency (df_j) from the collection of the cases and the inverse case frequency (idf_j) are calculated thereafter, and finally the $tf_{i,j}$* idf_j product gives the weight for each term.

$$tf_{i,j} = \frac{tf_{i,j}}{\max_k(tf_{j,k})} \quad \textbf{(2)}$$

Equation 3 is modified slightly to give more emphasis on the terms, an adaptation of $tf_{i,j}$ based on the frequency of occurrence of the instances in each case is computed in equation 2 where $max_k(tf_{j,k})$ is the frequency of the most repeated instance tf_k in C.

8.4.2 Altering Term Vector using WordNet

We believe additional domain information often improves results i.e., a list of synonyms or dictionaries provides comparable words [26][21] and relationships within the words. In traditional VSM model, terms vectors are generated by ordering terms in a case vector according to their occurrence in the case i.e. by a normalized *tf-idf* score where synonyms or relation of words are not used. However, the implemented system uses WordNet dictionary to provide necessary information about word relation employing synonyms, hyponym and hypernyms of words. Therefore, it is necessary to alter a term vector to a new vector, in this term vector previous terms are re-weighted and/or new terms are added on the basis of different conditions. The function for re-weighting a term is shown in equation 3.

$$W'_{i,j} = W_{i,j} + \sum_{sim(j,k) \geq T} W_{i,j}\, sim(j,k) \quad \textbf{(3)}$$

Where $W'_{i,j}$ is the new weighting function for a term j of a case vector i, adjusted by similar terms k within the same vector. T is a user defined threshold, we use T=0.8; that means each term in a vector will match with other terms in the same vector and the terms who have similarity value more than 0.8 will be added by multiplying their original weight. Let discuss it with an example *V1= {train=1, railway=0.3, metro=0.5}* a term vector with their original weight, then the term "train" will be re-weighted as *train=1+0.3*0.9+0.5*0.8*, where 0.9 and 0.8 are similarity values between {train, railway} and {train, metro} from the dictionary. The source term could obtain several related terms employing synonyms, hyponyms and hypernyms which means a term could be related with other terms those already existed in the case term vector. Now all the terms with similarity value greater than a threshold value (*T=0.9*) will be considered as new terms and added to the case term vector. These new terms are then weighted according to the similarity values of the terms in the case vector. If a related term is already exiting in the vector then only the similarity values of that term will be added with the original weight of the source term. Thus, the system identifies and gives higher preferences to these key terms comparing other terms in order to match a source case with query cases.

8.4.3 Enhanced term vector using ontology

A domain specific ontology or user defined ontology represents specific domain knowledge, i.e., relation between words using class and subclass [28]. Terms of a case can be compared with other cases by exact matching or synonym matching or using a co-occurrence. However, some words or terms can have a complex relationship (for example, the term Sympathetic reactivity and Bio-feedback), the weight of such terms can be increased automatically using a domain specific ontology defined by experts. The weights in the term vector of a case can be enhanced by altering the term vector according to the following conditions:

1. If a term T_j in a case vector is related to a term T_o in the ontology but the term T_o does not exist in the case vector, then the term T_o can be added as a *new* term with the same importance as the weight of the source term, i.e. the score of *tf-idf.*
2. If a term T_j in a case is related to a term T_o in the ontology and also the term T_o exists in the case, then the strength of relationship between the term T_j and T_o can be added to the original weights (i.e. score of *tf-idf*) of those terms.
3. If more than one term in a case are related to a term T_o in the ontology, then those terms of that case will get more importance by adding their relationship strength with T_0 to their original weight (i.e. score of *tf-idf*).

4. If a term T_j in a case is related to more than one term in the ontology then the normalized mean strength of such relationships can be added to the original weight of the source term T_j.

An example is shown in Figure 4 on how the ontology helps to improve the weight vector.

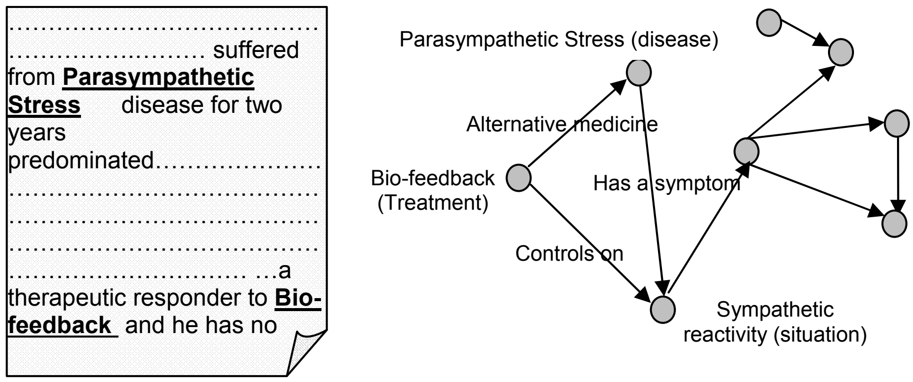


Figure 4. Weighting term vector using ontology

From Figure 4 "Bio-feedback" is a term that appears both in the case text and in ontology, it has a relation with another term "Sympathetic reactivity" in the ontology but the term "Sympathetic reactivity" does not exist in the case text, so the term "Sympathetic reactivity" is important for this case and the weight of this term can be added according to condition 1.

Again the terms "Parasympathetic Stress" and "Bio-feedback" both already exist in the case text and as well as has a relation in the ontology so the value of the strength of their relationship for those two terms ("Parasympathetic Stress" and "Bio-feedback") will increase the weights for their importance (condition 2).

Terms "Parasympathetic Stress" and "Bio-feedback" are related with another term "Sympathetic reactivity" in the ontology so the term "Sympathetic reactivity" will get more importance according to condition 3. Condition 4 is the vice versa of the condition 3.

8.5 Case retrieval and matching

Case retrieval is a key phase in CBR cycle where matching between two cases plays vital role because nearest or most relevant solved cases could be retrieved if an appropriate matching algorithm exists. To be more cautious, the proposed DSS decided to use fuzzy similarity by evaluating three different matching algorithms. The retrieval step is essential especially in medical applications since missing similar cases may lead to less informed decision. The reliability and accuracy of the diagnosis systems depend on the storage of cases/experiences and on the retrieval of all relevant cases and their ranking. In the DSS three implemented matching algorithms are 1) distance function for calculating similarity where distance between two cases are used for similarity calculation 2) similarity matrices defined by the expert where distance between two cases are converted into similarity values using matrices and 3) fuzzy set theory to calculate similarity between two cases. Similarity measurement is taken to assess the degrees of matching and create the ranked list containing the most similar cases retrieved according to equation 4.

$$Similarity\ (C, S) = \sum_{f=1}^{n} w_f * sim\ (C_f, S_f) \tag{4}$$

Where C is a current/target case, S is a stored case in the case base, w is the normalized weight defined by equation 5, 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.

$$w_f = \frac{lw_f}{\sum_{f=1}^{n} lw_f} \tag{5}$$

Here, a *Local weight (lw)* is defined by experts, assumed to be a quantity reflecting importance of the corresponding feature, *Normalized weight (w)* is calculated by equation 5.

8.5.1 Fuzzy Similarity

A triangular membership function (*mf*) replaces a crisp input feature with a membership grade of 1 at the singleton. For instance, as shown in Figure 5 a current case has the lower and upper bounds 2.5 and 7.5 represented by the membership grade 0 and an input value 5 is represented by the membership grade of 1 (fuzzy set *m1*). Again an old case has the lower and upper bounds -1.5 and 4.5 represented by the membership grade of 0 and an input value 3 is represented by the membership grade of 1 (fuzzy set *m2*).

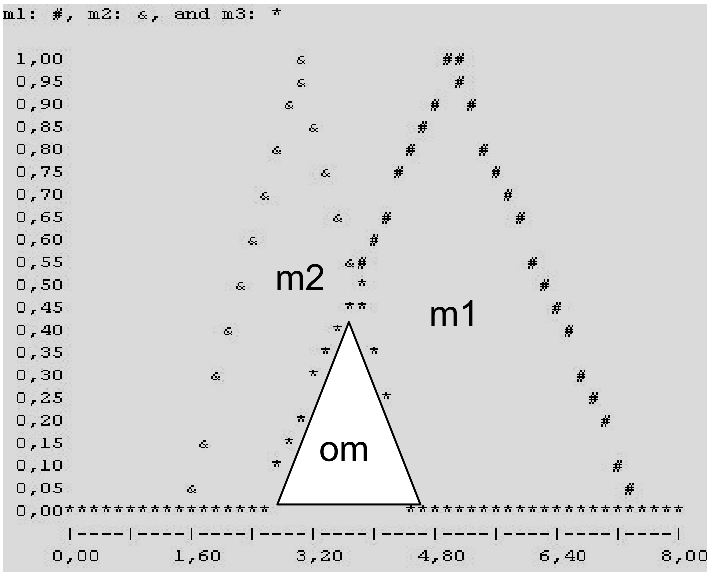


Figure 5. Fuzzy similarity using triangular membership functions

Similarity between the old case and the new case is now calculated using equation 6 where area of each fuzzy set (*m1*, *m2* and *om*) is calculated. The similarity equation according to [11] is defined as-

$$sim(C_f, S_f) = s_f(m1, m2) = \max(om/m1, om/m2) \qquad \textbf{(6)}$$

Where, s_f *(m1, m2)* calculates the local similarity on feature *f* between the new and old cases. Clearly, when the overlapping area (*om*) is bigger the similarity on the feature will increase and for two identical fuzzy sets the similarity will reach unity.

8.5.2 Similarity Matching for Textual Part

The similarity between a stored case vector C_i and new case as a query vector Q is calculated using the cosine similarity function [25] [13] [33] where the cases deal with the textual information. This ratio is defined as the cosine of the angle between the vectors, within the values between 0 and 1 and can be calculated by equation 7.

$$Cos\theta_{C_i} = Sim(Q,C_i) = \frac{Q \bullet C_i}{\|Q\|\|C_i\|} = \frac{\sum_j w_{q,j} w_{i,j}}{\sqrt{\sum_j w_{q,j}^2}\sqrt{\sum_j w_{i,j}^2}} \quad \mathbf{(7)}$$

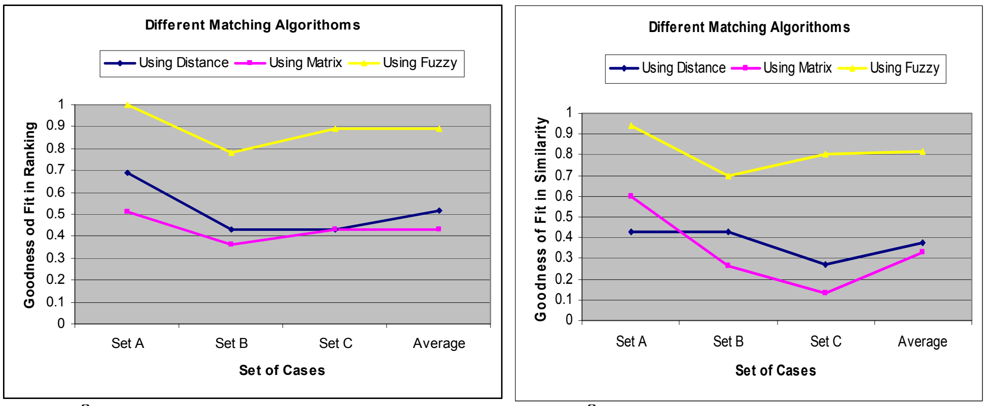
Where $Cos\theta_{C_i}$ is the *cosine of the angle* between a stored case and query case which is defined as the similarity function *Sim(Q, C_i)*. The dot product of a stored case and query case is $Q^\bullet C_i$ where zero products are ignored; then vector lengths are calculated for a stored case and query case where $w_{i,j}$ and $w_{q,j}$ are weights calculated through equation 7 (zero terms are ignored).

8.6 Evaluation

After implementing the proposed DSS, performance of the system has been evaluated where the evaluation is conducted on the similarity matching of the signal data and textual data respectively The accuracy of the matching algorithms on signal data as compared to the expert is calculated using a statistics index termed as *square of the correlation coefficient* or *Goodness-of-fit* (R^2) [9]. The performance of matching on textual data is evaluated by precision and recall of retrieval. The case base is initialized with 39 reference cases classified by the domain expert.

8.6.1 Similarity matching on signal data

We have discussed in the earlier section (section 5) about the three matching algorithms implemented in this system to choose the best one and now the performance of these algorithms is evaluated in this section. For the evaluation of matching algorithms on signal data we have chosen randomly three subsets of cases and three query cases, the subsets are as follows: 1) Set A: {7 cases} with query case id 4, 2) Set B: {11 cases} with query case id 16 and 3) Set C: {10 cases} with query case id 28. All the three sets have been sorted according to the similarity with the query case decided by a domain expert (human reasoning). The sorted cases are then converted to the rank numbers, i.e., the position of a case in the ranking. Likewise, the evaluation process is designed for the three algorithms including distance, matrix, and fuzzy matching, used in the system. Top six cases from each set according to the expert's ranking are used as standard for the evaluation process where both the similarity values and the ranking numbers are considered [5].



a) R^2 in ranking value b) R^2 in similarity value

Figure 6. Comparison among three different matching algorithms.

Comparison charts of the three matching algorithms using the three sets according to their goodness-of-fit (R^2) are presented in Figure 6, where a) shows calculated R^2 for ranking values and b) shows R^2 for similarity values [5].

8.6.2 Similarity matching on textual data

The evaluation of the similarity matching method on textual data has been conducted in two phases. At first, each algorithm implemented in this system is tested according to their outcome that is, from the technical point of view, to check whether algorithms for pre-processing (i.e tokenization, stop-word removal and stemming), generating terms vector of cases (initial term weighting) and alternating the term vectors (using dictionary and user defined ontology) are functioning properly. Furthermore, functionalities such as case retrieval and case retain are verified through a web-interface, where the similarity value of two same cases is computed as 100% match. During retain, a case is successfully stored into the case base and the case base is then updated by an external service according to the case term vectors with corresponding term-weights. Although this initial phase is not that much significant for this paper it is necessary to discuss this because it works as a baseline for the evaluation.

We have evaluated the system performance in terms of precision and recall. Recall and precision are two common metrics used to estimate the efficiency of the information retrieval in a CBR system. Precision is the fraction of a searched output that is relevant to a particular query. It represents the proportion of the relevant retrieved cases to all the retrieved cases, i.e. the less irrelevant cases are retrieved the better the precision will be. So the calculation requires knowledge of the relevant and non-relevant hits in the evaluation set of cases. It is possible to calculate the precision of our implemented CBR system because the case base is artificially made from the medical domain. Recall on the other hand measures the ability of a retrieval system to obtain all or most of the relevant cases from a collection of cases (i.e. case base). It represents the proportion of relevant cases retrieved to all the relevant cases in the case base. The more relevant cases are retrieved the better the recall will be. Thus recall requires knowledge not just for the relevant and retrieved cases but also those are not retrieved yet relevant. There is no proper method for calculating absolute recall of such retrieval system as it is impossible to know the total number of relevant cases, but for our system we only concern the cases in our case base of moderate size so the recall is calculable.

Table 1. Experimental results comparing two methods in terms of precision and recall.

	Traditional VSM		Implemented method	
	Precision	Recall	Precision	Recall
problem1	68.7%	68.7%	77.23%	81.23%
problem2	63.1%	72.1%	84.45%	75.45%
problem3	65.3%	71.3%	73.1%	88.1%
problem4	69.3%	67.3%	80.34%	77.34%
problem5	67.23%	69.23%	80.7%	77.7%
Average	66.72%	69.72%	79.16%	79.96%

In the second phase, the evaluation has been done to judge the system performance on retrieving textual cases. The precision and recall are calculated comparing the text retrieval methods i.e. the conventional Vector Space Model (VSM) against our retrieval method enhanced with knowledge. For the evaluation, 5 new problem cases as query are created where each query case contains around 7 to 10 terms after removing stop-words. The comparison results between the two methods in terms of precision and recall are stated in Table 1 where 0.3 is considered as a threshold value. The results from Table 1 indicate that the average precision of five new problems for traditional vector space model is 67% whereas our enhanced method has better precision rate i.e. 79%. As can be seen from Table 1, the average recall of the five problems for our implemented method is 80% whereas the traditional vector space model has lower recall i.e. 70%. On the whole, the results suggest that the enhanced method performs better in terms of precision and recall in this CBR system.

8.7 Related research

Research work addressed in this paper for providing decision-support to clinicians in the psycho-physiological medicine is of great significance in applying CBR and other artificial intelligence techniques in medical domain.

8.7.1 CBR in psycho-physiological medicine

A procedure for diagnosing stress-related disorders has been put forward by Nilsson et al. [17] 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. In our previous work [3], a stress diagnosing system using CBR has been designed based only on the variation of the finger temperature measurements, but this previous research did not explore whether any other subjective factors could also be used in diagnosing individual stress levels. In the earlier research [4] we have further demonstrated a system for classifying and diagnosing stress levels, exploiting finger temperature graphs and other features. This system and in [5] relies on CBR as well as on fuzzy sets theory. The current paper presents a result of the evaluation of a computer-aided stress diagnosis system comparing with a domain expert/clinician. In this system CBR-retrieval works with fuzzy similarity matching for signal data and cosine similarity for textual information. In addition, the calibration phase is extented with a reliability test using a visual analogue scale and considers subjective features in a textual data format.

8.7.2 CBR in other medical domain

Some other related research works in the medical domain using CBR are: MNAOMIA [7] has been developed for the domain of psychiatry. CARE-PARTNER [8] is a decision support system developed in stem cell transplantation. Auguste [15] project has been developed for diagnosis and treatment planning in Alzheimer's disease. Montani et al. [16] has combined case-based reasoning, rule-based reasoning (RBR), and model-based reasoning to support therapy for diabetic patients. In [19] Perner has proposed a methodology for image segmentation using case-based reasoning in which information is extracted from digital medical images. Perner et al. [20] has proposed and evaluated a method to identify spores in digital microscopic images. BOLERO [14] is a successfully applied medical CBR diagnosis system in diagnosing pneumonias which applies fuzzy set theory for representing uncertain and imprecise values.

8.7.3 Related work in textual CBR

For the time being the majority of medical CBR systems are based upon results of measurements/tests in order to construct representations of cases. Various features (both numerical and symbolic) are extracted from sensed values, time-series signals, as well as images to acquire the conditions of patients under investigation. The advantage of using measurements for case indexing is objectiveness, which reduces vagueness and uncertainty in knowledge and information delivered. On the other hand, textual message presents another aspect of information available from digital records of patients stored in many hospitals. Textual case-based reasoning has been addressed for medical applications by recent works [21] [30] [31]. However, cases can be ill structured [32] [30] or have structures that do not match between cases, especially when digitalizing past cases or they may contain terminology that does not contain accordance to the clinical standard and building a CBR system for such context is quite challenging. A case retrieval framework has been described in [30] where the authors have applied textual CBR approach to acquire and elicit knowledge from structured documents. The authors in [33] have used feature vector generalization to form structural cases for retrieving textual cases, where it captures semantic relationships by the way of association. In [27], a vector space model-based retrieval system using cosine similarity and manual weighting for full text document search in MEDLINE has been presented. However in our system we use a domain specific ontology instead of manual weighting. The authors in [13] have showed that a modified cosine matching function performs better in retrieval compared with the Nearest-Neighbor in the electromechanical domain. In [23][12] authors have demonstrated the applicability of CBR-IR (information retrieval), a hybrid approach in dealing with the quality of retrieved documents in large case base. The advantages of combining CBR and IR methodologies have further been indicated by Bichindaritz [6] in memory organization to handle large scale case bases in biomedical domain. Vector space model (VSM) is a widely used information retrieval technique [10][2][1] and some of these applications also have taken advantage of ontology in retrieving useful textual cases.

8.8 Summary and conclusions

This paper presents a hybrid case-based reasoning system dealing with combined time series signals and unstructured textual documents for clinical decision support in stress medicine. We believe that time series measurements and textual data in documents capture different yet complementary aspects of the subject to be studied and they are desired to be tackled simultaneously for more comprehensive situation awareness and thereby more reliable diagnoses and decisions. The contribution of the paper is two-fold. First, a fuzzy matching function is proposed for evaluating the partial similarity of cases based on signals. This similarity function uses the theory of fuzzy sets to cope with imprecise attribute descriptions extracted from signals of finger temperatures, making judgments of similarity more robust against noises in sensor readings as well as closer to human thinking and reasoning. Second, certain knowledge models such as Wordnet and ontology are incorporated into the reasoning process with textual parts of cases. We have demonstrated that the domain knowledge and information encoded in these models (wordnet, ontology) can be made use of to refine weights of terms to enhance the cosine case matching on the textual dimension.

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Chapter 9.

Paper B: Fuzzy Rule-Based Classification to Build Initial Case Library for Case-Based Stress Diagnosis

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Abstract

Case-Based Reasoning (CBR) is receiving increased interest for applications in medical decision support. Clinicians appreciate the fact that the system reasons with full medical cases, symptoms, diagnosis, actions taken and outcomes. Also for experts it is often appreciated to get a second opinion. In the initial phase of a CBR system there are often a limited number of cases available which reduces the performance of the system. If past cases are missing or very sparse in some areas the accuracy is reduced. This paper 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. The experimental results showed that the CBR system using the enhanced case library can correctly classify 83% of the cases, whereas previously the correctness of the classification was 61%. Consequently the proposed system has an improved performance with 22% in terms of accuracy. In terms of the discrepancy in classification compared to the expert, the goodness-of-fit value of the test results is on average 87%. Thus by employing the fuzzy rule-based classification, the new hybrid system can generate artificial cases to enhance the case library. Furthermore, it can classify new problem cases previously not classified by the system.

Key words

Case-based reasoning, fuzzy rule-based reasoning, stress, diagnosis, classification, and case library.

9.1 Introduction

Classification by analogy presents an interesting application area for case-based reasoning CBR) to handle various pattern recognition and diagnosis problems. Fundamental to CBR is the assumption that similar problems have similar solutions and hence it seems a sound attempt to reach solutions of problems by referring to similar known cases in history. As previous case data are reused directly, case-based classification eases the knowledge acquisition bottleneck and facilitates learning from experiences as new solved cases are recorded.

A component which plays a central role in CBR systems is the case library. It can be considered as a concrete knowledge model consisting of specific cases. 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. Case mining and case base maintenance have become an increasingly important issue in CBR research.

This paper presents a novel approach for case creation by means of fuzzy rule based reasoning. Such cases created by fuzzy rules are indeed artificial cases which are to be supplemented to real cases collected from an underlying domain. This proposed method aims at situations where neither the fuzzy rule base nor the primary case base (with real cases) is complete to convey satisfying system performance. However, it is expected that, combination of both will produce some synergic effect for enhanced and more reliable reasoning results. Also discussions with clinicians confirm that showing similar artificial cases, when no real cases are available is acceptable if it is clearly stated that the case is artificially. The utility of our method has been verified in a case study for stress diagnosis in the medical domain. This case study also demonstrated a feasible solution to combine fuzzy reasoning and case-based reasoning in a unified framework.

9.1.1 Related work

A procedure for diagnosing stress-related disorders has been put forward by Nilsson et al. [8]. In our previous work [2], a stress diagnosing system using case-based reasoning (CBR) has been designed based only on the variation of the finger temperature measurements. In the earlier research [3][4] we also demonstrated a system for classifying and diagnosing stress levels by exploiting finger temperature graphs and other features. This system relies on CBR as well as on fuzzy sets theory. Some related research works in the medical domain that use CBR and rule-based reasoning (RBR) to gain the advantages of both technologies bears mentioning here. CARE-PARTNER [5] is a decision support system developed in stem cell transplantation that uses both CBR and RBR to produce more reliable solutions. Montani et al. [7] has combined CBR, RBR, and model-based reasoning to support therapy for diabetic patients. The system also deals with the small case library problem in CBR integrating different methodologies. Auguste [6] project has been developed for diagnosis and treatment planning in Alzheimer's disease. The system uses CBR to decide whether neuroleptic drug should be given and RBR part decides which neuroleptic to use.

9.2 Case-based stress diagnosis

Learning from past experience and solve new problems by adapting similar previously solved cases is a cognitive model based on how humans often solve a large group of problems. A requirement is that the similarity of the case also indicates how easy the solution can be adapted to the current situation and reused. A CBR [1] [10] method can work in such way as solving a new problem by applying previous experiences. Aamodt and Plaza introduced the CBR cycle [1] with the four major steps as shown in Figure 1. Retrieve, Reuse, Revise and Retain. CBR has been applied successfully when the domain theory is weak. CBR is getting increasing attention from the medical domain [7] [11] [12] where case based reasoning receives a high acceptance in the medical domain.

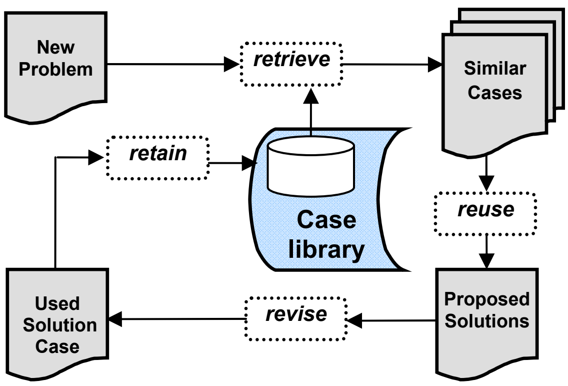


Figure 1. CBR cycle. The figure is introduced by Aamodt and Plaza [1]

A decision support system (DSS) for diagnosing individual stress condition based on finger temperature measurements follows these 4 steps of the CBR cycle. Some other important phases before entering into the CBR cycle required to be mentioned. For example, in the *Calibration phase* [2] the finger temperature (FT) measurement is taken using a temperature sensor to establish an individual stress profile and in *Sensor-signal abstraction* relevant features are extracted automatically from the outcome of the calibration phase. These extracted features are thereafter used to formulate a new problem case and which is then submitted into the case-based reasoning cycle. The new case is matched using fuzzy similarity matching algorithm [9] and the DSS can provide matching outcome in a sorted list of best matching cases according to their similarity values. A clinician thereafter revises the best matching cases and approves a case to solve a new problem case by using the solution of this old case; this confirmed solution is then prescribed to the patient. However, often an adjustment to the solution of the old case may be required since a new problem case may not always be completely the same as an old retrieved case. This adaptation could be done by clinicians in the domain. Finally, this new solved case is added to the case library functioning as a learning process in the CBR cycle and allows the user to solve a future problem by using this solved case in future.

Accurate classification of the finger temperature measurement plays an important role for a correct diagnosis of stress [2]; incorrect classification may lead to serious risk for the patient. One of the limitations in CBR method is that it depends on the case base; complete cases in a case base may produce better results (with the purpose of accuracy) otherwise there might be a drawback because of the lack of knowledge. Initially, when a system gets only a small number of reference (real) cases, an algorithm that can automatically classifies new cases or generates artificial cases would be valuable. In this paper, a fuzzy rule-based classification is proposed that facilitates to build an initial case library by generating artificial cases when enough cases to initialize the case library are not available.

9.3 Classification to build initial case library

A classification system for finger temperature sensor reading is generally divided into three stages which will be discussed in the following subsections. Extracted features from the finger temperature sensor signal helps to classify a case applying fuzzy rule-based reasoning. The rules used in this classification process have been defined by the domain expert and formulated with generalized feature from the sensor signal abstraction. Furthermore, a sharp distinction to classify individual level of stress may lead to misclassification. In order to overcome this disadvantage we introduce fuzzy rules in the classification system.

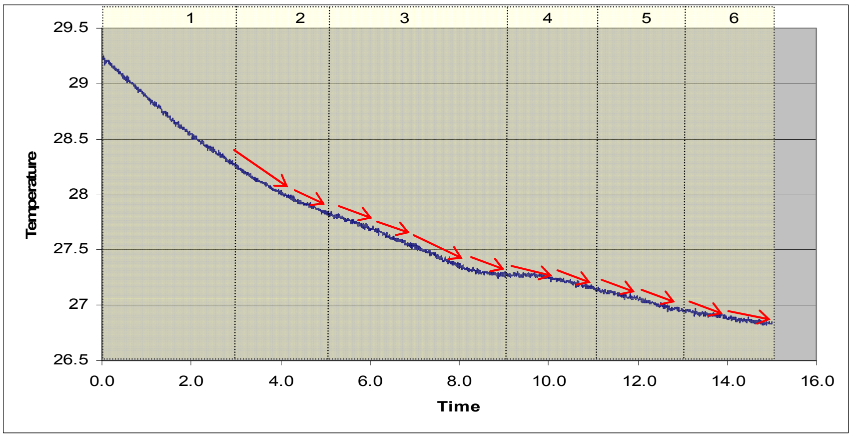
9.3.1 Sensor-signal abstraction

Appropriate features are extracted to abstract a sensor signal and help to represent rules for the system. A standard procedure followed by clinicians to establish a person's stress profile has already been discussed concerning the calibration phase [2]. An experienced clinician manually evaluates the FT measurements during different stress conditions as well as in non-stressed (relaxed) conditions to make an initial diagnosis. In this phase, the finger temperature is measured using a temperature sensor connected to a computer and the temperature is observed in 6 steps [2][3] (Baseline, Deep-breath, Verbal-stress, Relax with positive thinking, Math-stress and Relax). The FT sensor measurements are recorded using software which provides filtered data to the system. The signal data are then stored in a file in the local device and exported to the system. From these exported files, it retrieves 15 minutes temperature measurements (time, temperature) in 1800 samples.

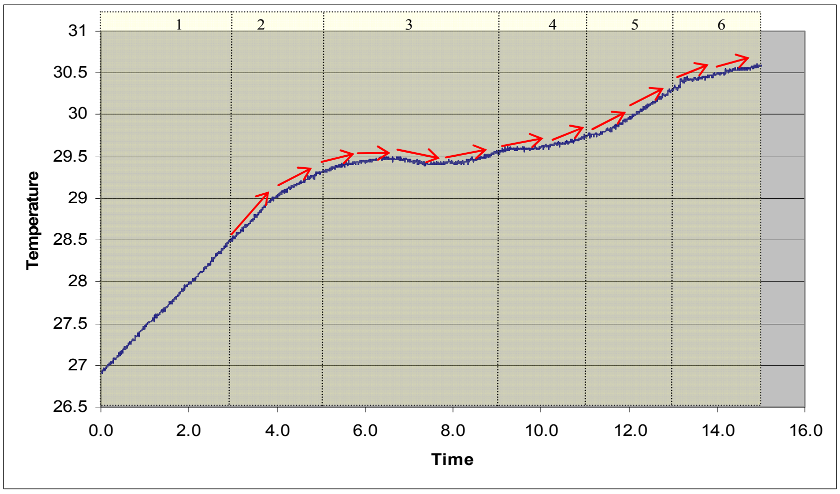
After analyzing a number of finger temperature signals, it has been found that the temperature rises or falls against time. According to a closer discussion with clinicians, standardization of the slope i.e. negative and positive angles makes a better visualization and provides a terminology to a clinician for reasoning. Therefore, we calculate the derivative of each phase to introduce "degree of changes" as a measurement of the finger temperature changes. A low angle value, e.g. zero or close to zero indicates no change or stability in finger temperature. Total signal from step2 to step6 is divided into 12 parts with one minute time interval. Step1 (baseline) is used normally to stabilize the finger temperature before starting the test hence this step does not need to be considered and the clinician also agreed on this point. Each step is divided into one minute time intervals (4 minutes step3 is extracted as 4 features) and each feature abstracts 120 sample data (time, temperature) [4]. A slope of the linear regression line is calculated through the data point temperatures (in Celsius) and times (in minute) for each feature extracted from the signal. The system thereafter uses these 12 features to calculate the number of negative slopes for the classification.

9.3.2 Classification and rules with generalized feature

Classifying individual level of stress is complex even for an experienced clinician. A signal can be classified by identifying familiar patterns from FT but in fact, one pattern can be classified in one class or several classes and several patterns can be classified in several classes or one class.



a) Very Stress: FT is consistently falling



b) Very Relax: FT is consistently rising

Figure 2. Visualizations of Very Stress/Relax class.

For instance, same signal pattern can have different temperature level, e.g., one can be from 26 to 28 and other can be from 32 to 35 so they will be classified in different classes. Figure 2 shows two examples for the classification of cases where Figure 2 (a) illustrates very stress and 2(b) illustrates very relax condition according to the clinician. It can be seen that the temperature in the calibration phase (from step2 to step6) is consistently falling in Figure 2(a) and rising in Figure 2(b). Furthermore, it can be observed that the degree values of all 12 slope features (step2 to step6) are negative ("-") e.g. percentage of negative slope features is 100% for Figure 2(a), and 11 features are positive ("+") and one feature "setp3_part3" is negative ("-"), i.e., the percentage of negative slope features is 8% for Figure 2(b). Thus a new generalized feature is derived from the 12 slope features which are extracted from sensor signal.

Table 1. Crisp rules used for the classification of cases

Crisp rules for classification
1. If Percentage_Negative_Slope > 90% then State = 5
2. If Percentage_Negative_Slope > 75% and Percentage_Negative_Slope < 90% then State = 4
3. If Percentage_Negative_Slope > 50% and Percentage_Negative_Slope < 75% then State = 3
4. If Percentage_Negative_Slope > 30% and Percentage_Negative_Slope < 50% then State = 2
5. If Percentage_Negative_Slope < 30% then State = 1

From the analysis above and according to expert remarks we could conclude that the condition is Very Stress when most of the slope features are negative and Very Relax when most of slope features are positive. Thus, a set of rules has been proposed and accepted by the expert where the number of negative slopes is calculated and presented in percentage. Table 1 summarizes a set of rules for the classification of sensitivity to stress where 1,2,3,4 and 5 denotes *Very Relax*, *Relax*, *Normal/Stable*, *Stress* and *Very Stress* respectively.

9.3.3 Fuzzy rule-based classification

Fuzzy set theory and fuzzy logic are a highly suitable and applicable basis for developing rule-based systems in medicine and has proved to be a powerful tool for decision support [13] applications for more structured domain knowledge.

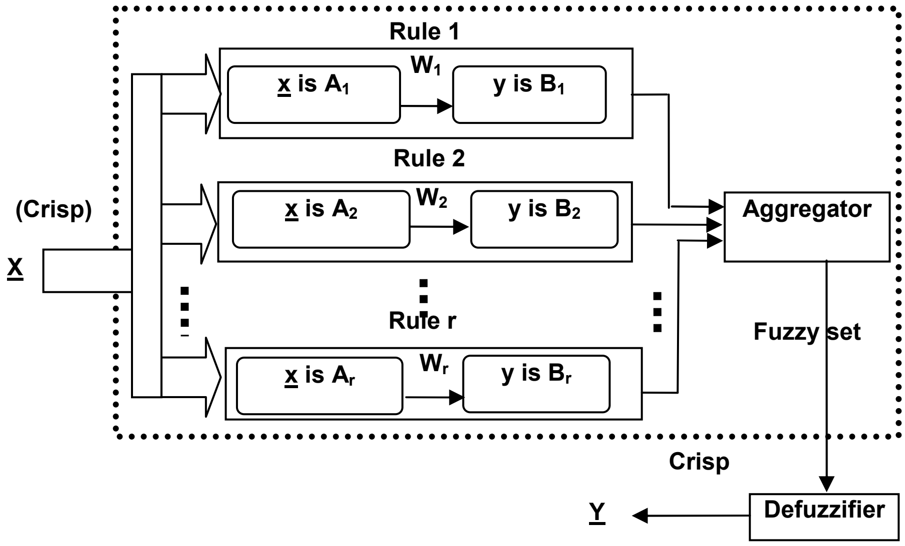


Figure. 3. Block diagram of a fuzzy inference system [14]

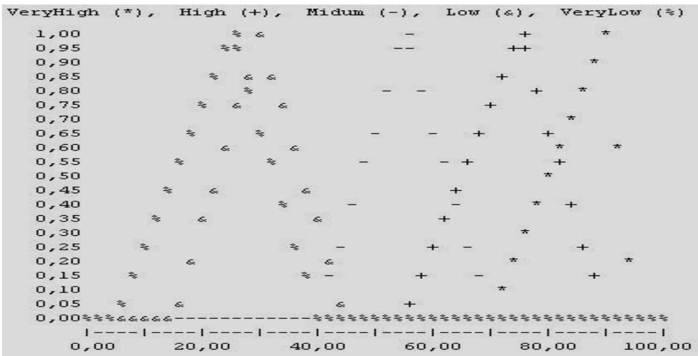
The basic structure of fuzzy logic expert systems, commonly known as fuzzy inference system (FIS) shown in Figure 3, is a rule-based or knowledge-based system consisting of three conceptual components: a rule base that consists of a collection of fuzzy IF–THEN rules; a database that defines the membership functions (*mf*) used in the fuzzy rules; and a reasoning mechanism that combines these rules into a mapping routine from the inputs to the outputs of the system, to derive a reasonable conclusion as output. Fuzzy rule-based models have some transparency and their information is interpretable, so it permits a deeper understanding of the system.

A single-input single-output Mamdani fuzzy model is implemented where the *percentage of negative slope* features is taken as the input variable and the corresponding *stress class* as output.

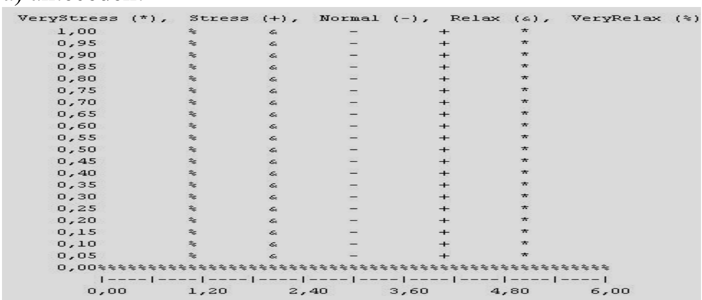
Table 2. Rules for the FIS

Fuzzy rules for classification		
Rule no.	Antecedent ========== *Percentage_Negative_Slope*	Consequent ======== *Stress_Class*
1.	VeryHigh	VeryStress
2.	High	Stress
3.	Medium	Normal/Stable
4.	Low	Relax
5.	VeryLow	VeryRelax

The parameters of the IF–THEN rules (known as antecedents or premise in fuzzy modeling) define a fuzzy region of the input space, and the output parameters (known as consequent in fuzzy modeling) specify a corresponding output as shown in Table 2.



a) antecedent



b) consequent

Figure. 4. Membership functions for the parameters of the fuzzy rules.

Percentage_Negative_Slope and *Stress_Class* are linguistic variables with universe of discourse [0, 100] and [1, 5] respectively. VeryHigh, High, Medium, Low and VeryLow are the linguistic values determined by the fuzzy sets "TriangleFuzzySet" on the universe of discourse of *Percentage_Negative_slope*; VeryStress, Stress, Normal/Stable, Relax and VeryRelax are linguistic values determined by the fuzzy sets "SingletonFuzzySet" on the universe of discourse of *Stress_Class*. Membership functions of the linguistic variables (antecedent & consequent) represented by triangular and singleton fuzzy sets are shown in Figure 4. As an example, when the input *Percentage_Negative_Slope* is 87.0, the generated output fuzzy set after rule matching and aggregation can be expressed as {0/4 0.23/4 0/4 0/5 0.85/5 0/5} and after the weighted average as defuzzification this fuzzy set is transformed into a crisp value i.e. 4.8 ≈ 5 which indicates the class *VeryStress* as output whereas the crisp classification has pointed this as *Stress* (4) class using 2nd rule from Table 1. Thereby, the fuzzy rules generate more reliable classification which is closer to human reasoning.

9. 4 Experimental results

The performance of the classification system is evaluated in two phases. First of all, the performance of the rule-based classification is evaluated where both the traditional and fuzzy rules are compared. Secondly, case-based classification is evaluated where CBR system uses both the real cases as well as the hybrid (real cases and cases generated by the rules) cases. In the both phases, the system performance in terms of accuracy has been compared with experts in the domain where the main goal is to see how close the system could work compared to an expert. The accuracy of the system as compared to the expert is calculated using a statistics *square of the correlation coefficient* or *Goodness-of-fit* (R^2). *Absolute mean difference* is also calculated to determine the deviation between expert and the system.

9.4.1 Rule-based classification

Classification of the cases has been conducted based on a set of extracted rules as suggested (see chapter 3) in two different approaches; one is using traditional crisp rule-based reasoning and another is using fuzzy rule-based reasoning. A dataset of 39 measurements from 24 patients previously classified by the clinical expert are used in the evaluation. Various indices including R^2 and absolute mean difference of the two classification approaches are computed and stated in Table 3.

Table 3. Evaluation results for two classification schemes

Classification Method	Goodness-of- fit (R^2)	Mean Absolute Difference
Rule-based	0.68	0.48
Fuzzy Rule-based	0.88	0.3

The results, reported in the table above, indicate fuzzy rule-based classification accuracy with 88% while crisp rule-based reasoning reaches 68% of fitness with expert's classification according to the R^2 index, as can be seen in Figure 5.

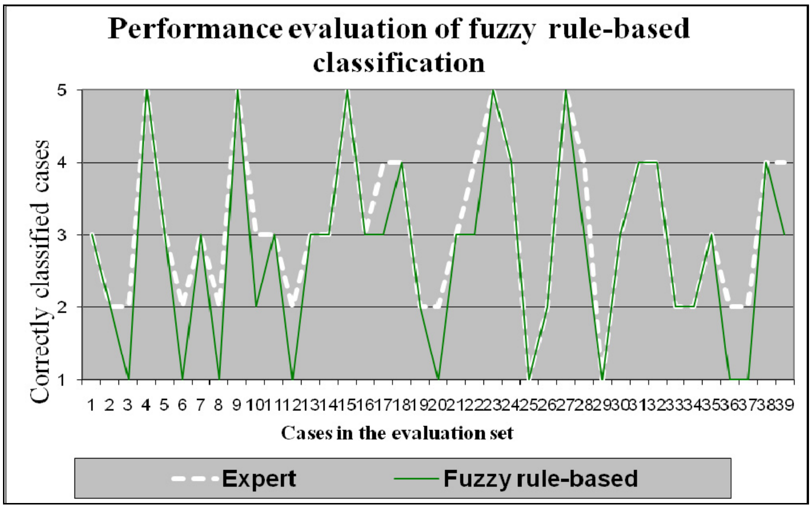


Figure. 5. Fuzzy rule-based classification compared to the expert's judgments

In figure 5, fuzzy rule-based classification is compared with expert's classification and the error got from the result is 0.3. It indicates that using fuzzy rule-based reasoning the system can improve 20% of accuracy in case classification. However, it could be noted that the error or the difference between the desired and obtained results is probably due to the small rule base size.

9.4.2 Case-based classification

Diagnosing stress is a complex task and the domain theory is not clear enough even for the expert in the domain. CBR is applied in our system for diagnosing individual stress in the Psycho-physiological domain. CBR method considers both the features from the sensor signal and patient contextual information such as gender, hours since last meal etc. whereas fuzzy rules are formulated upon the features extracted from the sensor signals. But CBR method depends on the available cases in the case library; so our goal is to provide enough cases in the case library. From the previous evaluation, it shows that we could apply fuzzy rule-based classification to generate artificial cases when there are not enough reference cases in the case library. Now it is time to see whether CBR system can improve the result (with the purpose of accuracy) using new hybrid case library (with enough cases).

Experiment has been done by defining two different case libraries as: *LibraryA* with only real cases classified by the expert and *LibraryB* being twice as big as *LibraryA* with hybrid cases classified by either the expert or the fuzzy rules. The CBR system uses k nearest-neighbour (KNN, where k=1) algorithm for classification.

Table 4. Experimental results for two test schemes

Experiment with *SetC*	Case library	Data sets	Goodness- of- fit (R^2)	Mean Absolute Difference
test1	*LibraryA*	*SetA*	0.69	0.33
	LibraryB	*SetA +SetB*	0.90	0.11
test2	*LibraryA*	*SetB*	0.79	0.44
	LibraryB	*SetB +SetA*	0.85	0.22

For the classification of test cases we consider the top most retrieved similar case. We have divided our experimental data set into three parts by selecting random cases as: *SetA*) classified cases by expert, *SetB*) classified cases by fuzzy rules and *SetC*) test caseswhose classes are assumed not known. *SetC* remains unchanged for all the experiment (test1 & test2). But in SetA and SetB cases are reclassified for the second experiment (test2) i.e. SetA is classified by the fuzzy rules and SetB is classified by the expert (see table 4). Whilst the tests have been completed, SetC is classified by the expert and compare it with the results from the test1 and test2.Table 4 displays the experimental results for test1 and test2 where SetC is classified four times using LibraryA and LibraryB. Goodness-of-fit (R2) and Mean absolute difference are calculated and presented in table 4 comparing the test results from test1 and test2 with the expert's classification for SetC. As can be seen from table 4, in test 1 compared to the expert for the real cases (SetA) the classification accuracy is 69% and 90% for the hybrid cases (SetA +SetB) and in test2 the classification accuracy is 79% for the real case (SetB) and 85% for the hybrid cases (SetB + SetA) according to the R2 index. Moreover, the result shows that error rate is less using hybrid cases (i.e 11% & 22%) compared to real cases where the size of the case library is small. Table 5 depicts the average result for test1 and test2 where a comparison is exposed between LibraryA (real cases) and LibraryB (hybrid cases) which is as double as LibraryA.

Table 5. Comparison results of case libraries

Average result for test1 and test2	Goodness-of-fit (R^2)	Mean Absolute Difference	Correctly classified cases
LibraryA	0.74	0.38	61%
LibraryB	0.87	0.16	83%

As shown in table 5, for the two tests (test1 and test2) on an average the LibraryB indicates the classification accuracy 87% while the LibraryA reaches 74% of fitness compared to expert classification. So there is 13% increase in the R2 value and 22% (Mean absolute difference) decrease in the error rate when the system employ LibraryB (hybrid cases) i.e. case library containing enough cases. For the two tests (using two case libraries) the number of correctly classified cases on average is presented in percentage (see 4th column) in table 5. Here, the CBR system can correctly classify 83% using LibraryB whereas using LibaryA the system can only correctly classify 61% of the cases.

From the above system evaluation and experimental results it indicates that we could build initial case library (when it is too small) using our proposed fuzzy rule based classification to achieve better classification for the CBR system. As a consequence, the CBR system can improve its performance in terms of accuracy to diagnose and/or classify stress by introducing fuzzy rule based classification into the CBR system, no matter the system uses small or empty case library.

9.5 Conclusion

The paper has outlined a classification scheme by applying fuzzy rule-based reasoning to build an initial case library of a case-based system to diagnose stress. According to our previous research a case-based reasoning system has already been developed assisting the clinician as a second opinion to diagnose individual stress levels. However, in terms of accuracy, due to the small amount of available real cases in the case library, the system performance is weak, especially in areas where few or no cases exist. A fuzzy rule-based classification procedure is introduced into the CBR system to generate artificial cases for the case library. The fuzzy rule-based classification can also classify new case when the CBR system fails to classify a case caused by lack of cases in the case library similar to the problem case (it may be a balance how many artificial cases are generated and when to use the classification procedure if there are too few cases). The contributions of the paper are: introducing generalized features generated from the extracted features based on the sensor signal abstractions, rules are formulated applying the extracted features and after expert assessment, a fuzzy rule-based classification scheme is introducing a fuzzy inference system, and finally, experimental work is done to show that the CBR system can improve its performance in terms of the accuracy.

The procedure of the fuzzy rule-based classification, which also accommodated uncertainty in clinicians reasoning, is introduced into the CBR system to achieve improved performance in the classification. The proposed method is implemented and validated in a prototypical system. According to our experimental work, the new proposed CBR system can augment the system performance with 22% in terms of accuracy i.e. the new combined system can correctly classify 83% whereas previous system only correctly classified 61% of the cases. The result shows how the proposed classification technique functions within the CBR system and improves the performance. Moreover, this approach even enables the use of the system with an empty case library is empty or contains fewer reference cases.

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Chapter 10.

Paper C: A Multi-Module Case Based Biofeedback System for Stress Treatment.

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Abstract

Biofeedback is today a recognized treatment method for a number of physical and psychological problems. Experienced clinicians often achieve good results in these areas and their success largely builds on many years of experience and often thousands of treated patients. Unfortunately many of the areas where biofeedback is used are very complex, e.g. diagnosis and treatment of stress. Less experienced clinicians may even have difficulties to initially classify the patient correctly. Often there are only a few experts available to assist less experienced clinicians. To reduce this problem we propose a computer assisted biofeedback system helping in classification, parameter setting and biofeedback training. By adopting a case based approach in a computer-based biofeedback system, decision support can be offered to less experienced clinicians and provide a second opinion to experts. We explore how such a system may be designed and validate the approach in the area of stress where the system assists in the classification, parameter setting and finally in the training. In this case study we show that the case based biofeedback system outperforms trainee clinicians based on a case library of cases authorized by an expert.

10.1. Introduction

Biofeedback is an area of growing interest in medicine and psychology and it has proven efficient for a number of physical, psychological and psychophysical problems [1][2][3]. The basis of biofeedback therapy is to support a patient in realizing their self ability to control specific psychophysiological processes [4]. One example is nearsightedness, where a laser measures the distance between the surface of the lens and the retina. When a patient is able to clench the eye-muscles to reduce/increase the nearsightedness, the system gives feedback based on this biological information. Some patients are able to significantly reduce or even eliminate nearsightedness. Biofeedback is today often carried out with instructions from an experienced clinician and in some patient groups it may even be hazardous without supervision. The general strategy is that, patients get feedback in a clear way (e.g. the patient observes some measurement visualizing some physical process in their body) and with this feedback enabling the train of the body and/or mind to biologically respond in a better way.

The use of computers in biofeedback enables new possibilities, e.g. the use, reuse and adaptation of past cases of experience in the form of cases containing initial symptoms, classification, parameter setting, biofeedback training, and outcome of training and expert authorization/comments. We propose a case based approach to computer based biofeedback systems in this article. To show the potential the approach is validated in the domain of stress. Different parts of the systems have been implemented and evaluated and shown to perform better than novice clinicians. An increased number of expert's authorized cases in the system will further improve performance [5] and the system may act both as a decision support system for less experienced clinicians and as a second opinion for experts. By making the cases rich, e.g. including expert comments, discussions etc such a system will also promote knowledge transfer between users [6] (not explored further in this paper).

10.1.1 Sensor-based biofeedback

Sensor-based biofeedback is drawing increasing attention and one reason is the development of sensors able to measure processes in the body previously not able to measure. Clinicians tend to agree that sensor-based biofeedback applications have three phases, 1) analyze and classify patient and make a risk assessment, 2) determine individual levels and parameters needed for the personalized biofeedback session, and finally 3) initialize and perform the biofeedback session. All phases are carried out with an interaction with the patient and/or clinician. The result from the biofeedback phase is used the next time the user initiates a biofeedback session starting with the classification and risk assessment. If the patient does not need any more biofeedback phase one may recommend this. During the biofeedback, a session is normally broken down in sub-sessions and after each sub-session new biofeedback parameters (phase 2) are determined based on the patients' progression or regression. If the clinician only uses sensor readings shown on a screen then the classification is highly experience based. The clinician normally asks a number of questions and makes a number of more or less systematic measurements/calculations and then decides the patient's classification. In the second phase a number of measurements are made to determine parameters needed to tailor the biofeedback session to the patient in order to achieve as good results as possible.

10.1.2 Computer-based biofeedback

A computer-based biofeedback system is traditionally processing the sensor signals (e.g. removing noise) and presenting the results on a computer screen. Sometimes the system also makes some processing of the signals and may label data in different ways, e.g. colors indicating if a threshold is exceeded. A simplified version of the visualization may be used in the biofeedback training. We suggest that a computer-based biofeedback system has a much larger potential and can be used as decision support system for clinicians, or be a second opinion for an expert. Based on discussions with clinicians, we suggest that a computer-based biofeedback system follow the three phases that a clinician performs in many biofeedback applications (see figure 1 outlining the complete biofeedback session). The dotted arrows from the phases indicate interaction either with sensor readings from patient, visualization of data as biofeedback and/or allowing adjustments by the clinician. When a biofeedback session does not follow the expected route, adjustment of biofeedback parameters may automatically be initiated. A risk assessment is made in phase one, but of course the risks is monitored continuously during the whole session. If there is a risk for the patient the system should stop the session. This is highly domain dependent, but in biofeedback treatment of stress patients with heart problems or severe stress reactions, there may be a serious risk if something goes wrong.

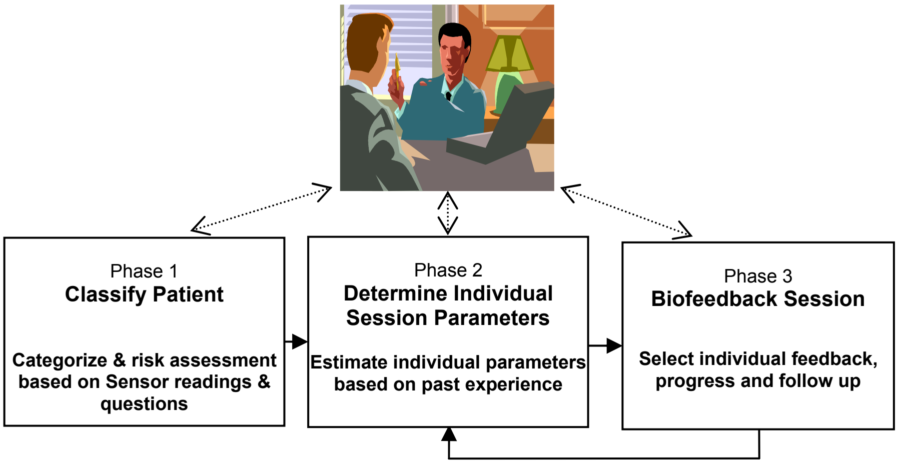

Fig. 1. Sensor-based biofeedback with the three phases patient classification, determine individual session parameters and biofeedback session, all three sessions are performed with interaction with patient and/or clinician. Phase 2 and phase 3 are repeated until the desired change has occurred.

Stress is a more complex area for use of biofeedback and different patients have very different physical reactions to stress and relaxation. A clinician is commonly supervising patients in biofeedback in the stress area and makes together with the patient an individual's adjustments. The clinician initiates with a calibration phase where a number of different sensor readings are made and analyzed to determine how the patient reacts in different situations and then gives feedback to a patient. The results are largely experience based and a more experienced clinician often achieves better results.

In this paper we have proposed an original architecture for a computer assisted sensor-based system for the biofeedback training using biomedical signals. The paper addresses three key modules for the biofeedback training applying CBR as a core technique. To our knowledge, the system proposed in this paper is an initial attempt to apply CBR in biofeedback training. This CBR system provides important information about individual treatment i.e. biofeedback reusing the previous experiences in stress problems. One of the strengths of the system is that it bears similarities with how the clinicians work manually i.e. avoids sharp distinction in decision making applying fuzzy logic. The system can be used as a tool for the clinician in a clinical environment and can also be used by the normal users during every day situations for health reasons. Furthermore, one of the advantages of the proposed system is that it will reduce the set up time such as, time for parameter estimation for a biofeedback session and also limited the time involvement of the clinicians.

10.2. Related work

In [7] authors have applied artificial neural networks (ANNs) to give biofeedback of the success of muscle coordination to improve sporting performance. Schröder et al. [8] for biofeedback training of patients with Epilepsy have classified EEG signals using ANNs. A biofeedback system to treat anxiety disorder patients in [9] uses independent component analysis and neural network to extract feature and pattern recognition from the GSR and EMG signal. The current paper proposes a multi-module CBR system for biofeedback treatment to deal with psycho-physiological disorder, e.g. negative stress. Some other related research works in the medical domain using CBR are: A procedure for diagnosing stress-related disorders has been put forward by Nilsson et al. [10]. In our previous work [11], a stress diagnosing system using CBR has been designed based only on the variation of the finger temperature measurements. In the earlier research [12][13] we have further demonstrated a system for classifying and diagnosing stress levels, exploiting finger temperature graphs and other features. This system relies on CBR as well as on fuzzy sets theory. MNAOMIA [14] has been developed for the domain of psychiatry. CARE-PARTNER [15] is a decision support system developed in stem cell transplantation. Auguste [16] project has been developed for diagnosis and treatment planning in Alzheimer's disease. Montani et al. [17] has combined case-based reasoning, rule-based reasoning (RBR), and model-based reasoning to support therapy for diabetic patients. In [18] Perner has proposed a methodology for image segmentation using case-based reasoning in which information is extracted from digital medical images. Perner et al. in [19] has proposed and evaluated a method to identify spores in digital microscopic images. BOLERO [20] is a successfully applied medical CBR diagnosis system in diagnosing pneumonias which applies fuzzy set theory for representing uncertain and imprecise values. In [21], the authors used fuzzy logic approach to find the similarity among the case features in the retrieval system. RHENE [22][23] is a case-based system in the domain of nephrology for the management of end stage renal disease patients treated with hemodialysis. Marling et al. [24], describes a case-based decision support system assisting daily management in patients with Type 1 diabetes on insulin pump therapy. The Mémoire Project [25], offers a framework to exchange case bases and the CBR systems in biology and medicine. In the ISOR [26], the authors propose a system to identify the causes of ineffective therapies and advise better recommendations to avoid inefficacy to support in long-term therapies. The KASIMIR project [27] is an effort to provide decision support for the breast cancer treatment based on a protocol in Oncology.

10.3. Biofeedback system for stress treatment

An area where biofeedback has proven to give results is the area of practicing relaxation and there is a correlation between skin temperature and relaxation. This change in temperature reflects the state of the peripheral blood vessels which in turn are controlled by the sympathetic nervous systems (SNS) – where a biological significant decrease in the SNS relaxation activity results in an increase in diameter in the peripheral blood vessels. This increase in the peripheral blood vessels in turn results in increased blood flow which in turn increases the skin temperature. Finger temperature (FT) measurement is an effective biofeedback parameter [28][29] for the self regulation training and has a clinical consensus that it is an important parameter in stress treatment. One of the difficulties is that the reaction to stress and relaxation is individual and also varies among individuals and it is a highly complex relation that only experienced experts are able to classify reliably [30]. For the domain of stress and skin temperature there is only a weak domain theory and with regard to the complexity of the sympathetic nervous system it will be stay weak for the foreseeable future. A less experienced clinician needs help with all of the three phases in figure 1 and an expert may appreciate a second opinion from a colleague or a decision support system.

10.3.1 Case based biofeedback system

Experts often reason in terms of cases, “I have once seen a similar ... “, and in terms of different individuals having similar reactions. Based in the nature of the domain and the expert’s way of working we suggest the use of a case-based reasoning using and reasoning with past cases, either real cases or prototypes created by an expert. An overview of the architecture of a computer-assisted biofeedback system is described in figure 2. Each phase is implemented as a module using case-based reasoning. The overall system could be viewed as three closely integrated case-based reasoning systems. All modules use FT as input and have individual case libraries. From the FT measurement the relevant features are extracted automatically. The extracted FT features are then used to represent a new problem case. The problem case is thereafter used in a CBR approach to find a suitable solution. Stored cases that match the problem case are retrieved by employing a fuzzy similarity matching algorithm.

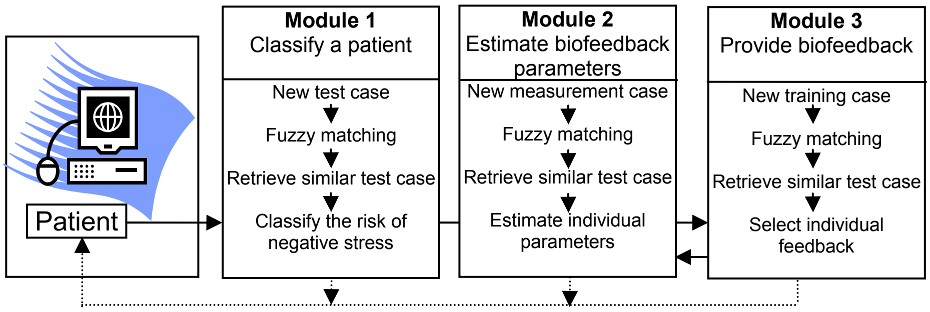

Fig. 2. An example of a sensor and computer-assisted biofeedback system in stress treatment, Solid lines symbolize input to the phases, e.g. sensor data, parameters. The dotted lines are interaction with the patient/clinician

Individual capability to cope with stress in stress management is especially important to know before a biofeedback session. Module 1 is a well specified test procedure, classify a patient depends on the risk and risk-reduction (e.g. stress reactivity and recovery/capacity) of stress. Module 2 deals with the parameter estimation which is a pre-requirement to biofeedback training. Finally, Module 3 generates recommendations for the biofeedback training. Sensor-signal abstraction, case-based reasoning and fuzzy logic are used in these phases which will be described in more details in the next sections.

10.3.2 Module 1: classify patient

The first task a clinician faces before starting a biofeedback session is to classify a patient and also look at safety aspects, e.g. if the patient has heart problems, even categorization of patient may be unwise without proper precautions. Before any measurements are performed patients fill in a questionnaire on their life circumstances, medical history and problems, eating, sleeping and working circumstances. In module 1, a patient is examined whether he/she needs to receive a biofeedback training treatment. A measurement procedure is used to identify the risk of developing negative stress. For a person this assessment includes also analysis of relaxation capacity which is applied in this phase. People react differently in different situations. So, individual coping capacity is important to identify which can be used as a platform for planning of the biofeedback treatment. For example, if a person/patient can relax/rest in his/her body and mind during work then he/she is under low or no risk level otherwise there is a risk of negative stress.

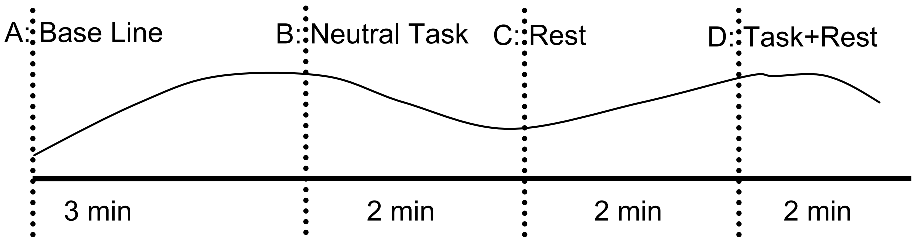

Fig.3. A test protocol for patient's relaxation capacity using finger temperature

A nine minutes finger temperature (FT) measurement is administrated through the protocol as shown in figure 3. In this protocol, a person starts with a baseline for 3 minutes where the main task is to adjust the finger temperature that shows individual's rest condition i.e. cognitive and physical rest. Second step is 2 minutes neutral task where a person could do some neutral but meaningful activity, e.g. "write about his/her work" etc. Step C is 2 minutes relaxation where a person tries to relax his/her mind and body by him/her self (without any feedback). Step D is to return to work again which is assigned in step B but now the person will do the task relaxed i.e. without any stress. Thus the FT measurements are observed/analyzed during relaxation as well as when working with relaxation.

In the CBR system, 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 capability to cope with stress. To identify the risk level of a new test case, most similar cases are retrieved from a case base and proposed to a clinician. These proposed cases are then reviewed by the clinician to decide a final solution and thus classify a patient's risk level of stress. Moreover, it is possible to modify a solution manually by a clinician before the final decision is taken and retain this new case into the case base. On the basis of a patient's risk level of stress reactivity, the system suggests biofeedback training and lets the patient enter into the next phase.

10.3.3 Module 2: individual parameter estimation

Prior to biofeedback training, some of the initial parameters such as baseline temperature (air to skin temperature, also individual's base line is individual's rest condition i.e. cognitive and physical rest), temperature of ceiling (maximum temperature a patient can accomplish), and floor (minimum temperature a patient could have) are essential to estimate. During the biofeedback training using FT, the main goal of a patient is to increase the finger temperature up to his/her ceiling level and the system generates feedback while the finger temperature is decreasing. Therefore, it is necessary to identify several parameters such as ceiling, floor, and baseline temperatures. For example, a patient might have his/her ceiling temperature at 35 degree Celsius and during the biofeedback session the patient reaches his/her ceiling temperature at the beginning, then he/she will probably not be able to increase his/her finger temperature at any length. Again, a patient's finger temperature could lie above his/her baseline temperature and decrease during the training, then the system might need to generate suitable suggestions i.e. more efficient behavioral strategies for him/her.

In the clinical environment, several methods (such as hot/cold water therapy and arm ups/down) are used along with the FT to identify these parameters. Clinicians use their experience and observation of FT measurements to identify these parameters. Such kind of parameters estimation is a very complex yet important task to get correct information about the results of the training. These parameters are also highly individual and there is no general set of rules to estimate these. It is very important to note that these parameters could be changed with time or be different from start up for any patient. We therefore propose to use CBR approach where a case base will use some parameter-estimated cases. Module 2 aims to estimate these personalized parameters using CBR with fuzzy similarity matching algorithm where finger temperature is used as input and estimated parameter value is provided as output. Initially, previous cases with their estimated parameter values from the clinician's are stored in a case base as reference cases and these cases are then used to estimate the parameter values of a new problem. Finally, this new estimated case can be added to the case base for future use.

10.3.4 Module 3: biofeedback

Biofeedback is biological feedback of on-going physiological behaviors and activities. It can be used as direct feedback while observing or just after or temporarily during the evolution of the FT measurement profile. Biofeedback session uses the same sensor data as the previous module, or may use fewer sensors, since once the classification is determined and verified, some sensor readings may give a sufficiently reliable state description for a patient so that an efficient biofeedback session can be carried out.

The final Module in figure 2 is the biofeedback training; this training time is flexible, which means that a patient can choose duration of his/her training between 6 minutes (as minimum) to 20 minutes (as maximum). Nevertheless, the system generates feedback with appropriate suggestions in every 2 minutes if necessary. Thus, for each individual, the biofeedback cases are formulated with a feature vector from biomedical signal (i.e. with 2 minutes FT measurement) in the conditional part and suggestion for the relaxation in the solution part. A new biofeedback case is compared to previously solved cases applying the fuzzy similarity matching algorithm and displays the outcome as feedback. Here, the feedback is defined with a pair i.e. it presents evaluation of FT measurement and a recommendation for the next training. This generated feedback is then presented to the clinician as proposed solution. The clinician thereafter reviews the proposed cases and takes the final decision to suggest a treatment to a patient. Thus the system assists a clinician, as a second option, to improve patient’s physical and psychological condition.

10.4. Common methods and techniques used in the three modules

The three modules are closely integrated in the computer based biofeedback system and all three use case-based reasoning as their main method. This section describes the design choices made in the system and modules.

10.4.1 Feature extraction

The FT temperature is sampled four times per second and the signal is initially filtered to remove artifacts and disturbances. According to a closer discussion with clinicians the rise and fall of temperature is a key feature they use in the classification. The introduction of standardized slope i.e. negative and positive angles gives an intuitive terminology to discuss features with the clinician and enables more consistent classification and visualization. The derivative of each phase is calculated as “degree of changes” of finger temperature. A low angle value, e.g. zero or close to zero indicates no change or stability in finger temperature. The measurement series of 9 minutes in module 1 is divided into 9 parts. Module 2 and 3 are divided into 4 parts with 30 seconds intervals. The slope of the linear regression line is calculated through the data points, as y is temperature (in Celsius) and x is time (in minute) by equation 1 for each feature extracted from the signal.

$$slope_f = \frac{\sum_{i=0}^{n}(x-\bar{x})(y-\bar{y})}{\sum_{i=o}^{n}(x-\bar{x})^2} \quad \textbf{(3)}$$

Where f denotes the number of the features (9 for phase 1 and 4 for phase 2 & 3), i is the index of samples (240 for phase 1 and 120 for the rest) and $\bar{x}, \bar{y}$ are the average of the samples. Then this slope value is converted to arctangent as a value of angle in radians (*-pi/2* to *+pi/2*) and finally the arctangent value is expressed in degrees by multiplying 180/*PI* where *PI* is 3.14 as a standard value [13]. The system thereafter formulates a new problem case using sensor-signal abstractions and then the new case is applied in the CBR cycle.

10.4.2 Case retrieval and similarity matching

Retrieval is essential in medical applications since missed similar cases may lead to less informed decision. Two of the reasons on which the reliability and accuracy of the system depend on: 1) which cases are stored in the case library i.e. quality of the cases; 2) the retrieval of the relevant cases and their ranking. In all the three modules, similarity measurements are used to assess the degrees of matching applying the standard nearest-neighbor method as a global similarity algorithm [33] [12].

A new FT measurement (formulated as a problem case) is inputted into the CBR cycle and then matched using different matching algorithms including *modified distance function*; *similarity matrix* [13] and *fuzzy similarity matching* [12] [32]. A *modified distance* function uses Euclidean distance to calculate 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 the domain expert. For example, the similarity between the same genders is defined as 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.

$$sim(C_f, S_f) = s_f(m1, m2) = \max(om/m1, om/m2) \quad \textbf{(4)}$$

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.

The local weight defined by the domain expert is normalized [12], assumed to be a quantity reflecting importance of the corresponding feature. The semantics of similarity for a symbolic feature is usually defined in the form of a numeric matrix quantifying the degrees of similarity for every pair of symbolic values associated with that feature [13]. The proposed system prefers to apply fuzzy similarity matching for the sensor-signal abstraction (i.e. numerical values) evaluating three different matching algorithms (mentioned above in this section) [13] and for symbolic values (such as gender, before/after lunch and so on) it uses the expert-defined similarity matrix. Clinicians often reason in fuzzy terms and in fact fuzzy similarity function also increases the performance of the system [13]. Here the fuzzy similarity matching helps to reduce the sharp distinction and avoid multiple rules in implementing the expert-defined similarity matrix.Thus the system provides matching outcome as a sorted list of the best matching cases according to their similarity values.

10.5. Experimental study and discussion

All three modules (figure 2) have been developed in a prototypical system. Functionalities such as local similarity, case retrieval and case retain are verified through the interface, where the similarity value of the two same cases is computed as 100% match. Module 3 has not been used in the experimental study due to the unavailability of the reference cases. Module 1 and module 2 have been evaluated using a case-base initialized with 53 reference cases from 31 subjects which is increased by adding 14 more reference cases in the previous case library [13]. All these 53 reference cases are analyzed and classified by an experienced clinician. The developed system has been tested in a small pilot study through a marine simulator with the aim of the safety navigation. The objective of this study1,2 is to detect any differences in individual task loads and stress levels on mariners using radar and nautical chart displays in north-up and head-up modes. Seven subjects, six men and one woman with the age range of 27 to 54 are participated in this study. The study was carried out in three days to measure the stress level of each of the subject. Finger temperature was measured through a sensor and 14 expert approved cases are selected as test cases for our experimental work. An experienced clinician and three trainee clinicians are involved within this study. These 14 test cases are classified by the clinicians and then the system performance is evaluated comparing their classification. In both modules, the system performance in terms of accuracy is compared with the experts of the domain where the main goal is to see how close the system could work compared to an experienced clinician. The accuracy of the system is computed using a statistics square of the correlation coefficient or Goodness-of-fit (R^2) [33], absolute mean difference and percentage of the correctly classified cases.

10.5.1. Evaluation of module 1

As the paper described in section 3.1, this module is used to classify a patient i.e. level of their stress. The reference cases stored into the case-base are classified into five classes: 1) Very Stressed 2) Stressed 3) Normal/Stable 4) Relaxed and 5) Very Relaxed. System performance has evaluated first as a comparison between three local similarity functions: a) modified distance function b) similarity matrices and c) fuzzy similarity and has been presented in our previous paper [13]. The paper presented the evaluation result depending on matching query case with stored cases i.e. similarity value of the cases and their ranking. In addition, this paper presents the comparison between three local similarity functions depending on correctness of their classification i.e. the number of correctly classified cases in percentage. An illustration for the classification of 14 cases both by the senior clinician and three methods is shown in table 1.

[1] http://www.sspa.se/research/projects/baltic-sea-safety-surship-project-bassy
[2] http://www.surship.eu/project/bassy/overview

Case Id	Senior Clinician	Modified Distance	Similarity Matrix	Fuzzy Similarity
Case_001_40	1	1	2	1
Case_024_41	4	4	4	4
Case_011_42	1	1	1	1
Case_101_43	1	1	1	1
Case_201_44	3	5	5	4
Case_012_45	3	4	3	3
Case_041_46	2	1	1	2
Case_071_47	2	2	1	2
Case_103_48	3	5	4	5
Case_141_49	5	4	3	5
Case_033_50	4	4	4	4
Case_018_51	5	4	3	5
Case_233_52	2	2	2	2
Case_116_53	2	2	2	2
Correctly Classified Cases		57%	50%	85%
Goodness-of-fit (R^2)		0.64	0.46	0.86
Absolute Mean Difference		0.57	0.71	0.21

Table1. Classification results comparing three methods with senior clinician. Class are converted into number as: 1=VeryStressed, 2=Stressed, 3=Normal/Stable, 4=Relaxed and 5=VeryRelaxed

The CBR system uses k nearest-neighbour (kNN, where k=1) algorithm for the classification of the test cases i.e. considers the top most retrieved similar case. From table 1, it can be seen that using fuzzy similarity function the system can correctly classify 85% i.e. number of the correctly classified cases in percentage. On the other hand, using other two functions the percentage of the correctness of classified cases are 57 and 50. In Goodness-of-fit (R^2) i.e. how close the system classification compare to the expert, fuzzy similarity shows the classification 88% close as the expert. Whereas, the R^2 values are comparatively low for the other two functions i.e. 64% for the modified distance and 46% for the similarity matrix. In terms of the classification error i.e. absolute mean difference table 1 shows that fuzzy similarity has less error than the other two functions. The mean value of the absolute difference for the fuzzy similarity is 0.21.

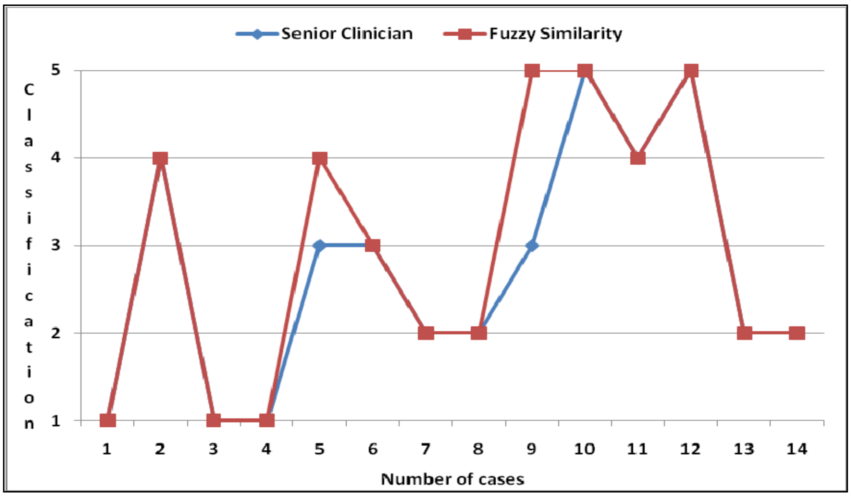

Fig.4. Comparison between classifications by the system using fuzzy similarity and the expert

A line chart is formulated from the classification value of the 14 test cases and presented in figure 5. The figure depicts how close the system can classify using fuzzy similarity function compare to the expert. It can also be seen that 12 out of the 14 test cases are correctly classified and only 2 cases are not correct.

From the above experimental results it indicates that the classification performance is better i.e. close to a clinician using fuzzy similarity function as a local similarity. The other methods uses conventional crisp values whereas fuzzy similarity function converts crisps values into the fuzzy sets which reduces the sharp distinction thereby helps to capture human reasoning and provides better classification. As we have discussed earlier, there are only 53 reference cases available into the case-base for this experiment, the overall system performance could be improved if the number of the reference cases is increased [34]. Furthermore for the system classification, only the top most retrieved similar case is selected. However, if the second or third top most similar cases were considered, classification result will vary. For this reason a multi-objective decision making procedure is proposed using fuzzy logic and fuzzy clustering which is further described in section 5.4.

10.5.1.1 System performance vs. trainee clinicians

The 14 test cases are further classified by the three trainee clinicians who have less experience in this domain. The main goal is to see how good the system can classify compare to the trainee clinicians i.e. whether the system can be useful to assist the trainee clinician in the classification task. The three trainee clinicians have informed about the classification process from the senior clinician and they have used the same classes discussed earlier. The classification of the 14 test cases by senior and all trainee clinicians is presented in table 2. The order of the trainee clinicians is set by the order of their experience level (1= less experienced, and 3= high experienced). Column 6 in table 2 presents the system classification using fuzzy similarity.

Case Id	Senior Clinician	Trainee Clinician 1	Trainee Clinician 2	Trainee Clinician 3	The System using Fuzzy Similarity
Case_001_40	1	2	1	2	1
Case_024_41	4	3	3	3	4
Case_011_42	1	1	2	2	1
Case_101_43	1	2	1	2	1
Case_201_44	3	3	3	4	4
Case_012_45	3	4	3	4	3
Case_041_46	2	1	2	2	2
Case_071_47	2	1	2	2	2
Case_103_48	3	3	4	3	5
Case_141_49	5	4	5	5	5
Case_033_50	4	3	5	4	4
Case_018_51	5	5	5	5	5
Case_233_52	2	2	1	2	2
Case_116_53	2	4	3	2	2
Correctly Classified Cases		36%	57%	57%	85%
Goodness-of-fit (R^2)		0.55	0.80	0.81	0.86
Absolute Mean Difference		0.71	0.43	0.43	0.21

Table 2. Comparison results between the system and three trainee clinicians. Class are converted into number as: 1=VeryStressed, 2=Stressed, 3=Normal/Stable, 4=Relaxed and 5=VeryRelaxed and the system uses fuzzy similarity.

The last three rows at the bottom of table 2 presents the calculated results comparing all the trainee clinicians and the system classification to the senior clinician. From the table 2 it can be seen that the system can classify correctly better than all the trainee clinicians. The number of the correctly classified cases in percentage is 85 by the system whereas the trainee clinicians have succeeded to classify correctly as 36, 57 and 57 in percentage. The Goodness-of-fit (R^2) value (86%) for the system classification against the senior clinician is almost same or little better than the trainee clinician 2 and 3. The R^2 value of the trainee clinician 1, 2 and 3 are as 55%, 80% and 81% respectively. Consequently, the absolute mean difference value is lowest for the system compare to the trainee clinicians. According to the results illustrated in table 2 we can say that the system could work as same as or may better than some less experienced clinicians. One important issue is that both the test data set and the case base which are very small, result could vary with large data set and enough cases into the case base. On the other hand, a trainee clinician who has just started his/her practice in this domain can use the system as an assistant to support him/her in the classification task.

10.5.2. Decision analysis and evaluation in module 2

Module 2 is different from module 1 and module 3, as the parameter estimation is a regression problem in this module. The task is to decide outputs which are continuous real numbers rather than discrete classes. The system provides three different strategies to estimate individual parameters in this phase. A) Perform kNN, where k=1 i.e. can take the value of the top most retrieved case as the approximation of a new estimation. B) Calculate average, for multiple retrieve cases more exact parameter estimation is expected. For instance, adaptation of the two retrieved cases which have ceiling points at 28 C and 30 C, by averaging these two pints the system can get 29 C as the estimated ceiling point for a new patient. C) Weighted average, the retrieved cases are adapted to a solution where similarity degrees of cases are introduced as weights, the estimated ceiling point will be the weighted average of the ceiling points of the retrieved cases. Considering the previous example cases where the similarity values are 88% and 85% respectively, the new ceiling point will be $\{(28\times88 + 30\times85) \div (88+85)\}= 5014 \div 173 =28.9$ as approximation.

10.5.2.1 Evaluation of module 2

Module 2 is used to estimate initial parameters such as ceiling and floor temperatures which have been discussed in section 3.2. Fuzzy similarity is employed as a local similarity for the case matching and the system retrieves the most similar cases. The 14 test cases are contributed to estimate their ceiling and floor temperatures comparing 53 stored cases in the case base. The parameters, ceiling and floor temperatures are continuous real numbers rather than discrete classes. Therefore the paper proposes three strategies in the previous section (section 5.2) to compute the parameters value.

Strategies / Evaluation method	**kNN where k=1**	**Average k=5**	**Weighted average, k=5**
Goodness-of-fit (R^2)	0.76	0.86	0.91
Absolute Mean Difference(error)	1.59	0.99	0.88

Table 3. Comparison results between the three strategies against the clinician. R^2 and error are computed for the estimated initial parameter “ceiling temperature”.

Strategies / Evaluation method	**kNN where k=1**	**Average k=5**	**Weighted average, k=5**
Goodness-of-fit (R2)	0.80	0.86	0.88
Absolute Mean Difference(error)	1.28	0.80	0.81

Table 4. Comparison results between the three strategies against the clinician. R^2 and error are computed for the estimated initial parameter “floor temperature”.

Goodness-of-fit (R^2) and absolute mean differences (error) are calculated using the estimated parameter value by the system using each strategy and the estimated parameter value by the senior clinician. The comparison result between these strategies is presented in table 3 and table 4. Table 3 presents the result for the parameter ceiling and table 4 presents the result for the parameter floor temperature. From the table 3 and 4, maximum R^2 value is found using weighted average strategy i.e. system can estimate ceiling temperature 91% and floor temperature 88% close to the senior clinician. On the other hand R^2 value for the average strategy is little bit less than the weighted average i.e. 86% for both the ceiling and floor temperatures. But only selecting the top most retrieve case the system cannot provide better estimation against the senior clinician. This strategy (kNN, where k=1) can estimate 76% for ceiling and 80% for floor temperature which is as close as the clinician. In terms of error i.e. absolute mean difference both from table 3 and 4; average and weighted average strategies have less error than the strategy to selecting top most similar case for the parameter estimation. In this strategy, error is 1.59 for the ceiling temperature and 1.28 for the floor temperature.

10.5.3. Evaluation of module 3

In the beginning of the chapter we have mentioned that lack of having sufficient reference cases, this module is not ready for the specific evaluation. But the problem description part of the cases is same as module 1 and 2, same methods and functions have employed in this module. We have discussed in section 4.1 and 4.2 that the method for signal abstraction and similarity functions for matching are common for all the modules. Therefore we could consider the evaluation results from module 1, but of course it is interesting to see the experimental result since each module functions on individual case-base. Our intention is to collect sufficient reference cases and implement the system and use the complete system in a clinical context including all three modules which would provide sufficient material for evaluation of module 3.

10.5.3.1 Decision analysis in module 1 and 3

Generally most CBR systems retrieve a subset of cases from the case base by using kNN (k nearest neighborhoods) or a specified similarity threshold [10]. These retrieved cases are then presented along with their similarity scores for a final decision. But in some situation the similarity scores are close to each other whereas ranking of these cases might separate them. For example, 10 cases are retrieved from case base and presented as a sorted list based on similarity values; top most case has the similarity value as 92.5% and the last one has a little lower similarity value that is 87.2%. So clinicians might ignore this later case and treat it as an irrelevant one, but in reality this case has a good similarity with the new problem case and might contain useful information. Our proposed system adopts four linguistic terms such as less similar, slightly similar, similar, and very similar to make a fuzzy partition of the universe of discourse concerning similarity values. The membership functions of these four linguistic terms as fuzzy sets are shown in Fig. 4, in which we can see that a crisp similarity value is transformed into four membership degrees with respect to the different fuzzy sets. By doing this we achieve fuzzy clustering of all cases in the case base according to their similarity values against a query case (rather than mutual distances as done in conventional clustering schemes). Fuzzy clustering produces soft boundaries when dividing cases such that any case in the case base belongs to each cluster with a certain degree.

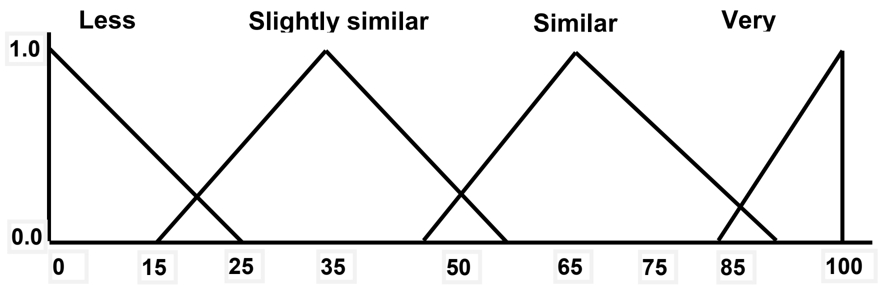

Fig. 5. Fuzzy sets for similarity values. X-axis represents the degrees of membership function and Y-axis represents the similarity values in percentage

Of course the grouping of cases can also be done using the traditional way of setting similarity thresholds. But sharp boundary could bring too harsh distinction in decisions without sufficient justification. Fuzzy logic, in this case, prevents this sharp distinction and enables soft treatment of cases in favor of decision support. Our system will thus examine all cases and group them into fuzzy clusters based on degrees of membership. Clinicians could choose any fuzzy cluster and can see the relation of all cases with respect to that cluster.

We are also concerned about some other factors which could be valuable for evaluating cases such as case usefulness involved in module 1 and module 3. Likewise the range for the values of usefulness can be fuzzy partitioned with fuzzy sets (linguistic terms) such as less useful, slightly useful, useful, and very useful. These fuzzy sets further allow for fuzzy clustering of the whole case base into different fuzzy clusters as done with the linguistic terms for similarity. Finally, case retrieval is considered as a multi-objective decision making problem in selecting cases from the case base that are both similar and useful. In view of this, we just need to focus on the overlapping between the clusters for similar and useful cases. This is achieved by constructing the intersection between both clusters as a fuzzy subset, which indicates to what extent a case in the case base is recommended to be retrieved.

10.6. Summary and conclusions

This paper presents a computer-based decision support system for biofeedback training in health care. The system aims to facilitate experience sharing and reuse among clinicians by utilizing CBR methodology from artificial intelligence. The main contribution of this research is a three-module system architecture enabling decision support to clinicians carrying out biofeedback. Classification, parameter estimation as well as biofeedback training are dealt with. The approaches employed in our system have been validated in a case study related to stress diagnosis and treatment. The results of the case study reveal that our case-based system for biofeedback training outperforms novice clinicians in patient diagnosis by making judgments even closer to senior experts in the underlying domain. We believe that our developed system will be valuable to help less experienced clinicians making more accurate and prompt decisions as well as offer useful second opinions for experts in dealing with complex and controversial situations. Our future work would focus on the interaction among the three modules in the existing system and also investigate the ways to further improve the overall performance of the system using delayed reports of treatment effects of patients.

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Chapter 11.

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

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Abstract

Health science is, nowadays, one of the major application areas for case-based reasoning (CBR). The paper presents a survey on the recent medical CBR systems based on literature review and e-mail questionnaire to the corresponding authors. 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 aimed to be commercialized.

Key-Words

Case-based reasoning, Medical system, Construction-oriented properties, Purpose-oriented properties, Survey.

11.1 Introduction

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

The origin of CBR stems from the work of Schank and Abelson in 1977 [54] at Yale University. The early work exploiting CBR in medical domain were performed by Konton [56], and Braeiss [55][57] in the late 1980's. Case-based reasoning 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. CBR is an appropriate method to explore in medical applications where symptoms represent the problem, and diagnosis and treatment represent the solution. Aamodt and Plaza [1] have introduced a life cycle of CBR with four main steps, Retrieve, Reuse, Revise and Retain as shown in Fig. 1.

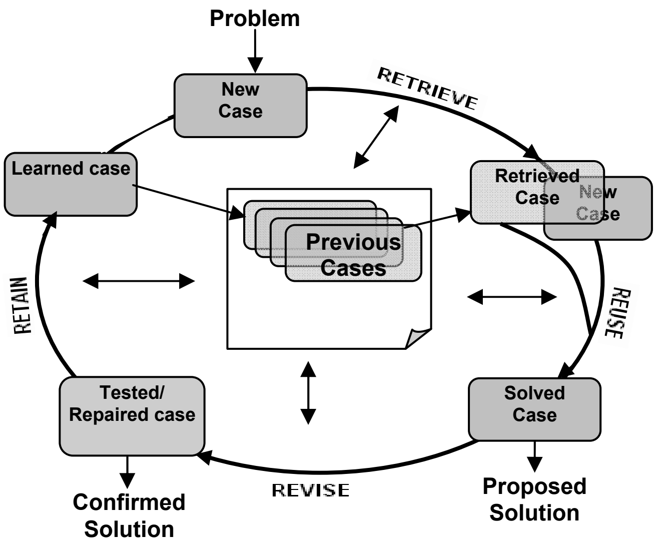

Fig. 1. CBR cycle, introduced by Aamodt & Plaza [1]

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 and the similarity reflects an estimate of how suitable the solution is for the current problem. The most relevant cases are proposed as solutions (after some adaptations if necessary). The selected case may be revised before they are reused as a solution. The problem and the solution are retained in the case library for the future use. Prior to the case formulation some CBR systems typically need preprocessing and filtering. For example, if the data are collected from the sensor signals, images, free text sources etc. the system may require feature extraction, feature mining, indexing, weighting etc.

In the medical domain, a clinician or a doctor may start his practice with some initial experiences (solved cases). Afterwards s/he reuses these past experiences to solve a new problem. This may result in some adjustment of the previous solutions to solve the new problem. Thus a new experience (case) being created which as a consequence enriches the clinician's/doctor's experiences. In fact, this is how the traditional CBR cycle works. So, case-based reasoning 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 research advances. Important research issues are:

1) Feature extraction is becoming complicated in the recent medical CBR systems due to a complex data format where the data are coming from the sensors or images or as time series or free text format.
2) Feature selection and weighting are two other important factors for which many CBR systems depend on expert's knowledge. Cases with hidden features could also affect the retrieval performance [23].
3) The component that plays a central role in CBR systems is the case base or case library. A case base can be considered as a concrete knowledge of a model consisting of specific cases. The cases stored in a case library should be both representative and comprehensive to cover a wide spectrum of possible situations. As in an initial step of a medical CBR system, the case base is often initiated with a limited number of cases, which may reduce the system performance. For example, due to missing past cases or very sparse cases the accuracy can be reduced. Therefore, case library maintenance and case mining have become increasingly important issues in the CBR research [2].
4) Many CBR systems avoid automatic adaptation strategies due to number of the problems, such as complexity in medical domains, rapid changes of medical knowledge, large number of features, reliability, and risk analysis

etc. [36]. As a result, the adaption step in the medical domain is often performed manually by an expert of the domain.

The 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 L. Griel et al. [24]. Another survey for the medical CBR systems/projects reported between the years 1999 to 2003 was done by M. Nilsson et al. [38].

Due to the area's fast and successful development and progress there is a need for a systematic survey to indentify recent trends in the medical CBR systems. This paper focuses on the medical CBR systems/projects created or reported about during the years 2004 to 2008. The discussion is further extended for the systems/projects reported in the year 2009 through a literature review. The aim of the survey is to investigate the recent trends particularly, why the recent systems are being built i.e. the purpose and how they are developed i.e. the construction of the systems. The motivation behind the review of the recent progress on this particular topic is to provide reader an easier access to the current state of the knowledge on how the systems are building today and applying in practice. We have done an exhaustive literature search in CBR conferences i.e. ICCBR/ECCBR 2004-2009 and their adjunct workshops in CBR in medicine for the relevant papers. Some of the references from other journals such as Journal of IEEE Intelligent Systems, Computational Intelligence, Artificial Intelligence in Medicine, International Journal of Hybrid Intelligent Systems, Transactions on Case-based Reasoning on Multimedia Data, Applied Intelligence, Knowledge-based System, European Journal of Operational Research, IEEE transactions on Knowledge and Data Engineering, Applied Soft Computing, Expert Systems and Applications etc. are also included. An e-mail survey to the authors is conducted mainly to define 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 (as some of them have added in this survey) 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 study describe certain significant trends which characterize the recent medical CBR systems depending on their system properties.

The paper is organized as follows: in Section 11.2, we describe the categorization of the system properties based on which the different systems are compared. Section 11.3 presents the survey result and summarizes the recent trends in the tables based on the purpose-oriented and construction-oriented properties.

Section 11.4 discusses the overall trends. Section 11.5 contains conclusion and a short summary and references of the included systems are provided in appendix A.

11.2 Categorization of the system properties

This survey is conducted by following the same approach of M. Nilsson et al. [38] where the systems' developments are followed by analyzing a set of distinctive system properties. The system properties are divided into two parts:

A) Purpose-oriented properties: the functions like diagnosis, classification, tutoring, planning, knowledge acquisition/management etc. that is/are performed by a system.

B) Construction-oriented properties: how the systems are constructed i.e. case type, adaptability, hybridity etc.

11.2.1 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 diagnosis process.

2) Classification: Classification is a method by which a new situation is distributed or categorized in a group (i.e. things are arranged in a class or category).

3) Tutoring: A tutoring system acts as a trainer which generates individualized instructions or feedbacks for students. Some CBR systems attempt to function as tutoring systems typically by either using a case library or learning new cases from learner experience.

4) Planning: In medical domain, planning generally refers to a treatment procedure or a therapy management. For instance, the RHENE system [34] provides planning expertise for the 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.

11.2.2 Construction-oriented properties

1) Subjects: The number of persons/patients involve in the system's evaluation.

2) Number of cases: The quantity of cases for each CBR system.

3) Case type: The nature e.g. real, prototypical, generic etc. of a case or cases (a group) used for the evaluation purpose.

4) Prototype: This property shows whether and to what extent a system is implemented i.e. in a form of a model or a trail product.

5) Adaptability: The recent CBR systems are investigated to see up to what extent the systems are using automatic adjustments of the cases in the medical domain.

6) Hybridity: This property explores the synergy among the CBR and other AI methods. This often enriches the reliability and efficiency of a system through gaining advantages of different AI techniques.

7) Autonomy: It indicates the degree of automaticity or the level of human intervention needed to complete and/or evaluate a system's result. A fully independent system could provide result without any human intervention, which is particularly rare in medical diagnosis and planning systems.

8) Commercialization: Successful commercialization of CBR systems is still not so common in the medical domain. This property investigates the status of each medical CBR systems which are targeted for commercial production of the system.

9) Clinical use: This property differentiates each systems/projects with respect to their use in clinical environment i.e. whether the system is used in clinical/hospital environment for evaluation and/or routine clinical use.

10) Reliability: This is an important property of a medical CBR system where it investigates to what extent the system is trustworthy i.e. how dependable a system is. The functionality of a system should be tested to see if it provides an accurate solution when needed.

The method for examining the recent trends in this survey follows the above distinctive properties in system development to differentiate a system from another. Furthermore, it also concerns about the application domain or the context of the system to see how well CBR is suited for the medical domain. Besides, looking at the recent medical CBR systems, we are also interested in investigating the different similarity matching techniques applied in the case retrieval. All these have been done to discover the trends in the development of the recent medical CBR systems as compared to the previous years.

11.3 Survey results and trends in medical CBR

The results from the survey are summarized in tables to get a clear picture on recent trends in developing the medical CBR systems. A matrix illustrated in Table I, presents the CBR systems with their application domains/contexts and the purpose-oriented properties. Systems and their construction-oriented properties are summarized in Table II and Table III.

11.3.1 Purpose-oriented properties

Fig. 2 illustrates a comparison on the basis of the purpose –oriented properties between the survey performed by M. Nilsson in [38] (i.e. the medical CBR systems reported or created about the year 1999-2003) and the survey presented in this paper (i.e. the medical CBR systems reported or created about after the year 2003).

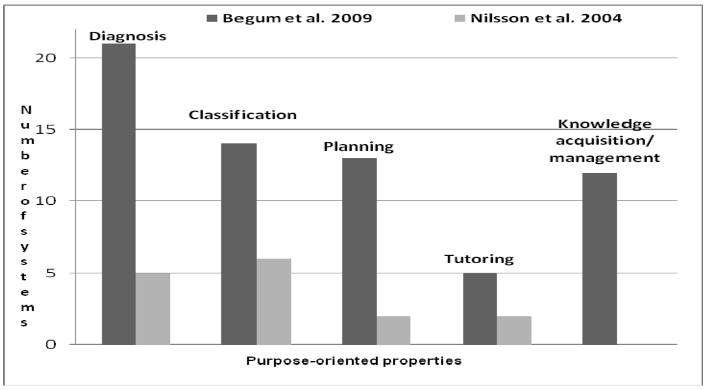

Fig. 2. Number of the systems belonging to each purpose-oriented category

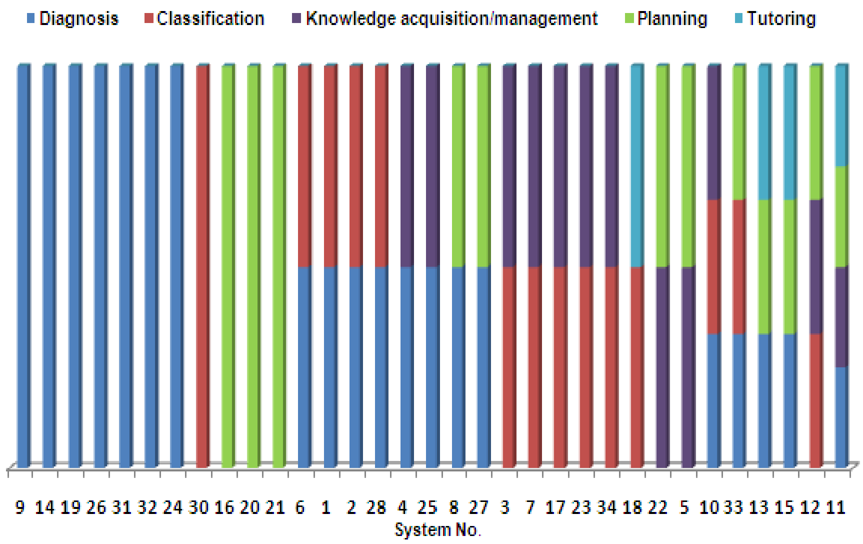

Fig. 3. Overlapping areas among several purpose-oriented properties. X axis denotes the systems no. according to Table I

It shows that besides a new category, knowledge acquisition/management, many systems address diagnosis and planning in the recent years compare to the years 1999-2003. During the recent years the increase of classification systems is moderate, few systems address tutoring and many of the systems address planning as shown in fig. 2. According to our survey, numerous systems are multipurpose-oriented i.e. perform more than one task in medical domain. As can be seen from Table I, out of the 34 systems, only 11 systems are serving as single purpose while the others are multi-purpose systems. Fig.3 describes recent trends in developing multi-purpose oriented systems in the medical domain. Every purpose is given by a color, but the size/area of the color has no significance since we don't know the balance among the different purposes in a system. It depicts that the first 11 are single purpose systems i.e. 7 are diagnosis, 1 is classification and 3 are 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	[43][42]
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	[25][19]
7	Perner/HEp2-PAD	Classification, Knowledge acquisition/ management	Image classifier	[45][44][41]
8	Schmidt/ISOR	Diagnosis & planning	Endocrine	[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 and 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	Neuropsychiatric	[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 cancer	Diagnosis & classification	Melanoma cancer	[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	Diabetic	[66]

The next 16 systems are two-purpose systems e.g. first 8 are all addressing diagnosis as one of their purpose-oriented categories (hence, the systems 6, 1, 2, 28, 4, 25, 8, 27 come first in the category of two-purpose systems). So, in Fig. 3 the systems are displayed in the order of the number of purposes first the one purpose systems, then the two purpose systems and three purpose systems and so on. Note that the systems are numbered according to Table I.

11.3.2 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 the CBR to complete a system. Various other techniques integrated or combined with CBR in these systems/projects are- rule-based reasoning (RBR), knowledge management (KM) technique, neural network (NN), data mining etc.

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

No	Author/system	CBR and other techniques	Matching techniques
1	McSherry/CaseBook	CBR & HDR	Author's defined similarity algorithm
2	De Paz/ExpressionCBR	CBR,NN & Statistics	Nearest Neighbour and Minkowski distance
3	Perner/Fungi-PAD	CBR & Image processing	Author's defined similarity measurement function
4	Cordier/FrakaS	CBR	Using adaptation knowledge
5	Corchado/GerAmi	CBR & Variational calculus	Hierarchical, multivariate conglomerates analysis and Mahalanobis distance
6	Glez-Peña/geneCBR	CBR, RBR & Fuzzy logic	Author's defined fuzzy similarity metric
7	Perner/HEp2-PAD	CBR, Image processing & data mining	Euclidian distance, Nearest Neighbour
8	Schmidt/ISOR	CBR & Statistic	Keyword based similarity
9	Begum/IPOS	CBR & Fuzzy Logic	Fuzzy similarity, similarity matrix, Euclidian distance, Cosine similarity
10	D'Aquin/KASIMIR	CBR, semantic web, belief revision theory, fuzzy logic & ergonomy	Matching of source (general) cases using adaptation knowledge
11	Bichindaritz / Mémoire	CBR, RBR, Data mining & Statistic	Ontology assisted case matching including semantic information
12	Montani/RHENE	CBR & Temporal abstractions	Euclidian distance, Nearest Neighbour
13	Kwiatkowska/Somnus	CBR & Fuzzy logic	Fuzzy logic and semiotic approach
14	Lorenzi/SISAIH	CBR	Nearest Neighbour

15	Ochoa /SIDSTOU	CBR & Data mining	Author's defined method
16	Ahmed ./Biofeedback	CBR & Fuzzy logic	Fuzzy similarity matching, similarity matrix
17	Brien/ADHD	CBR	Modified nearest neighbour matching
18	Doyle/Bronchiolitis	CBR & RBR	Nearest Neighbour
19	O'Sullivan/ Dermatology	CBR, KM & image processing	IR metrics [46]
20	Marling/Type-1diabetes	CBR & RBR	Nearest Neighbour and similarity matric
21	Song/Radiotherapy planning	CBR, Fuzzy logic, Dempster-Shafer theory & Simulated annealing	Fuzzy sets, distance function and author's defined similarity function
22	Wu/ Dietary counseling	CBR, Data mining & Ontology	Nearest Neighbour
23	Zhuang/Pathology	CBR, Data mining and clustering	Kohonen's self-organizing maps
24	Ahn/ Breast Cancer Diagnosis	CBR & genetic algorithms	Genetic algorithms, Nearest Neighbour
25	Huang/ Chronic Diseases	CBR & data mining	knowledge-guide method & Weight ratio functionality
26	Chang/Children development	CBR	Nearest Neighbour
27	Houeland/Palliative care	CBR, rule-based & probabilistic model-based methods	Semantic matching
28	Nicolas/Melanoma cancer	CBR & RBR	Normalized Euclidian distance
29	Töpel/Metabolic disease	CBR	Similarity tables & difference-based similarity functions
30	Arshadi/MOE4CBR	CBR, Spectral clustering & logistic regression	Modified Nearest Neighbour
31	Kurbalija/multiple sclerosis disease	CBR	Case retrieval net
32	Obot/Hepatitis	CBR, Rule base & neural networks	Binary search algorithm
33	CBSMS/Stress management	CBR, RBR, textual information retrieval & Fuzzy logic	Fuzzy similarity matching, modified distance function, similarity matrix
34	Yuan/ HDCU	CBR & support vector machine	Self-Organizing Map

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	Hybridity	Autonomy	Commercialization	Clinical use	Reliability
1	McSherry/CaseBook	Not applicable									
2	De Paz/ ExpressionCBR	212	212	Real	Yes	Yes	Yes	Highly	No	Clinician evaluation	Clinician
3	Perner/ Fungi-PAD	8	400	Real, prototypical	Yes	No	Yes	Highly	Planned	Clinician evaluation	Expert level
4	Cordier/ FrakaS	Not relevant	10	Prototypical	Yes	Yes	No	Some extent	No	No	Not relevant
5	Corchado/ GerAmi	20	4000	Real	Yes	Yes	Yes	Highly	Yes	Day-to-day use	always
6	Glez-Peña/ geneCBR	7	43	Real	Yes	No	Yes	Highly	No	Clinical evaluation	Expert Level
7	Perner/ HEp2-PAD	10	300	Real	Yes	No	Yes	Highly	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	Some extent	Planned	Clinical evaluation	Expert level
10	D'Aquin/ KASIMIR	Not relevant	100	Real, generic	Some extent	Yes	Yes	Some extent	No	Clinical evaluation	Expert Level
11	Bichindaritz/ Mémoire	Simulator	122	Real, prototypical	Yes	Yes	Yes	Highly	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	Some extent	No	No	Not relevant
14	Lorenzi/ SISAIH	5	70	Real	Yes	No	Pure CBR	Highly	No	No	Expert Level
15	Ochoa/ SIDSTOU	47	100	Real	Yes	Some Extent	Yes	Some extent	Planned	Clinical evaluation	Clinician
16	Ahmed ./Biofeedback	24	39	Prototypical	Yes	No	Yes	Some extent	Planned	Clinical evaluation	Expert Level
17	Brien/ADHD	152	-	Real	Yes	-	No	Some extent	-	Clinical evaluation	-
18	Doyle/ Bronchiolitis	400	40	Real	Yes	Some Extent	Yes	Some extent	No	Clinical evaluation	Clinical

19	O'Sullivan/ Dermatology	1000	150	Real	-	-	Yes	Some extent	-	-	-
20	Marling/ Type-1diabetes	20	50	Real	Yes	Planned	Yes	Some extent	Planned	Planned	Testing underway
21	Song/Radiotherapy planning	6	72	Real	Some extent	Yes	Yes	Highly	Planned	In progress	87% of cases
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	Some extent	No	No	Expert Level
25	Huang/ Chronic Diseases	3	15751	Real	Yes	Yes	Yes	Some extent	No	No	Always Right
26	Chang/Children development	210	210	Real	Some extent	No	No	Some extent	-	Clinical evaluation	-
27	Houeland/Palliative care	Not applicable									
28	Nicolas/Melanoma cancer	-	150	Real	Some extent	-	Yes	Some extent	-	-	-
29	Töpel/Metabolic disease	-	750	Real	Yes	No	No	Some extent	-	Day-to-day, clinical evaluation	-
30	Arshadi/MOE 4CBR	-	580	Real	Yes	Yes	Yes	-	-	Clinical evaluation	-
31	Kurbalija/multiple sclerosis disease	Not applicable									
32	Obot/Hepatitis	70	70	Real	Some extent	Yes	Yes	Some extent	-	Clinician evaluation	-
33	CBSMS/Stress management	31	53	Real, Prototypical	Yes	No	Yes	Some extent	Planned	Clinical evaluation	Expert Level
34	Yuan/ HDCU	-	-	-	Some extent	No	Yes	Some extent	-	-	-

Matching technique or similarity measurement between cases plays an important role during the case retrieval in a CBR system. Several matching techniques reported in the recent medical CBR systems are: nearest neighbour, euclidian distance, genetic algorithms, and author's defined similarity algorithm etc. as summarized in Table II.

Some of the construction-oriented properties, such as the degree of autonomicity, prototype, commercialization, reliability etc. of the systems do not always present in the reference papers. Therefore, an email questionnaire is send to the corresponding authors of the systems. In terms of the answers to the questionnaire we formulate a construction-oriented property table as displayed in Table III. Some of the systems which are not completed yet or describe rather general research issues are not included in table III e.g. [33]. An empty cell in Table III denotes that the property could not be determined. From Table III it can be seen that the number of cases involved in different systems/projects varies from 10 to 1548122. The case type identifies whether a system is using real or artificial cases and/or a combination of the both. Majority of the systems involved in this survey are implemented using real cases and a few systems are based either on the prototypical cases or a combination of the real and artificial cases. Only some of the systems develop automatic adaptation strategies whereas the majority of systems/projects provide manual/conventional adaptation. Almost all the systems are multi-modal or hybrid i.e. combined more than one AI technique but only a small number of them still depend on the pure CBR only. A large part of the systems address user interaction. Until now only few systems are commercialized. However, many of the systems have an intention to go for the production. Some of the recent systems also address the standardization of CBR systems and cases (i.e. formalization, case representation, reasoning procedures etc.) to exchange or share among the CBR systems, for example, the Memoire project by Bichindariz [7].

11.4 Overall trends

Comparing the different CBR systems based on the distinctive system properties as 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 of applying CBR in health science is increasing. Moreover, the systems in [62] [52] [19] [25] [22] indicate an increasing advancement of using CBR in the bioinformatics domain.

Multi-purpose systems: An interesting observation of the purpose-oriented properties is that the systems are being developed today serve multiple tasks in the medical domain. The majority of the systems address more than one purpose-oriented category in this survey i.e. about 68% of the systems has had two or more purposes (Fig. 3.). However, until the year 2003 [38], only 2 (13% of the systems) of the evaluated systems were multipurpose. Note that, M. Nilsson et al. [38] investigated 15 CBR systems yet did not explicitly mention overlapping among their purpose-oriented properties. Hence, the systems today are not only concentrating on the diagnosis and treatment tasks as the early CBR systems did but also provide multi-task facilities. In fact, the recent CBR systems tend to support additional complex tasks in the health science domain for example standardization of CBR systems as defined in [8].

Combination of the purposes: In particular, it is observed that the use of CBR systems for knowledge acquisition/ management have attained an increasing attention in the recent years. Besides, it is popular to combine classification and knowledge acquisition/management, as evidenced by 7 systems in Table I. At the same time, planning in the medical domain offers interesting challenges to CBR researchers and/or being an application where the CBR methodology may offer valuable progress and commercial applications (as shown in Table III many systems are aiming at commercialization).

Data pre-processing: Majority of the health science domains require pre-processing of datasets which perform feature extraction or feature mining prior to the case representation. Also some of the systems/projects have successfully extracted features from the 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 which helps to represent cases with original implicit and complex features. 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 made in the medical CBR systems is that almost all the participated systems/projects in this survey implemented their systems in a form of prototype. Only a few medical systems i.e. Perner [44] and Corchado et al. [17] have shown successful commercialization of their systems. 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. But the day-to-day routine use in clinical setting is not so common.

Automatic adaptation: Adaptation is often a challenging issue in health sciences and has 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 of automatic and semi-automatic adaptation strategies.

Hybrid systems: Although a few systems still depend on CBR today almost all the medical CBR systems combine more than one AI method and technique and turn into hybrid systems. Among the hybrid systems, many systems use 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, artificial cases generation etc. in a system. In fact the multi-faced and complex nature of the medical domain motivates to design such multi-modal systems [36] [38]. The integration of CBR and RBR was common in the past CBR systems such as in CASEY [28], FLORENCE [14]. Recent research trends in hybrid CBR systems are also using many other techniques or methods such as data mining, fuzzy logic, statistics, neural network etc. 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 old case is commonly applied in most systems. The nearest neighbor retrieval algorithm is still widely applied in medical CBR systems. However, in recent years several other techniques are also employed in some systems for instance, 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 trustable or operational secure in some degree of expert level, others are on earlier stages.

Data types: Most of the systems are using real medical data sets as presented in Table III (column 'Case Type'). Some applications depend on artificial or prototypical data sets. Several of these later systems depict rather generic methods or algorithms which could be applicable using data sets from other domain such as [33] [15]. By developing the more general solutions it also drives the research area of CBR forward.

Looking at some new systems/projects mainly reported in the year 2009, for example, [2][5][53][58][59][60][64][65] demonstrate that there are no dramatic changes in their system properties from the previous years (2004-2008). Research trends also reveal that the most of the systems are functioning as multi-purpose. These systems are also reported as multimodal or hybrid. Same as the previous years, most of the systems are commonly implementing the feature extraction, case retrieval and so on. Automatic adaptation is still infrequent and performing manually in some systems.

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

11.5 Conclusion

This paper presents a survey of applied research of CBR in medical domains. A number of the recent medical CBR systems are reviewed in terms of their functionalities and the techniques adopted for system construction. In particular, we outline 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 is revealed from our survey that CBR has been applied in many medical scenarios for various tasks such as diagnosis, classification, tutoring, treatment planning, as well as knowledge acquisition/management. It also leaves us with the awareness that hybridization of CBR with other AI techniques such as ontology, rule-based reasoning, data mining, fuzzy logic, neural network, as well as probabilistic and statistical computing would create promising opportunities to enhance CBR systems scaling them up to handle increasingly large, complex, and uncertain data and information in clinical environments.

APPENDIX:

CBR Systems in the Health Sciences

1. CaseBook [33] [*Purpose: Diagnosis, Classification*] is a hypothetico-deductive CBR system for classification and diagnosis. It applies hypothetico-deductive reasoning (HDR) in conversational CBR systems. The HDR helps to identify the significant hypothesis. It could rule out a hypothesis proposed by a system or user and minimize the number of the tests. Though the strategy is exemplified in recommending the types of the contact lenses in the contact lenses classification domain it is also applicable in data sets other than medical domain.

2. ExpressionCBR [22] [*Purpose: Diagnosis, Classification*], is a decision support system for cancer diagnosis. The system classifies the Leukemia patients automatically from the Exon array data and helps in the diagnosis of different cancer patients. It uses a data filtering algorithm that deals with the dimensionality problem in the data sets. In addition, a clustering algorithm is also used 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. The system applies case-based reasoning and image processing techniques. Due to the large biological variations it is difficult to generalize the appearance of the fungal spores to a model. The system uses a set of cases to explain the appearance of an object. It compares an object in an image to the original object. This original object is generated using a template which is a prototypical case produced by a semi-automatic process.

4. FrakaS [18] [*Purpose: Diagnosis, Knowledge acquisition/ management*] is a prototype implemented using CBR in the domain of oncology. The authors proposed a conservative adaptation strategy for the knowledge acquisition from the experts. The evolution of the domain knowledge is highlighted into the paper in a way when inconsistency between the domain and the expert knowledge is added as a new knowledge. The paper emphasizes on the proper management of the domain knowledge to avoid wrong decisions in medical decision support systems.

5. GerAmi [17] [*Purpose: Planning, Knowledge acquisition/ management*] '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. It included CBR system to provide case-based planning mechanism to optimize work schedules and present up-to-date patient data. A prototypical system has been implemented at a care facility for Alzheimer patients in geriatric residences.

6. geneCBR [19, 25] [*Purpose: Diagnosis, Classification*] focuses on the classification of cancer, based on gene expression profile of the microarray data. Several AI techniques are combined to optimize the classification accuracy. Each of the cases contains 22,283 features. The system aims to keep the original set of features as small as possible. Cases are represented using fuzzy sets. Fuzzy-prototype based retrieval is applied in the case retrieval phase. The patients are also clustered into group 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 the image segmentation in the medical image diagnosis. The system combines CBR, image processing, feature extraction and data mining techniques to optimize image segmentation at the low level unit. CBR performs the segmentation parameter selection mechanism based on the current image characteristics. The cases are represented with the image and non-image information. The similarity value is also calculated using both the image and non-image information.

8. In the ISOR [50] [*Purpose: Diagnosis, Planning*], the authors specially address the endocrine domain. The system identifies the causes of ineffective therapies and advises better recommendations to avoid the inefficacy to support in the long-term therapies. The system is exemplified in diagnosis and therapy recommendations of Hypothyroidism patients treated with hormonal therapy. The system is not only depending on the case base but also on the other knowledge components, such as a knowledge base, prototypes i.e. generalized cases and medical histories of a patient. The knowledge base represents the domain theory in a tree structure. Information of these containers worked in a form of dialogue and key words are used for the case retrieval.

9. The IPOS [6] [*Purpose: Diagnosis*] project aims at proving a case-based decision support system to assist clinicians in diagnosing individual stress condition based on the finger temperature measurements [58]. The system uses calibration phase to generate an individual stress profile. Case-based reasoning is applied as the key methodology to facilitate experience reuse and decision explanation by retrieving the previous similar temperature profiles. Further, fuzzy technique is incorporated into the CBR system to handle vagueness, uncertainty inherently existing in clinicians reasoning as well as imprecision of feature values. A hybrid CBR system illustrated in [4] deal with the unstructured textual information along with the time series data in a clinical decision support in the stress medicine. The time series measurements and textual data capture the different yet complementary aspects of a subject with a desire to tackle more comprehensive situation awareness and thereby provide more reliable diagnosis and decisions.

10.The KASIMIR project [20] [*Purpose: Diagnosis, Classification, Knowledge acquisition/ management*], is an effort to provide decision support for the breast cancer treatment based on a protocol in Oncology. It focuses on the adaptation of the protocol in order to provide the therapeutic decisions for the cases those are out of the protocol. The authors implement an adaptation protocol that depends on a revision operator. The conservative protocol adaptation to a new case provides a consistency between the domain knowledge and the target case. Also, the system [18] stresses particularly on the importance of the proper management of the domain knowledge to avoid wrong decisions. The analysis of that failure adds as a new dimension of knowledge into the domain knowledge which enables automatic evolution of the knowledge into the system.

11.The Mémoire Project [8] [*Purpose: Diagnosis, Planning, Knowledge acquisition/ management, Tutoring*], at the University of Washington, offers a framework to exchange case bases and the CBR systems in biology and medicine.

It is an effort to apply semantic web approach in biomedical domain. Mémoire uses OWL representation language to make the case bases interoperable. A number of the researches have been taken place [9, 12] in the Mémoire project to validate the different roles of the prototypical cases. In [10] the author deals particularly with the prototypical cases, where the prototypical cases act as maintenance cases by keeping the knowledge up-to-date with the rapid development in the biomedical domain. The author argues that this maintenance prototypical case can be generated by mining from the medical literatures which could in turn lead to building and maintaining of case bases in an autonomous way in the medical domain. The project explores prototypical cases and how they can serve in various ways in a CBR system for example, maintenance of memory, maintenance of knowledge, management of reasoning and bootstrapping a case base. Bichindaritz have developed several other systems that addresses the issues related to prototypical cases in the biomedical domain such as, ProCaseMiner [9] that automatically builds the initial case base.

12.RHENE [34, 35] [*Purpose: Classification, Planning, Knowledge acquisition/ management*], is a case-based system in the domain of nephrology for the management of that end stage renal disease patients treated with hemodialysis. It mainly concentrates on the retrieval of the patterns of failure over time and allows the physician to analyze the solution within and between the patients. RHENE assists to look for the consistency of a prescribed therapy plan to a proposed dialysis session and provides an assessment for the treatment efficacy. Each dialysis session is represented as a case in which static features characterize a patient and dynamic features are collected from the time series measurement. A case-based architecture is further described in [31] for the parameter configuration of the temporal abstractions on time-series data to reduce the dimensionality of the feature and is exploited into the RHENE system.

13.Somnus [29] [*Purpose: Diagnosis, Planning, Tutoring*], is a prototype implemented in the domain of Obstructive Sleep Apnea (OSA). 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 diagnosis and treatment process on a case by retrieving cases similar to a current case. The case base comprises 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 semiotic approach is used for the modeling of their measurements.

14. SISAIH [20] [*Purpose: Diagnosis*], is a decision support tool that assists in the decision making process to the hospital admission authorities in the Brazilian health public system. It helps to manage admission of the patients in a hospital, handles patients billing errors and medical procedures i.e. in general, performs managerial job. Each case contains the expert's knowledge to solve a problem. So 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 and makes the process more accurate.

15. SIDSTOU [39] [*Purpose: Diagnosis, Planning, Tutoring*], is an intelligent tutoring CBR system for providing the medical education on Tourette syndrome. It works as a tool for diagnosing the Tourette syndrome and could help to minimize the need of 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 comparing with an expert of the domain shows the reliability of the system.

16. Ahmed et al. [3] [*Purpose: Planning*], proposes a three phase sensor-based biofeedback decision support system to provide treatment for the stress-related disorders. A CBR framework is deployed to classify a patient, estimate the initial parameters and to make recommendations for the biofeedback training. Fuzzy techniques are incorporated into the system to better accommodate the uncertainty in clinicians reasoning as well as in decision analysis. The biofeedback training is most of time guided by an experienced clinician and the results largely rely on the clinician's competence. The intention of the system is to enable a patient to train himself/herself without any particular supervision.

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 is classifying 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. Although the hypothesis has not yet been established clinically the intention is to assist as a second option for the clinicians who have currently using multi-source system to diagnose ADHD. The paper exploits an iterative refinement strategy during the knowledge acquisition step to achieve a satisfactory performance in terms of the 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 focusing on the explanation in decision making. The system provides recommendations based on the precedent cases. Besides this, explanatory text imparts the supporting and non-supporting aspects of a selected case as well as indicates the level of confidence in the prediction. The CBR system is evaluated at the Kern Medical Center and the result shows that the recommendation with explanation is rather useful for the medical professionals in making the decision.

19.O'Sullivan et al. [40] [*Purpose: Diagnosis*] develop a case-based decision support system by exploiting patients' electronic health records delivered through the wireless networks. It allows a user to electronically input and compare the patient records. The system facilitates knowledge sharing in the domain and allows 'remote-access health-care'. The cases are represented in multimedia data format which contains a patient information i.e. medical image, annotations, endoscopies, and physician's dictations. Contextual expert knowledge for the relevant cases is also stored into the case base of the encapsulated patient cases. Cases consist of the textual features. Textual indices generated from each of the constituent features are used 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 daily management of the patients with Type 1 diabetes on insulin pump therapy [32]. It considers real-time monitor of patients' blood glucose level along with their life-style factors in adjusting patient-specific insulin dosage. It reduces the cumbersome manual review process for a physician in proving 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 the 20 patients articulates the potential applicability of CBR in managing diabetes on insulin pump therapy.

21.Song et al. [*Purpose: Planning*] propose a system in radiotherapy for the dose planning in prostate cancer [47]. The system able to adjust the appropriate radiotherapy doses for an individual while, at the same time, reduces the risks of possible side effects of the treatment. The system is implemented in cooperation with the City Hospital at the Nottingham University Hospital. The matching between cases applies the fuzzy similarity measurement to incorporate the experts' knowledge in retrieving the past similar experiences. Dempster-Shafer theory is introduced to fuse multiple cases in order to recommend a particular dose plan for a case, when in a real-world situation several retrieved similar cases provide different treatment solutions.

22.Wu et al. [52] [*Purpose: Knowledge acquisition/ management, Planning*], present a CBR framework based on NutriGenomics knowledge by considering person's genetic variation i.e. individual gene expression to provide personalized dietary counseling. Genetic variation of a person has an impact on the person's response to a 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 applying the data mining technique and represented in a form of ontologies. A distributed case base allows the system to save this knowledge, and generates new cases automatically if necessary, using a Case Builder based on this stored knowledge.

23.Zhuang et al [53] [*Purpose: classification and Knowledge acquisition/ management*] describe an intelligent decision support system (DSS) for the pathology ordering by the general practitioners. The authors integrate data mining and case-based reasoning approach to get effective decision support that facilitate 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 algorithm to improve the system's performance. It applies genetic algorithm (GAs) into the system to optimize the 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 in the chronic disease diagnosis and prognosis. Data mining, decision tree induction algorithms are applied to mine out a set of rules in the knowledge creation phase for the chronic disease prognosis. The four chronic diseases- stroke, cardiopathy, hypertension, and diabetes mellitus data are investigated by the authors.

26.Chang [16] [*Purpose: Diagnosis*] use diagnosis screening to determine children with development delay. The system applies case-based reasoning. It considers the language and communication, motor skills, sensory and cognitive development of a child to diagnose the development 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 process. Here, CBR is applied as a core component. The rule-based reasoning 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 CBR method. Depending on the strengths and weaknesses it could suggest to apply the current solution or to use alternative reasoning methods. 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 the melanoma cancer. The system applies CBR to facilitate experience reuse in the domain. It uses two melanoma diagnosis techniques based on the images in the domain. The pre-processed 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 result. The pre-processing algorithm generates a set of characteristics from the melanoma dataset. The result from the two individual CBR modules are then combined using the rules.

29.Töpel et al. [61][*Purpose: Diagnosis, Planning*] apply case-based reasoning in the diagnosis and therapy planning for the 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 pre-selection 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 CBR method in the biological domain. It uses three sets of datasets i.e. the ovarian mass spectrometry datasets, leukemia and lung microarray datasets. The author has argued that CBR is a suitable method for the application as it can function well when the domain theory is not clear enough as in the high dimensional biomedical domains. The system uses data mining and a logistic regression approach along with the CBR to improve the classification performance. The logistic regression helps to filter out the important features to define a case. The cases are also clustered in a similar group using the data mining technique. Thus, the system handles the so called 'curse dimensionality' problem in the biomedical domain.

31.Kurbalija V. [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 the beginner physicians and also could be used as a second option for the experts.

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

33.CBSMS [65] [*Purpose: Diagnosis, classification, planning*] addresses a multi-modal and multipurpose-oriented clinical decision support system for the stress management. The system, for the stress management, is not only based on the finger temperature sensor data but also considers contextual information i.e. human perception and the feelings in a textual format. It applies case-based reasoning as a core technique to facilitate experience reuse and decision explanation by retrieving the previous similar temperature profiles. The reliability of the diagnosis and decision making tasks into the system is further improved by using the textual information retrieval (IR) with ontology. Further, an effort has been made to enhance the performance of the stress diagnosis task when there is limited number of initial cases into the case library. A fuzzy rule-based classification scheme is introduced into the CBR system to cope with this problem. Another important goal is to assist a clinician to the treatment procedure. A three phase computer-assisted sensor-based DSS is proposed here for the biofeedback training in stress management.

34.HDCU [66] [*Purpose: classification and Knowledge acquisition/ management*] is a hybrid system that combines data mining, user modeling and case-based reasoning in order to achieve a fast, dynamic, reliable, personalized blood glucose level prediction for the diabetic patients. Support vector machine (SVM) is also introduced in this system to analyze the patient data i.e. for finding the patterns and regularities in the data sets.

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