A Three Phase Computer Assisted Biofeedback Training System Using Case-Based Reasoning

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Abstract. Biofeedback is a method gaining increased interest and showing good results for a number of physical and psychological problems. Biofeedback training is mostly guided by an experienced clinician and the results largely rely on the clinician's competence. In this paper we propose a three phase computer assisted sensor-based biofeedback decision support system assisting less experienced clinicians, acting as second opinion for experienced clinicians. The three phase CBR framework is deployed to classify a patient, estimate initial parameters and to make recommendations for biofeedback training by retrieving and comparing with previous similar cases in terms of features extracted. The three phases work independently from each other. Moreover, fuzzy techniques are incorporated into our CBR system to better accommodate uncertainty in clinicians reasoning as well as decision analysis. All parts in the proposed framework have been implemented and primarily validated in a prototypical system. The initial result shows how the three phases functioned with CBR technique to assist biofeedback training. Eventually the system enables the clinicians to allow a patient to train himself/herself unsupervised.

1. Introduction

Biofeedback is an area of growing interest in medicine and psychology and it has proven very efficient for a number of physical, psychological and psychophysical problems [1][11]. Biofeedback is today often carried out with instructions from an experienced clinician and in some patient populations it may even be hazardous without supervision following the process. The basics of biofeedback is that the patient gets feedback in a clear way (patient observes the graph and know from preceding education how it should change) and with this feedback can train the body and/or mind to biologically respond in a different better way. In the physical context (Normal life situations) an example is relaxation and how the patient can practice relaxation while observing the changes in skin temperature. This change in temperature reflects in 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. This increase in the peripheral blood in turn results in increased blood flow which in turn increases the skin temperature. A further example is nearsightedness, where a laser measures the distance between the surface of the lens and the retina. When the patient is able to clench the eye-mussels to reduce/increase the nearsightedness, the system gives feedback based on this biological information. A patient can severely reduce or even eliminate nearsightedness.

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 a computer assisted sensor-based system for the biofeedback training using biomedical signals. A case study of the proposed system is investigated in stress treatment using the finger temperature. The paper addresses three key phases for the biofeedback training applying CBR as a core technique. Fuzzy logic is applied in decision analysis and similarity matching between cases. 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. 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.

This chapter followed by a subsection where related research work is presented. In chapter 2 the general framework and a case study of a computer based system is presented. Section 3 presents the sensor signals abstraction and the case matching techniques. In section 4 the case retrieval and several strategies of decision analysis is explained. Finally, the paper ends with chapter 5 where a summary of the paper and its contributions are given.

1.1 Related work

In our previous work [3], a stress diagnosing system using CBR has been designed based only on the variation of the finger temperature measurements. In the earlier research [4][5] 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. The current paper proposes a three-phase CBR system for biofeedback treatment to control psycho-physiological problems, e.g. stress. A procedure for diagnosing stress-related disorders has been put forward by Nilsson et al. [15]. In [19] authors have applied artificial neural networks (ANNs) to give biofeedback of the success of muscle coordination to improve sporting performance. Schröder et al. [18] for biofeedback training of patients with Epilepsy, have classified EEG signals using ANNs. To our knowledge, the system proposed in this paper is an initial attempt to apply CBR in biofeedback training. Some other related research works in the medical domain using CBR are: MNAOMIA [6] has been developed for the domain of psychiatry. CARE-PARTNER [7] is a decision support system developed in stem cell transplantation. Auguste [12] project has been developed for diagnosis and treatment planning in Alzheimer's disease. Montani et al. [14] has combined case-based reasoning, rule-based reasoning (RBR), and model-based reasoning to support therapy for diabetic patients. In [17] 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 [16] has proposed and evaluated a method to identify spores in digital microscopic images. BOLERO [10] is a successfully applied medical CBR diagnosis system in diagnosing pneumonias which applies fuzzy set theory for representing uncertain and imprecise values.

2. Computer Assisted Biofeedback

As mentioned in the earlier chapter biofeedback is used for many medical areas today. After discussion with clinicians many 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 biofeedback session, 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. The clinician normally asks a number of questions and makes a number of more or less systematic measurements/calculations and then decides for a patient classification. In second phase a number of measurements have to be made to find out parameters needed to tailor the biofeedback session to a patient in order to achieve as good results as possible. A computer based biofeedback system can either be a decision support system for the clinician, or be a second opinion for an expert, used with on-line supervision. In figure 1 the 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 biofeedback session does not follow the expected route, reclassification of the patient may be necessary or adjustment of biofeedback parameters.

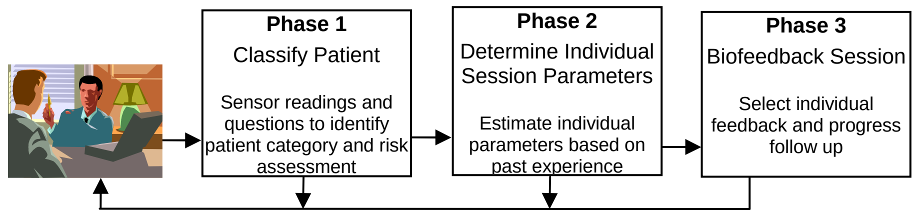

Fig. 1. A sensor and computer based biofeedback system with 3 phases, patient classification, parameter estimation and biofeedback session. All three sessions also give input to improvement of classification/parameters.

2.1 Case Study, Biofeedback for Treatment of Stress-Related Problems

In figure 2 we give an overview on how computer-assisted biofeedback is used in stress treatment. Finger temperature (FT) measurement is an effective biofeedback parameter [9][13] for self regulation training. In each phase, FT is taken though a protocol and a new problem case is represented using the features extracted from these FT measurement. In each phase, CBR approach is applied to predict solutions for a new problem referring to the solution of the similar and useful problems where the matching between the attribute values of two cases are performed employing the fuzzy similarity matching algorithm.

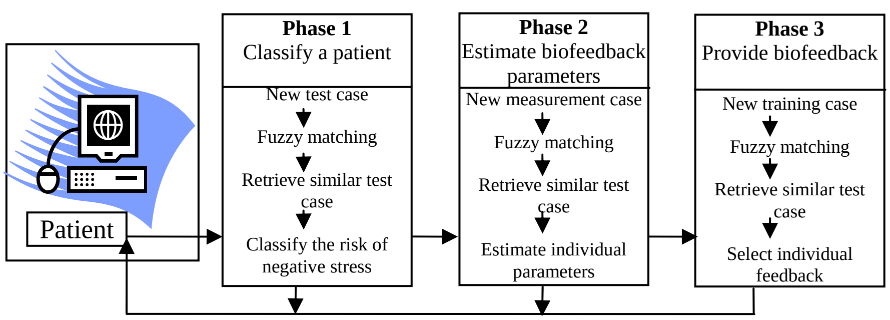

Fig. 2. An example of a sensor and computer-assisted biofeedback system in stress treatment

Individual capability to cope with stress is important to know before a biofeedback session in stress treatment. As can be seen from figure 2, phase one 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. Phase 2 deals with the parameter estimation which is a pre-requirement to biofeedback training. Finally, phase 3 generates recommendations for the biofeedback training. Sensor-signal abstraction, case-based reasoning and fuzzy logic are used in these phases described in more details in the next sections.

2.1.1 Classify a 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. Normally often patients have to start filling in a questionnaire on their life circumstances, medical problems, eating, sleeping and working circumstances. In phase 1, a patient is first 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.

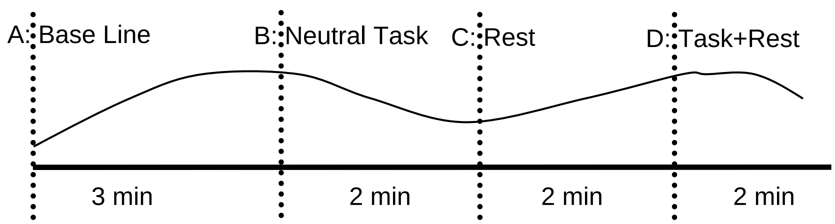

Fig. 3. A test protocol for patient's relaxation capacity using finger temperature

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 retains 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.

2.1.2 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 lay above his/her baseline temperature and decreases 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. Phase 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.

2.1.3 Biofeedback session

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 phases, 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 that an efficient biofeedback session can be carried out.

The final phase in figure 2 is the biofeedback training; this training time is flexible, which means 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.

3. Case matching and sensor-signal abstraction

This chapter describes the sensor-signal abstraction and case matching which is a common task for all the three phases illustrated in figure 2. The retrieval step is especially essential in medical applications since missed 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. So, matching between two cases plays a vital role in the CBR system. The Nearest-Neighbor (NN) method is a common matching technique in most CBR systems. In the proposed system, similarity measurement is taken to assess the degrees of matching applying the standard NN as a global similarity algorithm [20] [4] [5]. The local weight defined by the domain expert is normalized [4], assumed to be a quantity reflecting importance of the corresponding feature. The local similarity function is applied with a combination of the expert-defined similarity matrix [5] and fuzzy similarity matching [4] [8]. 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 [5]. The proposed system prefers to apply fuzzy similarity matching for the sensor-signal abstraction (i.e. numerical values) evaluating three different matching algorithms [2] and for symbolic values (such as gender, before/after lunch and so on) it uses the expert-defined similarity matrix. Here the fuzzy similarity matching helps to reduce the sharp distinction and avoid multiple rules in implementing the expert-defined similarity matrix.

3.1 Sensor-signal abstraction

Appropriate features are extracted abstracting a sensor signal and help to represent a case in CBR system. Representation of a case is often of great importance in performing accurate matching. The FT sensor measurements are recorded using software which provides filtered data to the system. The signal data for each phase (see figure 2) are then stored in a file in the local device and exported to the system. From the exported file of phase 1, the system retrieves 9 minutes temperature measurements (time, temperature) in 2160 samples. For phases 2 and 3 finger temperature measurements are extracted within 480 samples.

After analyzing a number of finger temperature signals, it is 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 gives 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. Phase 1 is divided into 9 parts with one minute time intervals and each part contains 240 samples data (time, temperature). Phase 2 and 3 are divided into 4 parts with 30 seconds interval where each part contains 120 samples data in time against temperature. First, a slope of the linear regression line has been 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.

$$slope_f = \frac{\sum_{i=0}^{n}(x-\bar{x})(y-\bar{y})}{\sum_{i=o}^{n}(x-\bar{x})^2} \quad \textbf{(1)}$$

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 [2]. The system thereafter formulates a new problem case using sensor-signal abstractions and then the new case is applied in the CBR cycle.

4. Case retrieval and decision analysis

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 decision making depends on the storage of good cases/experiences and on the ability to retrieve all relevant cases and their ranking. Generally most CBR systems retrieve a subset of cases from the case base by using *KNN* (*k* nearest neighborhoods) or a specified similarity threshold [14]. 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.

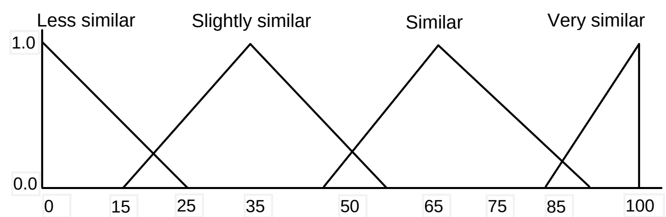

Fig. 4. Fuzzy sets for similarity values. X-axis represents the degrees of membership function and Y-axis represents the similarity values in percentage

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 phase 1 and phase 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.

However, Phase 2 is different from phase 1 and phase 3, as the parameter estimation is a regression problem in this phase. 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, two retrieved cases have 28 C and 30 C as their ceiling points, by simply averaging both; system can get 29 C as the estimated ceiling point for a new patient. C) Weighted average, 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.

5. Summary and conclusions

This paper has outlined a computer-based system for biofeedback training using biomedical signal to assist a clinician. A case study to stress management utilizing the finger temperature sensor readings is presented in this paper. CBR is working separately in each phase and finally the integration of them recommends biofeedback training for stress treatment. The main contributions of the paper are: a three phase CBR framework to construct a general biofeedback training procedure from classification of a patient, and estimate the preliminary parameters to the training session; sensor signal abstraction i.e. extracted important features from signal data and formulation of a case for CBR cycle; a multi-objective decision making procedure using fuzzy logic and fuzzy clustering; and multi-strategy to parameter estimation.

The method of case-based reasoning is employed to classify a patient, estimate initial parameters and to make recommendations for biofeedback training by retrieving and comparing with previous similar cases in terms of features extracted. Moreover, fuzzy techniques are incorporated into our CBR system to better accommodate uncertainty in clinicians reasoning as well as decision analysis. All such ideas have been implemented and primarily validated in a prototypical system. The initial result shows how the three phases functioned with CBR technique to assist proper biofeedback training. Additionally, it reduces the set up time i.e. time for classification of a patient and initial parameter estimation to start a biofeedback training session and also limit the time involvement of the clinicians which allows a patient to train himself/herself in everyday life for health reasons.

References

1. AAPB, The Association for Applied Psychophysiology and Biofeedback http://www.aapb.org/i4a/pages/index.cfm?pageid=3336 (June 2008)

2. Ahmed, M., Begum, S., Funk, P., Xiong, N., Scheele, B. V.: Case-based Reasoning for Diagnosis of Stress using Enhanced Cosine and Fuzzy Similarity, Proceedings of the International Workshop on Case-Based Reasoning on Multimedia Data CBR-MD 2008, Leipzig Germany, July, (2008)
3. Begum, S., Ahmed, M., Funk, P., Xiong, N., Scheele, B. V.: Using Calibration and Fuzzification of Cases for Improved Diagnosis and Treatment of Stress, The Proceedings of the 8th European Workshop on Case-based Reasoning, (2006) 113-122.
4. Begum, S., Ahmed, M., Funk, P., Xiong, N., Scheele, B. V.: Classify and Diagnose Individual Stress Using Calibration and Fuzzy Case-Based Reasoning. In proceedings of 7th International Conference on Case-Based Reasoning, Edited by Weber and Richter, Springer, Belfast, Northern Ireland, (2007) 478-491.
5. Begum, S., Ahmed, M., Funk, P., Xiong, N., Scheele, B. V.: Individualized Stress Diagnosis Using Calibration and Case-Based Reasoning. In Proceedings of the 24th annual workshop of the Swedish Artificial Intelligence Society, Borås, Sweden, Editor(s):Löfström et al., May, (2007) 59-69.
6. Bichindaritz, I.: Mnaomia: Improving case-based reasoning for an application in psychiatry. In Artificial Intelligence in Medicine: Applications of Current Technologies, AAAI (1996) 14–20.
7. Bichindaritz, I., Kansu, E., Sullivan, K.M.: Case-based reasoning in care-partner: Gathering evidence for evidence-based medical practice. In Advances in CBR: The Proceedings of the 4th European Workshop on Case Based Reasoning (1998) 334–345.
8. Dvir, G., Langholz, G., Schneider, M.: Matching attributes in a fuzzy case based reasoning. Fuzzy Information Processing Society, (1999) 33–36.
9. Healey J.A. and Picard R.W., "Detecting Stress during Real-world Driving Task using Physiological Sensors", *Intelligent Transportation System, IEEE Trans*, , Vol. 6, No. 2, June (2005) 156-166.
10. Lopez, B., Plaza, E.: Case-based learning of strategic knowledge Machine Learning EWSL-91, Lecture Notes in Artificial Intelligence, ed Kodratoff, Springer-Verlag (1993) 398-411
11. Lehrer M. P. et al. Respiratory Sinus Arrytmia Biofeedback Therapy for Asthma: A report of 20 Unnnmedicated Pediatric Cases Using the Smetaniknnnn Method. Applied Psychophysiology and Biofeedback, 25(3): (2000) 193-200.
12. Marling, C., Whitehouse, P. Case-based reasoning in the care of Alzheimer's disease patients. In Case-Based Research and Development, (2001) 702–715.
13. Mason L.J., "Control Symptoms of Stress with Temperature Training Biofeedback", EzineArticles, , *available* at http://ezinearticles.com/?Control-Symptoms-of-Stress-with-Temperature-Training-Biofeedback&id=90394, June, (2008).
14. Montani, S., Magni, P., Roudsari, A.V., Carson E.R., Bellazzi R., Integrating different methodologies for insulin therapy support in type 1 diabetic patients, 8th Conference on Artificial Intelligence in Medicine in Europe (AIME 2001), (2001) 121-130.
15. Nilsson, M., Funk, P., Olsson, E., von Schéele, B.H.C., Xiong, N.: Clinical decision-support for diagnosing stress-related disorders by applying psychophysiological medical knowledge to an instance-based learning system. Artificial Intelligence in Medicine, , (2006) 36:159-176.
16. Perner, H., Jänichen, S.: Recognition of Airborne Fungi Spores in Digital Microscopic Images, Journal Artificial Intelligence in Medicine AIM, Special Issue on CBR, Volume 36, Issue 2 , February (2006)137-157.
17. Perner, P.: An Architeture for a CBR Image Segmentation System, Journal on Engineering Application in Artificial Intelligence, Engineering Applications of Artificial Intelligence Vol. 12 (6), (1999) 749-759.

18. Schröder, M., Bogdan, M., Rosenstiel, W., Hinterberger, T., Strehl, U., Birbaumer, N.: Online classification of EEG signals using artificial neural networks for biofeedback training of patients with epilepsy, international workshop on systems, signals and image processing , Manchester, (2002) 438-446.
19. Verma, B. and Lane, C.: A Neural Network Based Technique for Muscle Coordination and Vertical Jump Height Prediction, *In* Proceedings of the IEEE International Joint Conference on Neural Networks, vol.3 (1998) 2163-2168.
20. Xiong, N., and Funk, P.: Learning similarity metric reflecting utility in case-based reasoning, Journal of Intelligent and Fuzzy Systems, 17 (2006) 407-416.