Diagnosis and biofeedback system for stress

S. Begum, M. U. Ahmed, P. Funk, N. Xiong, B.v. Scheele, M. Linden, and M. Folke

Abstract—**Today, everyday life for many people contain many situations that may trigger stress, or result in an individual living on an increased stress level under long time. High level of stress over time may cause serious health problems. It is known that respiratory rate in terms of hyperventilation (defined as low pCO_2) is an important factor and can be used in diagnosis of stress related dysfunctions and also for biofeedback training, but available measurement of respiratory rate and its metabolic consequences are not especially suitable for home and office use.**

The aim of this project is to develop a portable sensor system that can measure the stress level, during everyday situations e.g. at home and in work environment and can help the person to change the behavior and decrease the stress level. The sensor explored is a finger temperature sensor. Finger temperature reflects changes in sympathetic nervous system (SNS) and not hyperventilation but as SNS is an important marker of stress it is highly relevant. Clinical studies show that finger temperature, in general, decreases with stress and increase with relaxation; however this changed pattern shows large individual variations. Diagnosing stress level from the finger temperature is difficult even for clinical experts. Therefore a computer-based stress diagnosis system is important. In this system, case-based reasoning and fuzzy logic have been applied to assist in stress diagnosis and biofeedback treatment utilizing the finger temperature sensor signal. An evaluation of the system, comparing it with an expert in stress diagnosis shows promising result.

I. Introduction

TODAY, daily life for many people contain many situations that may trigger stress or result in an individual living on an increased stress level under long time. It is known that high level of negative stress may cause serious health problems. There are conventional methods to diagnose stress such as, respiration e.g. end-tidal carbon dioxide and respiratory rate, heart activity e.g. calculating the respiratory sinus arrhythmia and/or heart rate variability [1]. Correct respiration (alternative respiratory behaviour) can help the person to relax as well as calm breathing behaviours can prevent pronounced stress reactions. Measure of the respiratory rate or end tidal carbon dioxide will give a direct measurement of the breathing. This kind of measurement usually depends on the use of complex equipment, which also is close to the air ways, which often is unsuitable in home or office environment.

Finger temperature (FT) is a direct measurement of relaxation in terms of decrease of sympathetic activity but gives no direct information/feedback of respiratory rate but, as we show in this paper, contains information on how a person's physiological stress level changes. This enables new methods for low cost diagnosis and biofeedback treatment of stress to be developed. Clinical studies show that FT, in general, decreases with stress [2]. The pattern of variation within a FT signal could help to determine stress-related disorders.

However, the FT sensor signal is so individual and interpreting a particular curve and diagnosing stress level is difficult even for experts in the domain.

In practice, it is difficult and tedious for a clinician and particularly less experienced clinicians to understand, interpret and analyze complex, lengthy sequential measurements in order to make a diagnosis and treatment plan.

Therefore, the aim of this project is to design and evaluate a portable computer-based stress diagnosis system that can be used by people who needs to monitor their stress level frequently e.g. at home and at work for stress prevention. The system applies case-based reasoning (CBR) and combines fuzzy logic into the CBR to assist the clinician in stress diagnosis and treatment employing the FT sensor signal.

The CBR methodology is often used to solve new problems based on learning from similar cases stored in a case library, obtained by remembering a previous similar situation. The approach is inspired by a cognitive model on how humans sometimes reason when solving problems. Aamodt and Plaza introduce a life cycle of CBR [10] with four main steps: Retrieve, Reuse, Revise and Retain to implement such kind of cognitive model. CBR for health science is today both a recognized and well established method [3]-[9]. It has been applied successfully when the domain theory is not clear enough or even incomplete. The reasoning process is gaining an increasing acceptance in the medical field since it has been found to be suitable for decision making tasks e.g. diagnosis, and treatment [3]-[6], [11] in this area.

II. The System

The system consists of a FT sensor, thermistor, and an electronic circuit board, which through an USB-port is connected to a computer. The sensor is attached to a finger on a patient/subject, sensing the FT [12].

The system provides assistance for the person to relax using music and instructions to control the breathing. A

Manuscript received December 11, 2009.

S. Begum is working at the School of Innovation, Design and Engineering, Mälardalen University. Box 883, SE-721 23 Västerås, Sweden (corresponding author e-mail: shahina.begum@ mdh.se).

M. U. Ahmed, P. Funk, N. Xiong, B.v. Scheele, M. Linden, and M. Folke are with the School of Innovation, Design and Engineering, Mälardalen University. Box 883, SE-721 23 Västerås, Sweden (e-mail: firstname.lastname@ mdh.se).

calibration phase [13] helps to establish an individual stress profile and is used as a standard protocol in the clinical environment. For calibration purpose the FT is measured during different conditions in 6 steps (baseline, deep breath, verbal stress, relax, math stress, relax). The Baseline may be seen as indicating the representative level for the individual when he/she, at best, is neither under strong stress nor in a relaxed state, that is relatively not stressed. For subjects with a chronic physiological stress level it is expected to be their most non-stressed level. 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 relaxed state. Also how quickly the changes occur during this step is relevant and recorded together with observed fluctuations. The step Verbal-stress is initiated with letting the person tell about some salient stressful events they experienced in life. During the second half of the step the person thinks about the same or some negative stressful events in his/her life. In the Relax step, the person is instructed to think about something positive while breathing relaxed. The Math-stress step tests the person is requested to count backwards. Finally, the relaxation step tests if and how quickly the person recovers from stress.

Fig. 1 illustrates the examples of the FT changes during the calibration phase.

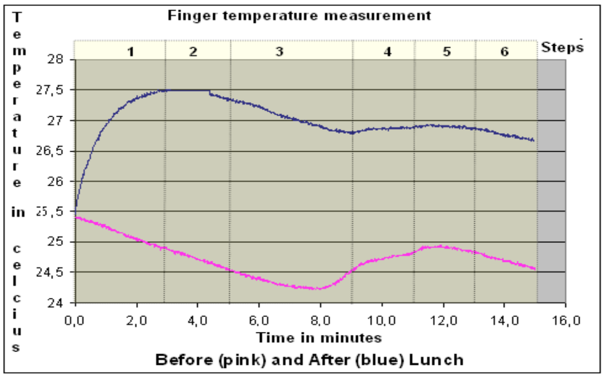

Fig. 1. Samples of finger temperature measurements to illustrate the variations during the six steps. Y-axis: temperature in degree Celsius and X-axis: time in minutes. It shows one person with typical response before (low temperature level) and after lunch (high temperature level)

It can be observed from Fig. 1, in step 3 during the verbal-stress condition, that FT decreases and during the relaxed condition (step 4) FT increases. This relates to the sympathetic intervention of the alpha-receptor in the vascular bed. When relaxation occurs, SNS activity decreases as well as the intervention of the alpha receptors which in turn increases the diameters in the blood vessels and increases the blood flow and the temperature.

Stress responses are different for different persons and so is the coping capability. Individual capability to cope with stress is important information to judge the harm of an identified stress level. A patient can be classified depending on the stress reactivity and her/his capacity/recovery of stress.

The proposed computer-based stress diagnosis system applied CBR and fuzzy logic to assist in diagnostic, classification and biofeedback treatment. The system performs several steps to diagnose individual sensitivity to stress as shown in Fig. 2

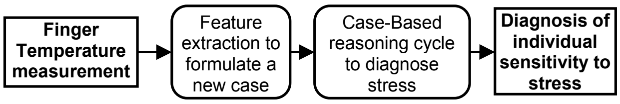

Fig. 2. Schematic diagram of the steps in stress diagnosis

The proposed CBR system takes the FT measurement as an input. Then it identifies the essential features and formulates a new problem case with the extracted features in a vector. This new problem case is then fed into the CBR cycle to retrieve the most similar cases. The case (i.e. feature vector extracted from FT signal) in this system is matched using different matching algorithms including *modified distance function*, *similarity matrix* and *fuzzy similarity matching* (see the dotted area in Fig. 3). The system [14] can provide matching outcome in a sorted list of best matching cases according to their similarity values in three circumstances: when the case is matched with all the solved cases in a case base (between subject and class), within a class where the class information is provided by the user and also within a subject.

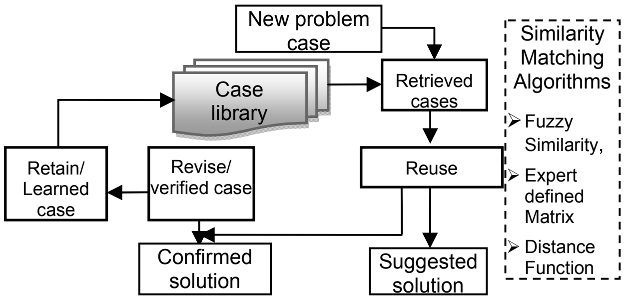

Fig. 3. Case-based reasoning cycle for stress diagnosis and treatment

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 the same as an old retrieved case. In the proposed system there is no adaptation of the cases. This adaptation could be done by clinicians in the domain. In the medical system, there is not much adaptation, especially in a decision support system where the best cases are proposed to the clinician as suggestions of solutions and when the domain knowledge is not clear enough [11]. 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 retain. Retaining of a new solved case could be done manually based on clinician's or expert's decision.

Similarly, for the biofeedback treatment procedure [15], [16] a cycle with several steps is considered. In this cycle, a patient/subject can see the changes of FT during several instructions in relaxation training. The FT measurements are performed in real time and in every 2 minutes the system evaluates the last 2 minutes measurement and if necessary generates instructions for the patient.

Similar CBR cycle shown in Fig. 3 is applied for the biofeedback training in stress management; this training time is flexible, which means a patient can choose duration of his/her training between 6 and 20 minutes [17]. Nevertheless, the system generates feedback with appropriate suggestions in every 2 minutes if necessary. Thus, for each individual, the biofeedback cases are formulated containing a feature vector from the 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 the previously solved cases by applying the fuzzy similarity matching algorithm. Then, the system displays the matching outcome as feedback. Here, the feedback is defined within 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 a 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 the physical and psychological condition of a patient.

III. METHOD

The performance of the FT system in terms of the accuracy has been compared with an expert in the domain where the main goal was to see how close the system could perform compared to the expert. The evaluation, in this paper, considers several test data sets to illustrate the overall system performance.

The initial case base comprises of 39 reference cases from 24 subjects (7 women and 17 men, age 24-51 yrs). A case, in the conditional or problem description part, contains a vector with the extracted features and the solution part consists of classification as diagnosis of stress. The levels of stress are defined by the expert into five classes ranging from 1 to 5 where 1=VeryStressed, 2=Stressed, 3=Normal/Stable, 4=Relaxed and 5=VeryRelaxed. For the experiment, 5 test groups (named as TG) are created. The groups consist of 5 to 14 numbers of cases: TG-A=5, TG-B=7, TG-C=9, TG-D=11 and TG-E=14. The cases in each group are selected randomly and classified by the expert. These formulated test cases are then used in the classification process of the CBR system.

After analyzing a number of FT signals, we find large individual variations, but also a similarity in the pattern that temperature decreases during stress and increases during relaxation for most people. That is an important feature that needs to be identified by an automatic classification algorithm searching for "similar" patients. During diagnosis, when performed manually, an experienced clinician often classify FT signal without being pointed out intentionally all the features he/she uses in the classification. However, extracting appropriate features is of great importance in performing accurate classification in a CBR system. Therefore, we need to extract important features from the FT sensor signal.

Together with clinicians we have agreed on a standardization of the slope to make changes visible which could provide a terminology to a clinician for reasoning about stress. The proposal is that, the X axis is defined in minutes and the Y axis in degrees Celsius (see Fig.1) hence a change during 1 minute of 1 degree gives a "degree of change" of 45°. A low angle value, e.g. zero or close to zero indicates no change or stable in FT. A high positive angle value indicates rising finger temperature, while a negative angle, e.g. -20° indicates falling FT. For the feature extraction, FT measurement from step 2 to step 6 of the calibration phase are considered. But step 1(the baseline), is not considered, since the step helps to stabilize the FT before starting the test. The clinician also agreed on this point. Each step in the calibration phase is divided in one minute time interval (e.g. 4 features are extracted from the step3 in 4 minutes) and each feature contains 120 sample data (time, temperature). Thus, 12 features are extracted from the 5 steps (step 2 to 6) and named as *Step2_Part1*, *Step2_Part2*, *Step3_Part1*, ………, *Step6_Part1*, *Step6_Part2*.

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

First, for each extracted feature, a slope of the linear regression line is calculated through the data points, as y is temperature (in degree Celsius) and x is time (in minute) by using (1). Where, f denotes the number of features (1 to 12), i is the number of samples (1 to 120) and $\bar{x},\bar{y}$ is average of the samples. After that, this slope value is converted to arctangent as a value of angle in radians (-*pi*/2 to +*pi*/2) and finally expressed arctangent value in degrees by multiplying 180/*PI* where *PI* is 3.14. So, these 12 features contain degree values comprising 120 sample data (time, temperature). Five other features which have also been extracted from the sensor signal are *start temperature* and *end temperature* from step2 to step6, *minimum temperature* of step3 and step5, *maximum temperature* of step4 and step6, and *difference between ceiling and floor*. Finally, seventeen features are extracted automatically from the fifteen minutes (1800 samples) FT sensor signal data.

IV. RESULTS

The results of the experiment for each test group are illustrated in Table I. In Table I, the first two columns present the name and the number of the cases for each test group. The classification of the cases in each group performed by the CBR system is then compared with the expert's classification. The *Goodness-of fit* (R^2) [18] and *absolute mean difference* (error) for the five groups are calculated and presented in Table I. The table shows, the R^2

values of all the sets are 0.94, 0.92, 0.67, 0.78 and 0.83 and error of the five sets are 0.20, 0.14, 0.33, 0.30 and 0.28. So, the average R^2 and error values of these sets are 0.83 and 0.25, respectively.

TABLE I
EXPERIMENTAL RESULTS FOR THE TEST GROUPS

Test Group	Number of Cases	Goodness-of-fit (R^2)	Absolute mean Difference
TG-A	5	0.94	0.20
TG-B	7	0.92	0.14
TG-C	9	0.67	0.33
TG-D	11	0.78	0.30
TG-E	14	0.83	0.28
Average	9.2	0.83	0.25

Again, a comparison for each group based on the number of the cases and correctly classified cases is shown in Fig. 4. Blue line presents the total number of the cases and red lines shows the number of the correctly classified cases for the groups. For each test group, the CBR system can correctly classify 80 %, 86 %, 78 %, 82 %, and 86 %. So, from Fig 4, it can be seen that the classification result on an average is 82% for all the five sets of the cases.

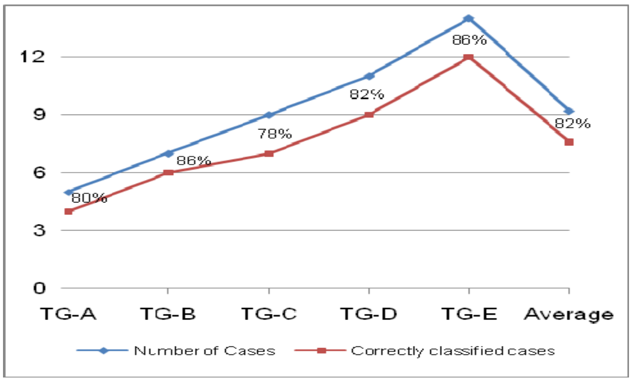

Fig. 4. Comparison results about the classification of the five test groups (i.e. TG-A, TG-B, TG-C, TG-D, TG-E and average of the all groups)

V. DISCUSSION AND CONCLUSION

The evaluation shows that the CBR system can classify a promising number of cases and only few cases are misclassified out of the total number of cases. Thereby we have shown that it is possible to reach near expert level performance of a decision support system based on case based reasoning for a problem even difficult for experts in diagnosing stress. It is crucial to understand what features an expert uses to see similarity between subjects. The development of the approach has also lead to experts more clearly seeing what features they use for classification which may lead to a standard procedure in diagnosis in future. Classification is also a key to biofeedback training since the feedback to the person training is needed. In a training situation it is not always essential that classification is 100 % correct since the exercises then will not lead to progress which means that other training may be needed. The approach is reliable enough for decision support for non experts, second opinion for experts and for use in biofeedback training.

The choice of FT instead of other sensor systems for diagnose of stress have the advantages that the sensor is stable and low cost.

REFERENCES

[1] http://www.adinstruments.com/solutions/research/Psychophysiology-Studies/ Last referred December 2009

[2] http://www.iworx.com/LabExercises/lockedexercises/LockedSkinTempNL.pdf, Last referred December 2009

[3] L. Gierl, and R. Schmidt, "CBR in Medicine. In Case-Based Reasoning Technology, From Foundations to Applications", Springer-verlag. Pp. 273 – 298. ISBN:3-540-64572-1. 1998

[4] R. Schmidt, S. Montani, R. Bellazzi, L. Portinale, and L. Gierl, "Cased-Based Reasoning for medical knowledge-based Systems", in *International Journal of Medical Informatics* 64 (2001) 355–367

[5] A. Holt, I. Bichindaritz, R. Schmidt, and P. Perner, "Medical applications in case-based reasoning", in *The Knowledge Engineering Review* 20(3) pp289-292, 2001

[6] I. Bichindaritz, and C. Marling, "Case-based reasoning in the health sciences: What's next?", in *Artificial Intelligence in Medicine*. 36(2) pp 127-135, 2006

[7] I. Bichindaritz, "Case-based Reasoning in the Health Sciences", in *Artificial Intelligence in Medicine* 36(2), 121-125, 2006

[8] S. Montani, "How to use contextual knowledge in Medical CBR Systems: a Survey on very recent trends", in *Workshop on CBR in the Health Sciences*, pp. 79-88 ECCBR'08

[9] I. Bichindaritz, "Case-based reasoning in the health Sciences: Why it matters for the Health Sciences and for CBR", in *9th European conference in CBR*, ECCBR'08. Pp 1-17

[10] A. Aamodt and E. Plaza E., "Case-based reasoning: Foundational issues, methodological variations, and system approaches." AI Communications, 7(1):39– 59, 1994.

[11] I. Watson, "Applying Case-Based Reasoning: Techniques for Enterprise Systems." Morgan Kaufmann Publishers CA 94104, USA, 1997.

[12] http://www.pbmsystems.se/system2/ft.asp. Last referred May 2009-05-15

[13] S. Begum, M. Ahmed, P. Funk, N. Xiong and B. V. Scheele, "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, pp 113-122

[14] S. Begum, M.U. Ahmed, P. Funk, N. Xiong, B.V. Schéele, "A case-based decision support system for individual stress diagnosis using fuzzy similarity matching", In *Computational Intelligence (CI)*, in press, 2009. Blackwell.

[15] J.A. Healey and R.W. Picard, "Detecting Stress during Real-world Driving Task using Physiological Sensors", *Intelligent Transportation System, IEEE Trans*, , Vol. 6, No. 2, June (2005) 156-166.

[16] L.J. Mason, "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).

[17] M.U. Ahmed, S. Begum, P. Funk, N. Xiong, B.V. Schéele, "A Three Phase Computer Assisted Biofeedback Training System Using Case-Based Reasoning", In *9th European Conference on Case-based Reasoning workshop proceedings. Trier, Germany* 2008

[18] C.H. CAROL, Goodness-Of-Fit Tests and Model Validity. Birkhäuser, 2002. ISBN 0817642099.