Classify and Diagnose Individual Stress Using Calibration and Fuzzy Case-Based Reasoning

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Abstract. Increased exposure to stress may cause health problems. An experienced clinician is able to diagnose a person's stress level based on sensor readings. Large individual variations and absence of general rules make it difficult to diagnose stress and the risk of stress-related health problems. A decision support system providing clinicians with a second opinion would be valuable. We propose a novel solution combining case-based reasoning and fuzzy logic along with a calibration phase to diagnose individual stress. During calibration a number of individual parameters are established. The system also considers the feedback from the patient on how well the test was performed. The system uses fuzzy logic to incorporating the imprecise characteristics of the domain. The cases are also used for the individual treatment process and transfer experience between clinicians. The validation of the approach is based on close collaboration with experts and measurements from 24 persons used as reference.

1 Introduction

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. It is known that high level of stress may cause serious health problems. Different treatments and exercises can reduce this stress. Since one of the effects of stress is that the awareness of the body decreases, it is easy to miss signals such as high tension in muscles, unnatural breathing, blood-sugar fluctuations and cardiovascular functionality. It may take many weeks or months to become aware of the increased stress level, and once it is noticed, the effects and unaligned processes, e.g. of the metabolic processes, may need long and active behavioural treatment to revert to a normal state [25]. For patients with high blood pressure and heart problems high stress levels may be directly life-endangered. A system determining a person's stress profile and potential health problems would be valuable both in a clinical environment as second opinion or in a home environment as part of a stress management program.

A well known fact is that finger temperature has a correlation with stress for most people, but large individual fluctuations make it difficult to use a traditional diagnosis system. In this paper we propose a system that uses case-based reasoning (CBR) and fuzzy logic along with a calibration phase. CBR [1, 9] is a method based on learning

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from similar cases and since this is spread practiced in clinical work, it is a method readily accepted by many clinicians. The calibration phase helps to determine a number of parameters that are important inputs both for a clinician to make the final diagnosis and treatment plan and also for the following system to classify the severity of the current stress level and makes a prognosis of its development so counter measures and treatment can be chosen.

2 Background

2.1 Stress Medicine

Psycho-physiology addresses the relation between psychology and physiology. Stress medicine is a branch of Psycho-physiology where the treatment of stress-related dysfunctions is studied. In psychology stress is defined as a condition caused by different factors in which human beings are inclining to change the existing normal stable state. When we react to certain events or facts it may produce stress. Stress may in worst case cause severe mental and physical problems that are often related to psychosomatic disorders, coronary heart disease etc. [24].

2.2 Establishing a Person's Stress Profile

We will give a brief description of the standard procedure followed by the clinicians to establish a person’s stress profile without going into clinical details, and only give a general understanding of the test procedure. Measurement of the finger temperature is taken using a temperature sensor connected to a computer during stress conditions as well as in non-stressed (relaxed) conditions as shown in fig.1.

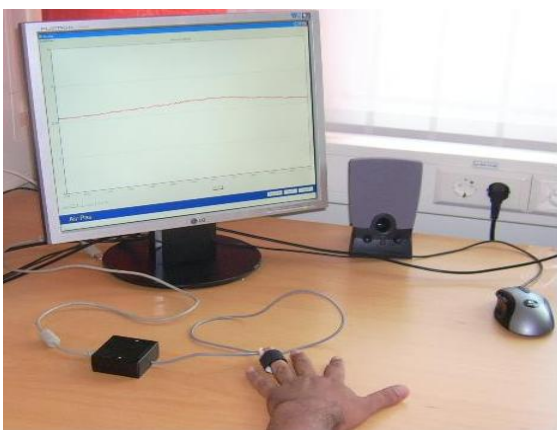

Fig. 1. Taking finger temperature measurement using a temperature sensor

Adjustments before starting the test conditions are achieved under the base-line measurement conditions, by securing a stable room temperature and allowing time for a person to adjust from the outdoor temperature (if the person has been outside recently). Thus it allows a person to stabilize the hand temperature and then temperatures are measured following a standard procedure (table 1).

Table 1. Measurement procedure used to create an individual stress profile

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

Step1 may be seen as indicating the representative level for the individual when he/she is neither under strong stress nor in a relax state. Sometimes clinicians let the person to read a neutral text during this step. A clinician not only identifies an individual's basic finger temperature, but also notes fluctuations and other effects, e.g. disturbances in the environment or observes person's behaviour.

During step2 the person breaths deeply which under guidance normally causes a relax state. Also how quickly the changes occur during this step is relevant and recorded together with observed fluctuations.

Step 3 is initiated with letting a person tell about some stressful events they experienced in life. It is important for the clinician to make sure that this really is a stressful event, since some persons instead select some more neutral event or tell about a challenge they were excited to solve. During the second half of the step a person thinks about some negative stressful events in his/her life.

In step 4, the person may be instructed to think of something positive, either a moment in life when he was very happy or a future event he looks forward to experiencing (this step may be difficult for a depressed person and adjusted accordingly by the clinicians).

Step 5 is the math stress step; it tests the person's reaction to directly induced stress by the clinician where the person is requested to count backwards.

Finally, the relaxation step tests if and how quickly the person recovers from stress.

2.3 Materials and Methods

Finger temperature is measured by attaching a temperature sensor to the little finger. The signal from the sensor contains the pattern of the finger temperature during different stress and relaxed conditions. An example of the finger temperature measurements is shown in fig. 2 demonstrating the variations on finger temperature.

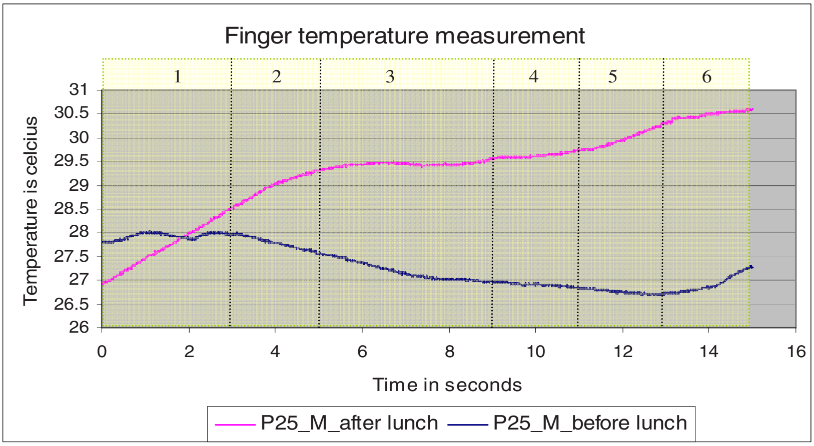

Fig. 2. Variations on finger temperature before and after lunch

Clinical studies show that when talking about any stressful events/experience finger temperature decreases and in extreme cases it decreases up to 5 to 10 degrees of Celsius. Recalling a minor misunderstanding could even decrease the temperature by 1 degree [13]. However, this effect of changes varies for different persons. Ideally the temperature is monitored repeatedly during a longer period, e.g. a week, to determine the temperature consistency or pattern for the person. This pattern could be different for different persons, e.g. some may have lowest representative temperature at 22C while for another person 28C may be the lowest. Changes in temperature before and after meal can be pronounced in some individuals, but for persons with some food allergy no changes or a decrease may occur. In general, temperature associated with stress may vary from 15.5 degree Celsius to 37.2 degree Celsius in a normal room temperature (20C to 23C).

The procedure described above for establishing a person's stress profile is used as a standard procedure in the clinical work in patients with stress related dysfunctions and an experienced clinician evaluates these measurements during the different test conditions to make an initial diagnosis. This diagnosis is complex and based on long experience and tacit knowledge [19]. The approach proposed here is based on feature extraction from temperature signals and case-based reasoning to detect appearance of stress and fuzzy set theory to tackle imprecision of input given by patient or clinician as well as imprecision of the domain.

2.3.1 Fuzzy Logic and Case-Based Reasoning

Fuzzy case-based reasoning is useful for some applications in representing cases where the information is imprecise [17, 18]. It is possible to define inexact medical entities as fuzzy sets. For a fuzzy set, the idea of fuzziness is initiated by the assignment of an indicator function (membership function) that may range from values 0-1. Also in retrieving cases fuzzy set theory can be useful for matching similarities between the existing cases and the current case. Fuzzy CBR matches the cases in terms of degrees of similarities between attribute values of previous cases and a new case instead the traditional Boolean matching. Several matching algorithms have been proposed [5, 26 and 7] to retrieve cases in fuzzy CBR systems.

3 Related Work

CBR has been applied in the psycho-physiological domain in several studies. For example, a procedure using CBR for diagnosing stress-related disorder was put forwarded by Nilsson et al. [15] where stress-related disorders were diagnosed by classifying the heart rate patterns. A CBR system was outlined in [2] where the cases were fuzzified depends on finger temperature changes for diagnosing stress in the psycho-physiological domain, but it is not sufficient to depend on only the temperature changes for classifying individual sensitivity to stress. Apart from the psycho physiological domain, CBR techniques were applied in several others diagnosis/classification tasks in the medical domain. Montani et al. [23] combines case-based reasoning, rule-based reasoning, and model-based reasoning to support therapy for diabetic patients. AUGUSTE [14] project was developed for diagnosis and treatment planning in Alzheimer's disease. MNAOMIA [3] was developed for the domain of psychiatry. CARE-PARTNER [4] was used in stem cell transplantation. BOLERO [12] is a successfully applied medical CBR diagnosis system in diagnosing pneumonias using fuzzy set theory for representing uncertain and imprecise values. A CBR technique with fuzzy theory is used for the assessment of coronary heart disease risk [22]. All these projects and others [8, 21, and 16] show significant evidence of successful application of CBR techniques in the medical domain.

4 Classification

Before defining the severity of stress for a person we consider the variation of the finger temperature with stress and define three categories such as: a. finger temperature decreases with increasing stress which is the most common situation, b. finger temperature increases with increasing stress and c. little or no changes i.e., remains in the stable situation when a person is experienced with stress which is exceptional but might happened for some persons. In such cases the clinical expertise is important, and also similar cases in a case library may give important clues on explaining the result. As the treatment advised for the different groups would be different this categorization provides valuable information for selecting the treatment procedure for each individual.

4.1 Classify Individual Sensitivity to Stress

According to the clinical experts step 3 and step 4 (table 1) are the most significant steps to classify a person's sensitivity to stress. Step 3, verbal stress is defined as reactions during lab stress conditions and step 4 which is a relaxation step soon after finishing the stress condition in step 3, is to see how quickly a person recover or cope with stress. We find that different persons behave differently in step 3, (talking about and thinking about a negative event) some have a very sharp drop in finger temperature, others a slow drop, a few have no drop in temperature (i.e. after lunch). Also some persons quickly recover in phase 4 (thinking positive event) others have slow increase in temperature, a few just continue dropping. According to the clinicians the later may be an indication of being more sensitive to stress, but in some cases there are normal explanations for these cases (i.e. a person having an exam after the test or being very hungry) and they are probably not needing treatment, but if this pattern is repeatedly consistent, then there may be a problem that need some treatment. Also a stressed person may not reach a stable or relaxed state if the body is misadjusted. This can be caused by different illnesses or by long periods of increased stress. One indication of such an increased stress level may be that the difference between a stressed state (step 3) and a relaxed state (step 4) is small. The time it takes for a person to switch from one state to another state is relevant information for a clinician, e.g. a person who still has a finger temperature level that corresponds to stressed state after spending time on relaxation exercises may need a different treatment than a person quickly reaching a finger temperature corresponding to a relaxed state. This kind of reasoning is what clinicians often doing, weighting different information. Therefore, the shape or 'behaviour' in step 3 and 4 are significant to classify a person's sensitivity to stress.

We propose to introduce "degree of change" as a measurement for finger temperature change. A low value, e.g. zero or close to zero is no change or stable in finger temperature. A high value indicating a steep slope upwards indicates a fast increase in finger temperature, while a negative angle, e.g. -20° indicates a steep decline. Together with clinicians we have agreed on a standardisation of the slope to make changes visible and patients and situations easier to compare. The proposal is that the X axis in minutes and the Y axis in degrees Celsius, hence a change during 1 minute of 1 degree gives a "degree of change" of 45° see fig.3.

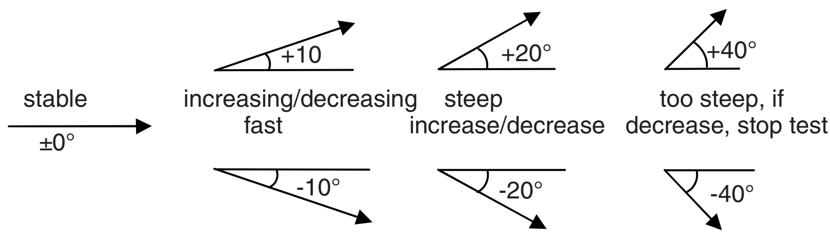

Fig. 3. Example of visualisations of temperature change, X axis minutes, Y axis 0.5 degree Celsius and clinicians response

Decrease of temperature may be an indication of stress and how steep the change is also of importance for the clinicians. Using negative angles make this more obvious and give the clinician a terminology to reason about change. This is shown in figure 4 as text under the arrows.

If a clinician classifies temperature change we have to be aware that this also is context dependent, e.g. -17° decline may be classified "decreasing fast" for one patient and "steep decrease" for another. This is important e.g. when explaining a case to a clinician or explaining the differences and similarities between two cases.

In a test step both the average drop and the steepest drop during a time frame are relevant. The first step in the decision support system is to translate the curves into relevant sections of interest and calculate their angles as illustrated for step 3 in fig.4.

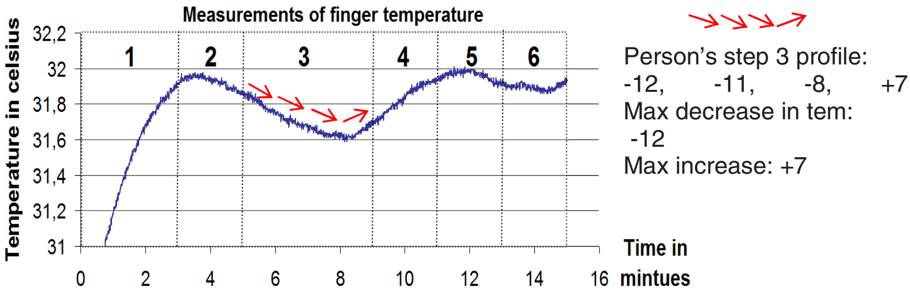

Fig. 4. The visualisations of temperature change and clinician's response

This notation makes it also easier to compare different person's differences and similarities during the test cycle, despite that their finger temperature differs widely.

4.2 Fuzzy Classification

Furthermore, improved classification is possible by using fuzzification of these angles. Instead of using the sharp distinction we can use the fuzzy membership function (mf) because this change of finger temperature in step 3 and step 4 is highly individual and difficult to make any sharp boundaries among the classified regions. For example in step 3, 10 degrees of changes in temperature towards the negative direction can be classified as '*fast decreasing*' but in real life a person who has the 13 degrees of changes in temperature in the same direction can be classified as the same level of severity (*fast decreasing*) by the clinician. An experienced clinician does this with his own judgment. So the sharp distinction to classify individual sensitivity to stress might not always provide us the accurate result. The fuzzy membership functions are applied to generate a more smooth distinction among the sensitivity levels to classify stress. By doing this a person can be diagnosed as having multiple severity levels of stress simultaneously whereas with different degrees.

In figure 5 an example is shown where the levels of severity of stress are defined (linguistic classifications) as too steep, steep, fast increasing/decreasing and stable depend on the 'degrees of changes' of the finger temperature in both positive and negative directions (i.e. -45 degree to +45 degree) with a set of fuzzy membership functions.

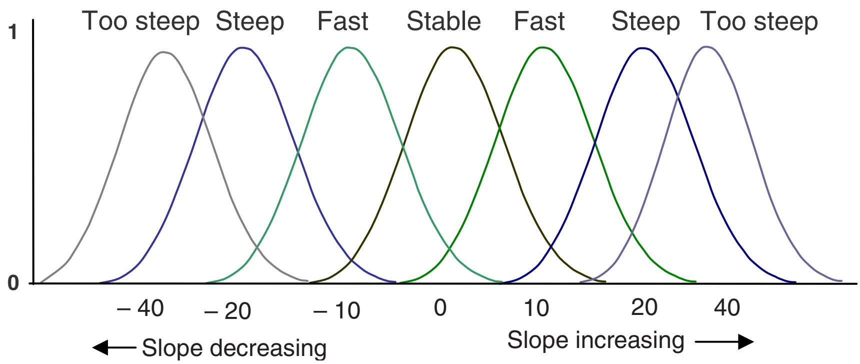

Fig. 5. Membership functions for different levels of sensitivity of stress for the similar individuals

5 Fuzzy Case-Based Reasoning

Initial case library was build using some reference cases from the experts then the new cases are adapted and retained manually by the expert. The output from the calibration phase is used to create an individual case. This case will contain the derivative values of various important steps. We consider the temperature from step 3 to step 5 because these are the most significant steps to determine the sensitivity to stress according to the expert. Each step is divided in one minute time interval (4 minutes step 3 is divided into four time windows) and the derivative is calculated for each window. These values along with other attributes (gender, different between ceiling and floor temperature, etc) are stored into the case library with different weight values.

5.1 Similarity Matching

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. Similarity measurement is taken to assess the degrees of matching and create the ranked list containing the most similar cases retrieved by equation 1.

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

Where; C is the current case, S is a stored case in the case library, w is the normalized weight, n is the number of the attributes in each case, f is the index for an individual attribute and *sim* is the local similarity function for attribute f in case C and S.

For the numeric attribute values, the distances between two attributes values are calculated through the Euclidean distance shown in equation 2.

$$sim\ (C_f, S_f) = \left| C_f - S_f \right| \tag{2}$$

After calculating the distance, this value is compared with the similarity values as depicted in table 2 where the similarity values for different matrices are defined by the expert.

Table 2. Different matrices for the similarity values

Similarity for step	
Distance	*sim*
0-2 degree	1
>2 and <4	0.8
>4 and <6	0.6
>6 and <8	0.4
>8 and <10	0.2
>10	0

Similarity for ceiling/floor	
	sim
>0,3	1
0,3 -0,5	0.8
0,5-0,7	0.4
<0,7	0

Hours since last meal					
T/S	0	1	2	3	>4
0	1	0.8	0.6	0.4	0
1	0.8	1	0.8	0.6	0.4
2	0.6	0.8	1	0.8	0.6
3	0.4	0.6	0.8	1	0.8
>4	0	0.4	0.6	0.8	1

Similarity for gender		
	m	f
m	1	0.5
f	0.5	1

So, finally the global similarity is calculated as a weighted sum of local similarities. An example is shown in table 3 where a current case is compared with two other stored cases (C_92 and C_115) in the case library.

Table 3. Similarity matching between cases

Attributes	**Local weight**	**Normalized weight**	**Current case**	**Stored case C_92**	**Similarity Function**	**Weighted similarity**	**Stored case C_115**	**Similarity function**	**Weighted similarity**
Gender	5	0.05	M	M	1.00	0.05	F	0.50	0.03
Hours since last meal	10	0.11	1	3	0.60	0.07	1	1.00	0.11
Room Temp	7	0.08	20	21	1.00	0.08	21.00	1.00	0.08
Step_3_part_1	7	0.08	-17.09	-1.39	0.00	0.00	-14.39	0.60	0.05
Step_3_part_2	7	0.08	-6.38	-10.91	0.60	0.05	-8.11	1.00	0.08
Step_3_part_3	7	0.08	-7.62	-7.55	1.00	0.08	-7.55	1.00	0.08
Step_3_part_4	7	0.08	1.52	3.15	1.00	0.08	3.15	1.00	0.08
Step_4_part_1	7	0.08	16.58	1.08	0.00	0.00	5.08	0.00	0.00
Step_4_part_2	7	0.08	8.34	6.34	1.00	0.08	7.13	1.00	0.08
Step_5_part_1	6	0.07	-8.66	-2.17	0.40	0.03	-6.17	0.40	0.03
Step_5_part_2	6	0.07	-9.44	-1.77	0.40	0.03	-1.77	0.80	0.05
Diff cealing /floor	9	0.10	0.75	0.59	1.00	0.10	0.59	1.00	0.10
					Global Similarity for C_92	**0.67**		**Global Similarity for C_115**	**0.80**

Here, the *Local weight (LW)* is defined by the experts, *Normalized weight (NW)* is calculated by the equation 3 where i=1 to n number of attributes, *Similarity function* calculates the similarity between attributes of the current case and the stored cases using the equation 2 and comparing the similarity values from the table 3, *Weighted similarity* for each attribute is defined by the normalized weight multiply the output of the similarity function, *Global similarity* between the cases are calculated as weighted sum of local similarities using the equation 1.

$$NW_i = \frac{LW_i}{\sum_{i=1}^{n} LW_i} \tag{3}$$

In table 3 the global similarity between the current case and case C_92 is 67% and current case and case C_115 is 80%.

5.2 Fuzzy Matching

The representation of a similarity value using a matrix as shown in table 2 often shows a sharp distinction which often provides an unrealistic solution. Moreover, multiple if-then rules are needed to implement the matrices. Fuzzy similarity matching is used to reduce this sharp distinction which also helps to avoid multiple rules. A triangular membership function replaces the crisp input attribute with the membership grade of 1. The width of the membership functions (*mf*) are provided by the expert's of the domain.

For example, in table 3 the attribute '*Step3_part2*' of the current case and the old case have the values -6.3 and -10.9 respectively. The weight of the *mf* is fuzzified with 50% in each side as shown in fig.6. For the current case the lower and upper bounds are -9.45 and -3.15 represented with an *mf* of grade 0. The input value is -6.3 with the *mf* grade of 1. The old case has the lower and upper bounds -16.35 and -5.45 with an *mf* grade of 0 and the input is -10.9 with an *mf* grade of 1.

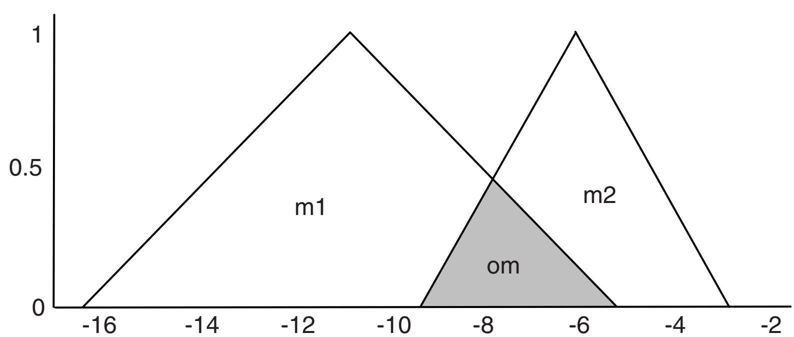

Fig. 6. Similarity matching using membership functions

The similarity between the old cases and the new case is calculated using the overlapping areas between the two fuzzy values in their membership functions [6]. The similarity equation is defined as-

$$S_{m_1 m_2} = \min(om/m_1, om/m_2) \quad (4)$$

Here m_1 is the area of one attribute value with one membership function and m_2 is associated with the second membership function and the overlapping area is denoted as om. In fig.6, m_1=5.45, m_2 =3.15 and om=0.92 where height is defined from the intersection point of the two fuzzy membership functions. So from the equation 4, the local similarity is *min (0.17, 0.29) =0.17* and *max* is 0.29. If the *mf*s are considered as 100% fuzzified then minimum local similarity will be 0.34 and maximum will be 0.58 which is close to the value of table 3. In this way the user has option both for tuning the *mf*s and choosing the min/max in the similarity function depends on the requirements. When the overlapping areas become bigger then the similarity between the two attributes will also increase and for a completely matched attributes similarity will be 1.

The system returns a ranked list with the most similar cases. Cases are sorted according to the percentage where 100% means the perfect match and represented the solution with the classification shown in the previous section. From the table 3, case C_115 has higher rank than C_92 that is the current case is more similar to the case C_115. A threshold value can be defined and modified by the user to get a list of similar cases and this list of cases are treated as candidate cases. From these candidate cases a case can be proposed by the user as an acceptable case and that can be reused to solve the new problem. If necessary, the solution for this acceptable case is revised by the expert that is often important in the medical domain. Finally, the current problem with confirmed solution is retained as a new case and added to the case library. In terms of adaptation any changes can be done by the expert before adding it into the case library and this could be done manually.

5.3 Reliability of the Test

Once the decision support system suggests a number of similar cases it is important for the clinician to know how reliable the similarity estimate is. One valuable indication of reliability in diagnosing stress is how well the person succeeded in doing the different test assignments or how sure a clinician is on a given value or judgment. Such input will make the foundation of a confidence factor [7] for a case.

A person can grade the severity of a stressful event (step 3) he/she was thinking by using a Visual Analogue Scale (-5 to +5) where +5 is very severe traumatic memory while 0 is not stressful and -5 is extremely positive. Discussing with the clinical experts and analysing the grade and measurement from the 24 persons it is clear that they are aware of their success rate in the specific step. But the grading does not have a high accuracy and needs to be fuzzified due to many factors such as humans tend to give a precise answer without really having a basis for this “preciseness”. The value is fuzzified using two membership functions (Fig. 7). The left linear mf (from -2 to +5) represents the fuzzy values for the negative range (rate of failure in test) and the right linear mf (from -5 to +2) represents the positive range (success in test) in the universe of discourse (-5 to +5) for the fuzzy variable scale. This will give a value for the success rate in some degrees of mf instead of just a precise value and also reduce the number of rules to one.

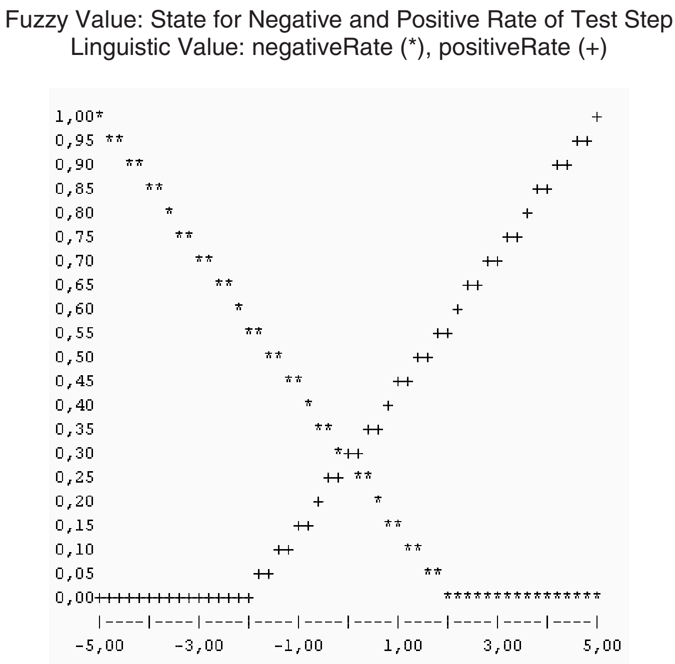

Fig. 7. Membership function of the positive and negative success rate of test

For example in table 3, the current case (CC) and case C_92 and C_115 have the success rate for the test step 3,4, and 5 are CC(7,3,6), C_92(5,6,5) and C_115(8,4,3) respectively. On an average the differences in success rate between CC and C_92 is 2 and CC and C_115 is 1.6. Suppose the global similarity between CC and other two cases are same then according to their rating of success the case C_92 will get more preference. Besides the same global similarities, this rating helps the clinician able to take a closer look at the suggested cases when the global similarities among them are different.

6 Summary and Conclusions

We have presented a decision support system based on a case-based method using a calibration procedure and fuzzy membership functions. Integration of CBR with fuzzy set theory enables the system to handle impreciseness in input features and domain knowledge in a way understood and accepted by the clinicians. The calibration phase also assists to individualize the system. The system extracts key features from the finger temperature signal and classifies individual sensitivity to stress. This provides important information to the clinician to make a decision about individual treatment plan. One of the strengths of the method is that it bears similarities with how the clinicians work manually and when clinicians are confronted with the concepts and functionality of the decision support system it is readily accepted by them. This support is valuable since clinicians are willing to participate actively in the project and validate the results. Our hope is that the classification system can be developed to a tool used by people that need to monitor their stress level during every day situations for health reasons. Such a system may be used in different ways: to monitor stress levels that are reported back to clinicians for analysis used in relaxation exercises or actively notify a person, in some suitable way, that stress levels are increased and counter measures are advisable and this may be important for patients with increased risk of stroke or heart problems.

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