# Using Calibration and Fuzzification of Cases for Improved Diagnosis and Treatment of Stress

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**Abstract.** In the medical literature there are a number of physiological reactions related to cognitive activities. Psychosocial and psychophysiological stress is such activities reflected in physiological reactions. Stress related symptoms are highly individual, but decreased hands temperature is the common for most individuals. A clinician learns with experience how to interpret the different symptoms but there is no adaptive diagnostic system for diagnosing stress. Decision support systems (DSS) for stress diagnosis would be valuable both for junior clinicians and as second opinion for experts. Due to the large individual variations and no general set of rules, DSS are difficult to build for this task.

The proposed solution combines a calibration phase with case-based reasoning approach and fuzzification of cases. During the calibration phase a number of individual parameters and case specific fuzzy membership functions are established. This case-based approach may help the clinician to make a diagnosis, classification and treatment plan. The case may also be used to follow the treatment progress. This may be done using the proposed system. Initial tests show promising results. The individual cases including calibration and fuzzy membership functions may also be used in an autonomous system in home environment for treatment programs for individuals often under high stress.

## 1. Introduction

Stress is an increasing problem in our society. High levels of stress puts a high strain on the body, shut and prepare the body for fight or flight. After a stress reaction the body needs time to recover and restore normal functionality. If short periods of stress occur this recovery does not leave any permanent damages to the body. Today every day life for many people contains many situations that may trigger stress or results in an individual to live on an increased stress level under long time. It is known today that high levels of stress may cause serious health problems.

It is known that different treatments and exercises can reduce the stress. Since one of the effects of stress is that the awareness of the body decreases, it is easy to miss signals such as high tension in muscles, unnatural breathing, blood-sugar fluctuations and cardiovascular functionality. It may take many weeks or months to become aware (perhaps first when symptoms reach a handicapping or dramatic level) of how high the stress has been, and once notified, the effects and unaligned processes, e.g. metabolic processes, may need long and active behavioural treatment to revert to a normal state [von Schéele and von Schéele, 1999]. For patients with high blood pressure and heart problems high stress levels may be directly life endangering. A system that notifies when stress levels are rising or too high is valuable in many situations, both in clinical environment and in other environments, e.g. the patients home and work environment.

A well known fact is that finger temperature has a correlation with stress for many persons, but individual fluctuations make it difficult to use in automatic systems since there are no absolute values of temperature with relation to stress levels. We propose a case-based system used in a calibration phase to determine a set of initial parameters and hypotheses that can be used as decision support for clinicians.

In this paper we will outline the case-based calibration method and fuzzification of cases to determine a number of parameters that are important input 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 make a prognosis of its development so counter measures and treatment can be chosen.

## 2. Related Work

Case-based reasoning (CBR) is getting increasing attention from the medical domain since it is a reasoning process that also is medically accepted. Some applications of CBR in the psycho physiological domain are: A procedure for diagnosing stress related disorder by Nilsson et al. [Nilsson et al. 2006 ] where stress related disorders were 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. The classifier, HR3Modul uses CBR approach with a wavelet based method to retrieve features from the signals. Moreover a second subsystem, the pattern identifier was introduced to find out the familiar patterns from the classified signals. A system was proposed in [Andrén and Funk 2005] that monitors a person’s stress level using biometrical data such as keystroke dynamics. This applies CBR approach to determine individual patient’s stress level within the keystroke patterns. Apart from the psycho physiological domain, CBR techniques were applied in several other diagnosis/classification tasks in medical domain. Montani et al. [Montani et al. 2001] combines case-based reasoning, rule-based reasoning, and model-based reasoning to support therapy for diabetic patients. AUGUSTE [Marling and Whitehouse 2001] project was developed to diagnosis and treatment planning in Alzheimer’s disease. MNAOMIA [Bichindaritz 1996] was developed for the domain of psychiatry which helps in diagnosis, treatment planning, clinical research assistance. CARE-PARTNER [Bichindaritz et al. 1998] was used in stem cell transplantation. It facilitates the diagnosis and treatment planning using a multimodal framework for reasoning. BOLERO [Lopez and Plaza 1993] 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 [Schuster 1997]. All these projects and others [Koton 1988, Gierl 1993, Gierl and Schmidt 2002, Perner et al. 2003] show significant evidence of successfully applying CBR techniques in medical domain. It seems that not so much work has yet been done using CBR in psycho physiological domain.

## 3. Establishing a Person's Stress Profile

If people feel stress, which can be experienced in different ways such as anxiety, muscle tensions/cramp and even panic.  T his influences SNS (Sympathetic nervous system). In general, temperature of the finger decreases when the person is stressed and increases during relaxation or in a non stressed situation. This relates to 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 lead to increased diameters in blood vessels and increase the blood flows and the temperature. In Post Traumatic Stress Disorders reverse reactions are observed.

The procedure described below is used as standard procedure in clinical work with patients with stress related dysfunctions and an experienced clinician is evaluating the measurements during the different test conditions to make an initial diagnosis. The diagnosis is complex and based on long experience and tacit knowledge [Polanyi 1976].

We will give a brief description of the procedure without going into clinical details, and only give a general understanding of the test procedure.

A temperature sensor is attached for measuring skin temperature of the finger. Data are collected from the sensor readings during stress conditions as well as in non stressed (relaxed) conditions. Adjustment before starting test conditions is achieved under the baseline measurement conditions, which is to secure stable room temperature and enable time for person to adjust from outdoor temperature (if the person has been outside recently). For example, during cold seasons hand temperatures tend to decrease which might bias the result, taking drinks like coffee also could bias the result. So try to keep away from other hot or cold contacts such as hot drinks or outdoor exposure in connection with finger temperature (FT) measurements. Base line period allows the persons to stabilize hand temperature and then temperatures are measured following a standard procedure (table 1).

*Step1* may be seen as indicating the representative level for the individual when neither under strong stress nor in a relaxed 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 observations of person's behaviours. Some changes in FT might also be related to inactivation, during sitting. If temperature does not reach a plateau level, this step may be extended in time.

During *step2* 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.

**Table 1**: Measurements 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 | | |

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

In *step 4*: *relaxation part,* 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 direct induced stress by the clinician where person is requested to count backwards.

Final *relaxation step* tests if and how quickly the person recovers from the stress.

Clinical studies show that when talking about the stressful events experience finger temperature decreases, in extreme cases up to 5 to 10 degrees Celsius, and even to recall a minor misunderstanding could decrease the temperature by 1 degree [Lowenstein 1995]. However, this effect of changes varies between 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. And it varies for different persons, e.g. some may have representative temperature of 22C as her/his lowest temperature while for other person 28C may be the lowest. Changes in temperature before and after meal can be pronounced in some individuals, but in persons with some food allergy no changes or a decrease may occur. Stress related temperature can vary from 15.5C (60 F) degrees Celsius to 37.2C (99F) degrees Celsius in persons in a normal room temperature (20C to 23C).

**4. Preparing Data for the Case-Based Classification System**

Finger temperature is measured using the sensor attached with the little finger of the non-dominant hand of a person. The signal from the sensor contains the pattern for the parameters of the finger temperature for different stress and relaxed conditions. These time series data [see Fig 1] could contain many redundant and noisy information such as in finger temperature data might be noisy with the loss of connection of the sensor or with the room temperature, so not all time points would contain the necessary information. Therefore, it is necessary to carefully reduce time series to extract the selected features that influence the whole series or a part of the series. Discrete Fourier Transform (DFT) and later also Discrete Wavelet Transform (DWT) have been used successfully in medical applications, e.g. in Nilsson's work [Nilsson et al 2006]. Wavelet Transform is an extension of Fourier Transform. DWT measures frequency at different time resolutions and locations. For the DWT the coefficients are inclined by the sub-series of different sizes. Wavelet packet analysis is the same as the wavelet analysis but it gives more flexibility to represent the signal [Coifman et al 1992]. To find the wavelet packet table which contains the wavelet coefficients, fast splitting algorithm [Bruce and Gao 1992] is used and this is an adaptation of the pyramid algorithm [Mallat 1989].

The basis function is

$$\psi_{j,b,k}(t) = 2^{j/2}\psi_b\left(2^j t - k\right) \qquad \textbf{(1)}$$

Where, j is the resolution level, b is the number of oscillations, k is the translation shift. A signal f (t) is represented as a sum of wavelet packet functions and different scales.

$$f(t) \approx \sum_j \sum_b \sum_k c_{j,b,k}\psi_{j,b,k}(t) \qquad \textbf{(2)}$$

Where, $c_{j,b,k}$ represents the wavelet packet coefficient

Feature extraction is done by the best basis algorithm [Coifman et. al. 1992] which selects optimal transforms from the wavelet packet tables.

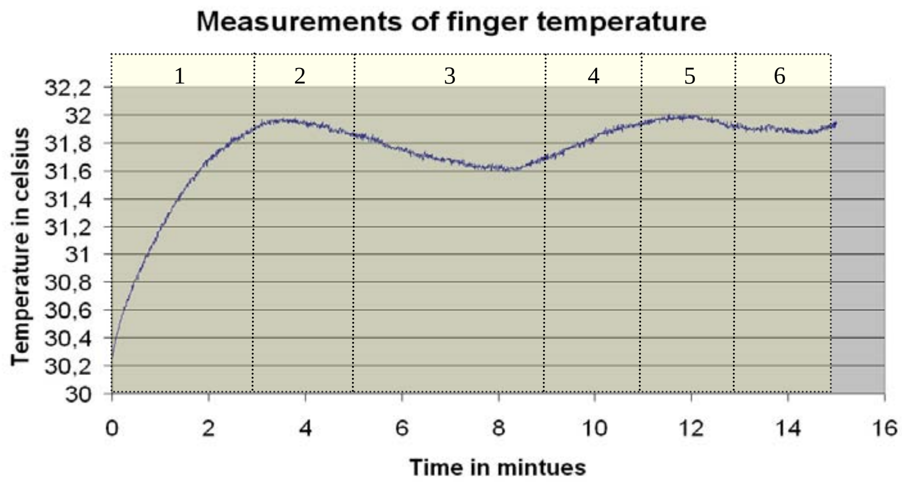


**Fig 1:** An example of measurements of finger temperature during the 6 steps in Table 1

### 5. Fuzzy Cases Capturing Variations and Probabilities

A specific finger temperature pattern is associated with a specific stress/relaxation level, but the correlation also depends on a number of other factors which will be discussed later. But if we look at the current situation without knowledge of any other influencing factors, we can use fuzzy set theory to determine the correlation between temperature and the different levels of stress. Later on we can make further adjustments when more information will be available about the current situation.

Fuzzy logic provides reasoning methods for approximate inference [Linkens 1988]. Fuzzy set theory, which was developed by Zadeh in 1965, instead of crisp or binary value, is used to explain the fuzziness existing in human's thinking. 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 on values 0-1. When the boundaries between different classes are not clear in such cases fuzzy set theory can be applicable. Fuzzy logic allows defining cases with vague attributes [Plaza and Lopez 1990, Jaczynski 1994]. It gives the linguistic representation of patterns. Features vectors from DWT are given as the input in the fuzzy classifier where they are fuzzified and classified using the rules defined by the expert of the domain.

The general membership function cannot be used directly for an individual, but data collected from the calibration phase provide the values needed to individualize the membership functions for an individual. After the calibration phase it should ideally not have other influencing factors, such as unusual room temperature, measured during unusual conditions etc.

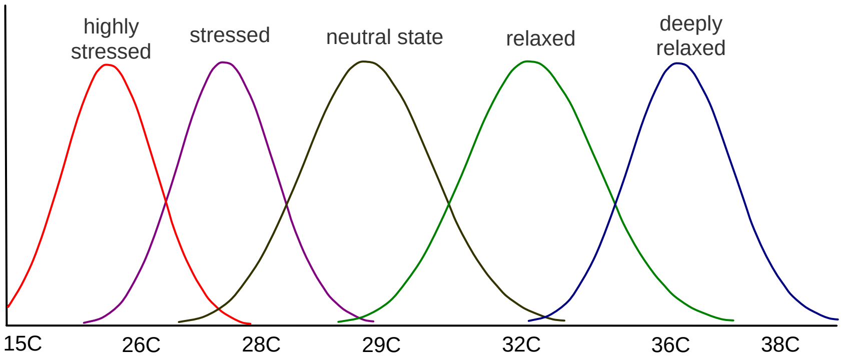


**Fig 2:** General membership function for the different levels of finger temperature for person belonging to category a

Considering the variation of temperature with stress three categories are defined such as: a. persons finger temperature decreases during the stress condition which is a general situation, b. finger temperature increases with stress and c. little or no changes i.e., remains in the stable situation when the person is experienced with stress which is exceptional but might happen for some persons. In such cases the clinical expertise is important, and also similar cases in the case library may give important clues on explaining the result.

Different levels of stress for individual persons depend on how much the temperature changes which is highly individual, so difficult to make any boundary between different regions. In this case, the levels of temperature are defined (linguistic classifications) as highly stressed, stressed, neutral state, relaxed, and deeply relaxed with a set of fuzzy membership functions. By doing this a person can be diagnosed as having multiple stress levels simultaneously whereas with different degrees. These fuzzy values are initially chosen with the help of the experts' knowledge in the domain. In representing cases, the fuzzy membership functions corresponding to the regions are stored as cases. It is also possible to use a Neuro-fuzzy system to tune the parameters of the membership function but this would require a large dataset for training [Begum et al. 2006].This would be possible once sufficiently many cases have been collected in the case library.

## 6. Case Representation and Matching

The output from the calibration phase is used to create an individual case. This case will contain the individualization parameters for the membership functions. The easiest level to determine is the stressed level, which is the temperature from *step 3* and *5*. But a stressed person may not reach a neutral or relaxed state since 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 and a neutral or relaxed state is small. Also the time it takes for a person to transfer from one state to an other state is relevant information for a clinician, e.g. a person that 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.

These parameters are set by the clinician based on experience and feedback from the persons and stored in the person's case. This is a "New Calibration Case", and since we add other relevant information important for diagnosis and treatment we call it "New Case" in the following. The new case can be used in a variety of situations, e.g. to assess the effect of treatment and recovery or to identify dangerous stress levels, e.g. on patients with increased risk for strokes.

Figure 3 contains an outline of the case-based method that identifies similar patient to help the clinician to diagnose the patient and select a treatment plan. The combination of fuzzy set theory and CBR systems supports two different tasks: 1) defining classes for indicating the levels of stress and 2) Selection of the matching cases from the previous experience. Case retrieval is made using a similarity measure based on these membership functions.

The proposed system consists of 6 steps: calibration, pre-processing including fuzzification, retrieval, reuse, revise and retain.

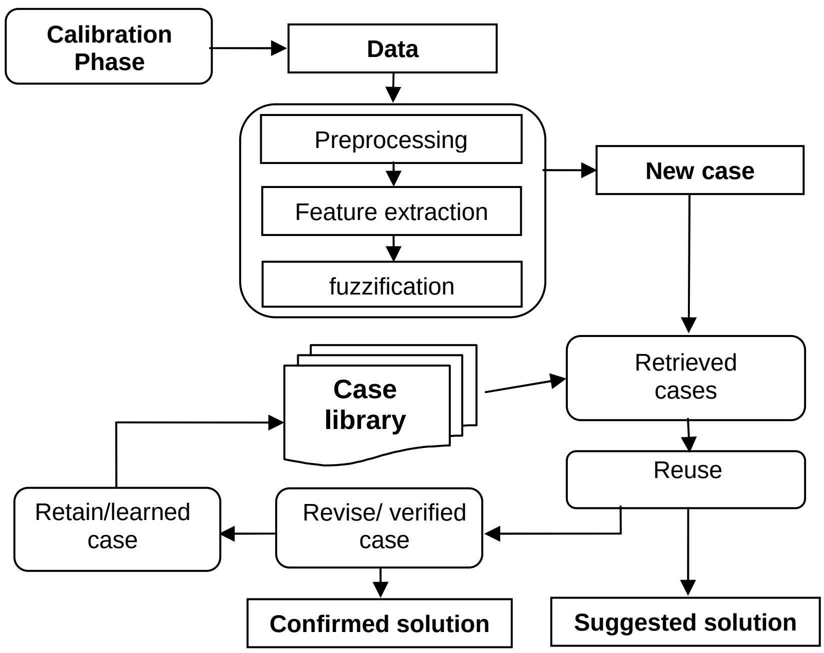


**Fig 3:** Case-based method to determine a person's stress level

The CBR systems include the essential steps such as retrieval, reuse, revise, and retain. The retrieval step is the most important step where proper similarity measurements should be done to retrieve the best matching one. Reliable and accurate function of the diagnosis systems depends on the storage of cases or experiences and on retrieving the most appropriate one for the current problem definition. But comparing each case stored in the case library to retrieve the similar one is a time-consuming task. Fuzzy set theory is applied to evaluate the similarity between the stored cases and the new case. The general matching approaches would require a large number of cases in the case library to cover all the given input queries. The fuzzy set theory applied makes it accurate and faster.

For matching cases, similarity measurement is done by fuzzy matching. A Gaussian membership function will be formed to replace the crisp attribute value for the similarity matching. Experts of the domain will define the membership function. The similarity of the old cases to the new case is calculated using the overlapping areas between two fuzzy values in their membership functions [Dvir et al. 1999].

In the reuse step the retrieved cases are reused to solve the new case. If necessary, the solution is revised. Finally, the current problem with corresponding final solutions is retained as a new case and added into the case library.

## 7. Summary and Conclusions

We have in this paper outlined a decision support system based on a case-based method using a calibration procedure and fuzzy membership functions. The method bears similarities with how 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. Initial evaluations show that using the calibration phase and individualized fuzzification also improves performance, but this needs to be confirmed and larger trails and measurements are ongoing. Representing fuzzy cases also enables following a patient's treatment progress and would enable self treatment if the person would have access to such a system and the calibration case produced under clinical conditions.

The method is also resistant to large variations since the fuzzification parameters are individual for each case. Once such a case library grows in size with cases it becomes a valuable clinical tool to discover causal relations that may be medically interesting and enable progress in diagnosis and treatment.

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 two ways, either just to monitor levels that are reported back to clinicians for analysis, or used actively to notify person, in some suitable way, that stress levels are increased and counter measures are advisable. This may be important in patients with e.g. increased risk of stroke or heart problems.

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