FUZZY RULE-BASED CLASSIFICATION TO BUILD INITIAL CASE LIBRARY FOR CASE-BASED STRESS DIAGNOSIS

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

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

1. Introduction

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

A component which plays a central role in CBR systems is the case library. It can be considered as a concrete knowledge model consisting of specific cases. The cases stored in the case library should be both representative and comprehensive to cover a wide spectrum of possible situations. The composition of the case library is one of the key factors that decide the ultimate performance of a CBR system. Case mining and case base maintenance have become an increasingly important issue in CBR research.

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

1.1 Related work

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

2. Case-based stress diagnosis

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

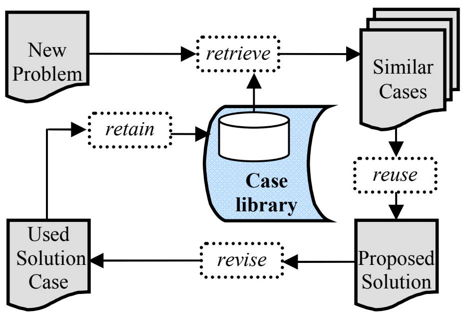


Fig. 1. CBR cycle. The figure is introduced by Aamodt and Plaza [1]

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

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

3. Classification to build initial case library

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

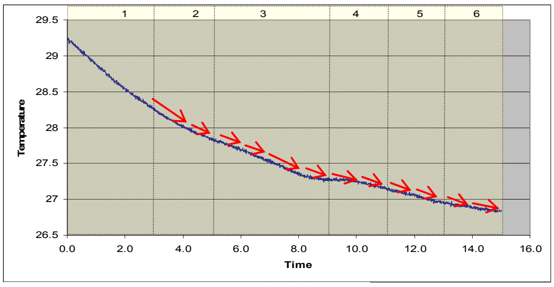
3.1 Sensor-signal abstraction

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

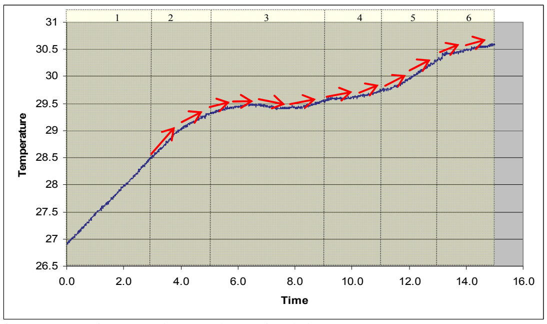
After analyzing a number of finger temperature signals, it has been found that the temperature rises or falls against time. According to a closer discussion with clinicians, standardization of the slope i.e. negative and positive angles makes a better visualization and provides a terminology to a clinician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

3.2 Classification and rules with generalized feature

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



a) Very Stress: FT is consistently falling



b) Very Relax: FT is consistently rising

Fig. 2. Visualizations of Very Stress/Relax class.

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

Table 1. Crisp rules used for the classification of cases

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

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

3.3 Fuzzy rule-based classification

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

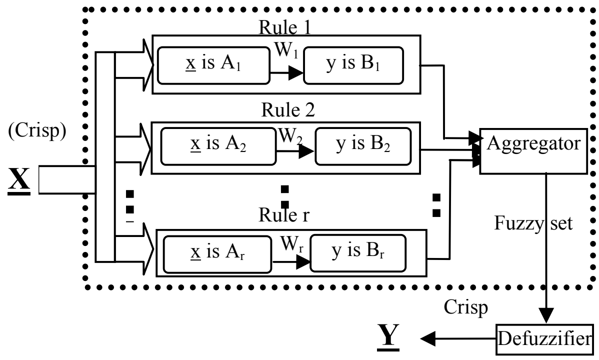


Fig. 3. Block diagram of a fuzzy inference system [14]

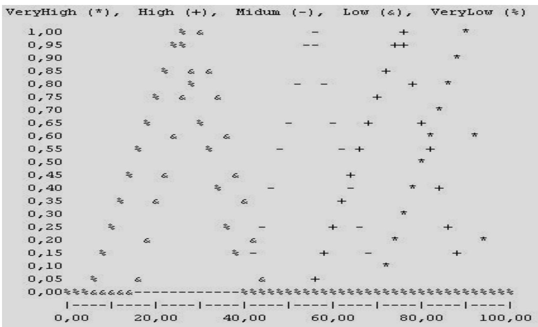
The basic structure of fuzzy logic expert systems, commonly known as fuzzy inference system (FIS) shown in Figure 3, is a rule-based or knowledge-based system consisting of three conceptual components: a rule base that consists of a collection of fuzzy IF–THEN rules; a database that defines the membership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

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

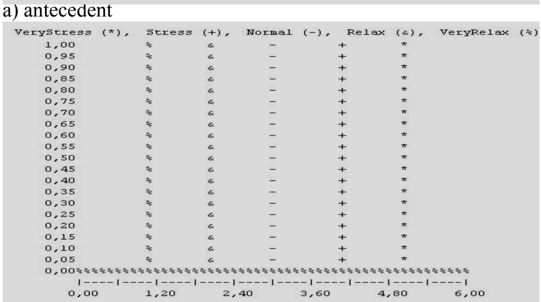
Table 2. Rules for the FIS

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

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



a) antecedent



b) consequent

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

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

4. Experimental results

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

4.1 Rule-based classification

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

Table 3. Evaluation results for two classification schemes

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

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

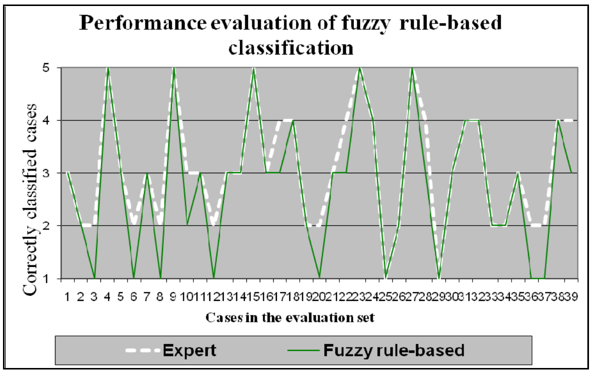


Fig. 5. Fuzzy rule-based classification compared to the expert's judgments

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

4.2 Case-based classification

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

Experiment has been done by defining two different case libraries as: *LibraryA* with only real cases classified by the expert and *LibraryB* being twice as big as *LibraryA* with hybrid cases classified by either the expert or the fuzzy rules. The CBR system uses k nearest-neighbour (KNN, where k=1) algorithm for classification. For the classification of test cases we consider the top most retrieved similar case. We have divided our experimental data set into three parts by selecting random cases as: *SetA*) classified cases by expert, *SetB*) classified cases by fuzzy rules and *SetC*) test caseswhose classes are assumed not known.. *SetC* remains unchanged for all the experiment (test1 & test2). But in *SetA* and *SetB* cases are reclassified for the second experiment (test2) i.e. *SetA* is classified by the fuzzy rules and *SetB* is classified by the expert (see table 4). Whilst the tests have been completed, *SetC* is classified by the expert and compare it with the results from the test1 and test2.

Table 4. Experimental results for two test schemes

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

Table 4 displays the experimental results for test1 and test2 where *SetC* is classified four times using *LibraryA* and *LibraryB*. Goodness-of-fit (R^2) and Mean absolute difference are calculated and presented in table 4 comparing the test results from test1 and test2 with the expert's classification for *SetC*. As can be seen from table 4, in test 1 compared to the expert for the real cases (*SetA*) the classification accuracy is 69% and 90% for the hybrid cases (*SetA +SetB*) and in *test2* the classification accuracy is 79% for the real case (*SetB*) and 85% for the hybrid cases (*SetB + SetA*) according to the R^2 index. Moreover, the result shows that error rate is less using hybrid cases (i.e 11% & 22%) compared to real cases where the size of the case library is small. Table 5 depicts the average result for test1 and test2 where a comparison is exposed between *LibraryA* (real cases) and *LibraryB* (hybrid cases) which is as double as *LibraryA.*

Table 5. Comparison results of case libraries

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

As shown in table 5, for the two tests (test1 and test2) on an average the *LibraryB* indicates the classification accuracy 87% while the *LibraryA* reaches 74% of fitness compared to expert classification. So there is 13% increase in the R^2 value and 22% (Mean absolute difference) decrease in the error rate when the system employ *LibraryB* (hybrid cases) i.e. case library containing enough cases. For the two tests (using two case libraries) the number of correctly classified cases on average is presented in percentage (see 4th column) in table 5. Here, the CBR system can correctly classify 83% using *LibraryB* whereas using *LibaryA* the system can only correctly classify 61% of the cases.

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

5. Conclusion

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

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

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