Case-based Reasoning for Diagnosis of Stress using Enhanced Cosine and Fuzzy Similarity

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Abstract. Intelligent analysis of heterogeneous data and information sources for efficient decision support presents an interesting yet challenging task in clinical environments. This is particularly the case in stress medicine where digital patient records are becoming popular which contain not only lengthy time series measurements but also unstructured textual documents expressed in form of natural languages. This paper develops a hybrid case-based reasoning system for stress diagnosis which is capable of coping with both numerical signals and textual data at the same time. The total case index consists of two sub-parts corresponding to signal and textual data respectively. For matching of cases on the signal aspect we present a fuzzy similarity matching metric to accommodate and tackle the imprecision and uncertainty in sensor measurements. Preliminary evaluations have revealed that this fuzzy matching algorithm leads to more accurate similarity estimates for improved case ranking and retrieval compared with traditional distance-based matching criteria. For evaluation of similarity on the textual dimension we propose an enhanced cosine matching function augmented with related domain knowledge. This is implemented by incorporating Wordnet and domain specific ontology into the textual case-based reasoning process for refining weights of terms according to available knowledge encoded therein. Such knowledge-based reasoning for matching of textual cases has empirically shown its merit in improving both precision and recall of retrieved cases with our initial medical databases. Experts in the domain are very positive to our system and they deem that it will be a valuable tool to foster widespread experience reuse and transfer in the area of stress diagnosis and treatment.

1. Introduction

In our daily life we are subjected to a wide range of pressures. When the pressures exceed the extent that we are able to deal with then stress is trigged. Moderate amount of pressures can be a great motivator that helps our bodies and minds work well and contribute to our mental health. But it is also well known that increased stress level can lead to serious health problems. Stress has a side effect of reducing awareness of bodily symptoms and people on a heightened level of stress often may not be aware of it and first notice it weeks or months later when the stress is causing more serious effects in the body and health [28]. Severe stress during long periods is highly risky or even life-endangering for patients with e.g. heart disease or high blood pressure. A computer-aided system that helps early detection of potential stress problems would bring vital benefits for treatment and recovery in both clinical and home environments.

Medical investigations have identified that finger temperature (FT) has a strong correlation with stress status for most people. Although interpreting and analyzing finger temperature profiles for diagnosing severity of stress and other related dysfunctions is receiving increasing significance within the psychophysiological domain, clinicians are also considering other factors such as patients feelings, behaviours, social facts, working environments, lifestyle and so on in diagnosing individual stress levels. Such information can be presented by a patient using natural text format and visual analogue scale. Furthermore, FT measurement requires a sensor and special software which may not be available or possible to use in some environment such as in some working places. Textual data of patients captures important data not contained in measurements and also provides useful supplementary information to better interpret and understand sensor readings and transferring valuable experience between clinicians important for diagnosis and treatment planning.

Clinicians are required to carefully inspect lengthy streams of measurements for capturing indicative characteristics from FT signal and recognizing any possible disorders. Diagnosing individual stress condition based on finger temperature measurements is not easy and understanding large variations of measurements from diverse patients requires knowledge and experience and, without adequate support, erroneous judgment could be made by a less experienced staff. It is also time-consuming and tedious task for humans to diagnose stress-related disorders from a semi or even unstructured text format. Therefore a system that can manage multimedia data e.g. signals from FT sensor as well as textual information is essential in this domain. This paper presents a case-based reasoning system using fuzzy and cosine similarity to cater decision support for clinicians with emphasis on hybridization of textual data with time series measurements as case representation. We use Case-based Reasoning (CBR) as it works well in such domain where the domain knowledge is not clear enough as in interpreting FT signal data [17] in the psychophysiological domain where even an experienced clinician might have difficulty expressing his knowledge explicitly.

The proposed system considers textual information as of the one component of the case index and the degree of matching of textual information is treated as a partial similarity evaluation. This partial similarity on the textual dimension is then combined with other partial similarities on signal measurement to reach a global similarity between cases of mixed data formats. The matching between textual information is implemented with the concise similarity function and term vectors are enhanced by the background knowledge expressed in WordNet and a domain specific ontology.

2. Overview of the system

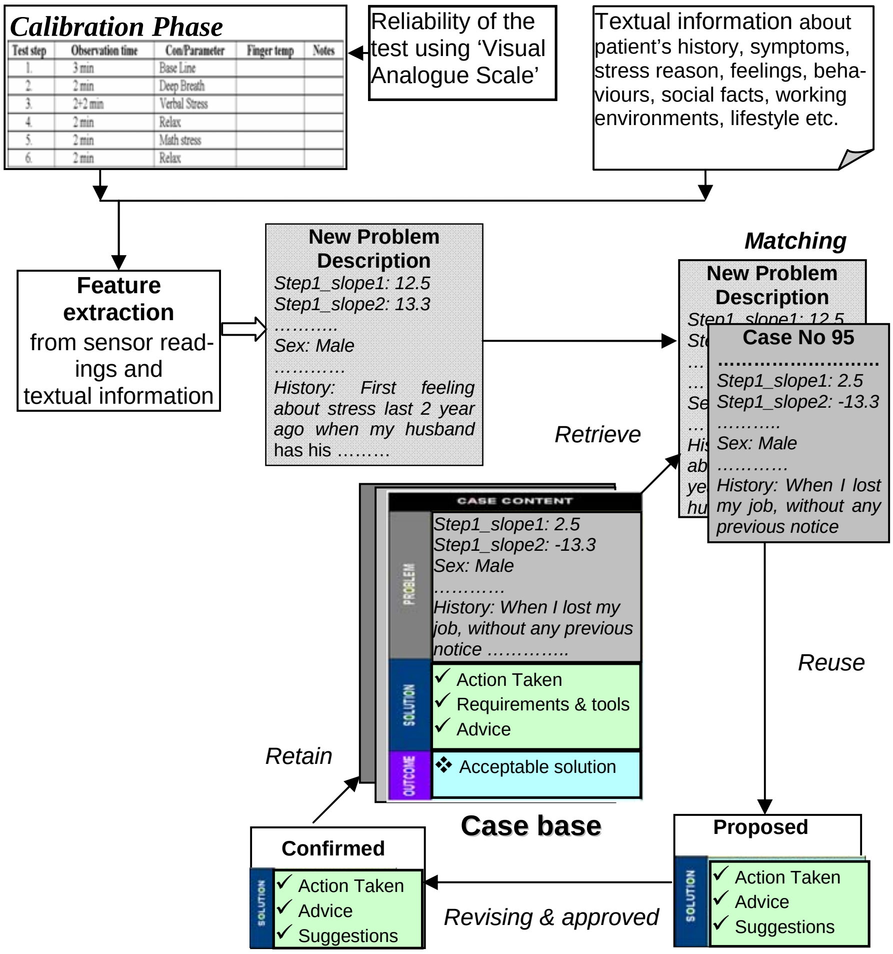


Fig. 1. Overview of the stress diagnosis system

A system for diagnosing individual stress level based on finger temperature measurements or textual descriptions works in several stages as illustrated in Figure 1. The first stage is the Calibration phase [3] where the finger temperature measurement is taken using a temperature sensor to establish an individual stress profile. Some extension has been done in this phase by adding a reliability test using a visual analog scale (VAS) after completing each step where a subject can describe his/her feelings about the test of each step by VAS. From the calibration phase 15 minutes finger temperature measurements and reliability test input are stored into an xml file to the local device. The system provides a user interface that receives either a signal data or textual information or combination of them. Features are extracted both from the signal and textual data before making a new problem case; several techniques have been applied for the feature extraction and are shown along with case representation in chapters 3 and 4.

As a result of the extracted features when a problem case has been formulated, CBR cycle is introduced to solve this new problem case. Then the new problem case is matched with each of the solved cases within the case-base to retrieve the best matched cases; matching algorithms are described in case retrievals and matching chapter. A sorted list of best matched cases along with their solutions has been proposed and presented to the user (i.e. clinician) for revision. A clinician thereafter revises the best matching cases and approves a case to solve the 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 require since a new problem case may not always be as same as an old retrieved case. However, there is no adaptation of the cases in the proposed system. This adaptation could be done by clinicians in the domain. 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 case retain.

3. Feature extraction from time series signal data

Extracting appropriate features is of great importance in performing accurate classification in a computer-aided system whereas in manual process an experienced clinician often classify FT signal without being informed of all the features he/she should use in the classification. A standard procedure followed by clinicians to establish a person’s stress profile has already been discussed concerning the calibration phase [3] whereby 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 (Baseline, Deep-breath, Verbal-stress, Relax with positive thinking, Math-stress and Relax). After the test, a person is requested to answer some questions for instance, when he/she had his/her meal, food habit, food allergy and so on. The output from the calibration phase is then used in extracting significant features and afterwards a new case is formulated employing these extracted features.

The FT sensor measurements are recorded using software which provides filtered data to the system. This signal data and answer to the questions from the calibration phase are then stored in a file in the local device and exported to the Decision Support System (DSS). From the exported file, system retrieves 15 minutes finger temperature measurements (time, temperature) in 1800 samples, together with other numeric (age, room-temperature, hours since meal, etc) and symbolic (gender, food and drink taken, sleep at night, etc) features. In fact, dealing with sensor signal is more complex than other static features such as age, gender, room temperature etc.

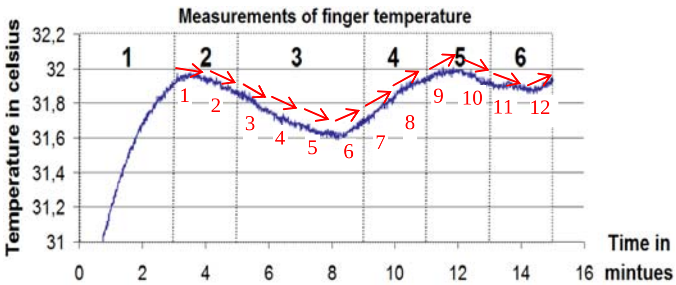


Fig. 2. Changes in FT data against time during different stress and non-stress condition

Figure 2 displays skin temperature of the finger during both the stress and non-stress conditions. As can be seen, after analyzing a number of finger temperature signals, the temperature is rising and falling against time and after an initial increase, finger temperature decreases in stress condition (step 3) and increases in relax condition (step 4). According to closer discussion with clinicians on the interpretation of such graph, it is concluded that, in general, the finger temperature could decrease with stress and increase in relax state and the changes between the steps are also of importance for the clinicians. A standardization of the slope that is using negative and positive angles makes a better visualization and gives a terminology to a clinician for reasoning about stress.

Therefore, we calculate the derivative of each step 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. A high positive angle value indicates rising finger temperature, while a negative angle, e.g. -20° indicates falling finger temperature. 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 contains 120 sample data (time, temperature). Thus 12 features are extracted from the 5 steps and named as *Step2_Part1*, *Step2_Part2*, *Step3_Part1*, ………, *Step6_Part1*, *Step6_Part2* as shown in Figure 2. First, a slope of the linear regression line has been calculated through the data points, as y is temperature (in Celsius) and x is time (in minute) by equation 1 for each extracted feature from the measurement.

$$slope_f = \frac{\sum_{i=1}^{120}(x-\bar{x})(y-\bar{y})}{\sum_{i=1}^{120}(x-\bar{x})^2} \qquad \textbf{(1)}$$

Where *f* denotes the number of features (1 to 12 see Figure 2), *i* is the index of the samples (1 to 120) and $\bar{x}, \bar{y}$ is average of the samples. Then this slope value is converted to arctangent as a value of angle in radians (*-pi/2* to *+pi/2*) and finally the arctangent value is expressed in degrees by multiplying *180/PI*. The converting function from radians to degree is described in equation 2 where *PI* is 3.14 as a standard value.

$$\deg ree_f = \left[\tan^{-1}(slope_f)\right] * \frac{180}{PI} \quad (2)$$

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, 17 (12+5) features are extracted automatically from the fifteen minutes (1800 samples) FT measurements signal data. Then a new case is formulated with 19 features as a total keeping in a vector above 12 features and adding *hours since last meal and gender*.

The DSS thereafter formulates a new problem case combining these extracted features and human defined static features. This new formulated case is then applied in diagnosing stress and making treatment plan by using the CBR cycle.

4. Feature extraction from textual data

For the textual feature the *tf-idf* (term frequency–inverse document frequency) [23] weighting scheme was used in the vector space model [24] together with cosine similarity to determine the similarity between two textual cases [29]. Additional domain information often improves results, e.g. a list of words and their synonyms or dictionaries that provide comparable words [25] [21] and relationships within the words using class and subclass. Our proposed system uses domain specific ontology that represents specific knowledge i.e. relation between words. The text tokenizer algorithm decomposes the whole textual information into sentences, and then into individual words. A filtering step is needed to improve retrieval effectiveness because of the huge amount of words.

The following three steps are used to extract the important textual features:

1. Remove the stop-words and special characters by the stop-words and special characters blacklist both from the users' query and patient record.
2. A list of synonyms of words from the WordNet is used to reduce the number of terms and Porter stemming algorithm [24] helps stemming the words that provide the ways of finding morphological variants of search term. After calculating the weight for each word, these words are represented as terms in a vector space.
3. Improve the importance assessments for candidate terms before measuring the cosine similarity value for the textual information between the stored case and user's query case by using domain specific ontology.

4.1 Term Frequency and Weighting

The *tf-idf* (term frequency–inverse document frequency) [23] weighting scheme is used for this system where the word "document" is treated as a case. The weight of a term computed as a function $W_{i,j}$, calculates the weight of each term or word of stored cases and a new case given in a user's query to perform further matching. The general equation for $W_{i,j}$ is shown in equation 3. There, $W_{i,j}$ is the weight of a term T_j in a case C_i, $tf_{i,j}$ is the frequency of a term T_j in a case C_i and idf_j is the inverse case frequency where N is the number of cases in a case base and df_j is the number of cases where term T_j occurs at least once.

$$W_{i,j} = tf_{i,j} * idf_j = tf_{i,j} * \log_2\left(\frac{N}{df_j}\right) \quad \textbf{(3)}$$

The cases are processed according to the vector space model and stored separately. First, from these collection of the cases an index of the terms is constructed and then the frequency of each term ($tf_{i,j}$) appearing in a case (C_i) and a new query case (Q) is counted. The case frequency (df_j) from the collection of the cases and the inverse case frequency (idf_j) are calculated thereafter, and finally the $tf_{i,j}* idf_j$ product gives the weight for each term. Equation 3 is modified slightly to give more emphasis on the terms, an adaptation of $tf_{i,j}$ based on the frequency of occurrence of the instances in each case is computed in equation 4 where $max_k(tf_{j,k})$ is the frequency of the most repeated instance tf_k in C.

$$tf_{i,j} = \frac{tf_{i,j}}{\max_k (tf_{j,k})} \quad \textbf{(4)}$$

4.2 Enhanced term vector using ontology

A domain specific ontology or user defined ontology represents specific domain knowledge, i.e., relation between words using class and subclass [27]. Terms of a case can be compared with other cases by exact matching or synonym matching or using a co-occurrence. However, some words or terms can have a complex relationship (for example, the term Sympathetic reactivity and Bio-feedback), the weight of such terms can be increased automatically using a domain specific ontology defined by experts. The weights in the term vector of a case can be enhanced by altering the term vector according to the following conditions:

1. If a term T_j in a case vector is related to a term T_o in the ontology but the term T_o does not exist in the case vector, then the term T_o can be added as a *new* term with the same importance as the weight of the source term, i.e. the score of *tf-idf.*

2. If a term T_j in a case is related to a term T_o in the ontology and also the term T_o exists in the case, then the strength of relationship between the term T_j and T_o can be added to the original weights (i.e. score of *tf-idf*) of those terms.

3. If more than one term in a case are related to a term T_o in the ontology, then those terms of that case will get more importance by adding their relationship strength with T_0 to their original weight (i.e. score of *tf-idf*).

4. If a term T_j in a case is related to more than one term in the ontology then the normalized mean strength of such relationships can be added to the original weight of the source term T_j.

An example is shown in fig.3 on how the ontology helps to improve the weight vector.

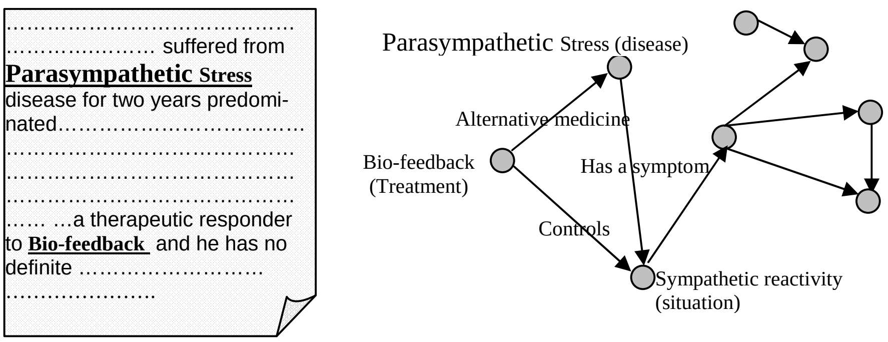


Fig. 3. Weighting term vector using ontology

From figure 3 "Bio-feedback" is a term that appears both in the case text and in ontology, it has a relation with another term "Sympathetic reactivity" in the ontology but the term "Sympathetic reactivity" does not exist in the case text, so the term "Sympathetic reactivity" is important for this case and the weight of this term can be added according to condition 1.

Again the terms "Parasympathetic Stress" and "Bio-feedback" both already exist in the case text and as well as has a relation in the ontology so the value of the strength of their relationship for those two terms ("Parasympathetic Stress" and "Bio-feedback") will increase the weights for their importance (condition 2).

Terms "Parasympathetic Stress" and "Bio-feedback" are related with another term "Sympathetic reactivity" in the ontology so the term "Sympathetic reactivity" will get more importance according to condition 3. Condition 4 is the vice versa of the condition 3.

5. Case retrieval and matching

Case retrieval is a key phase in CBR cycle where matching between two cases plays vital role because nearest or most relevant solved cases could be retrieved if an appropriate matching algorithm exists. To be more cautious, the proposed DSS decided to use fuzzy similarity by evaluating three different matching algorithms. The retrieval step is essential especially in medical applications since missing similar cases may lead to less informed decision. The reliability and accuracy of the diagnosis systems depend on the storage of cases/experiences and on the retrieval of all relevant cases and their ranking. In the DSS three implemented matching algorithms are 1) distance function for calculating similarity where distance between two cases are used for similarity calculation 2) similarity matrices defined by the expert where distance between two cases are converted into similarity values using matrices and 3) fuzzy set theory to calculate similarity between two cases. Similarity measurement is taken to assess the degrees of matching and create the ranked list containing the most similar cases retrieved according to equation 5

$$Similarity\ (C, S) = \sum_{f=1}^{n} w_f * sim\ (C_f, S_f) \qquad \textbf{(5)}$$

Where C is a current/target case, S is a stored case in the case base, w is the normalized weight defined by equation 6, n is the number of the attributes/features in each case, f is the index for an individual attribute/feature and $sim\ (C_f, S_f)$ is the local similarity function for attribute f in cases C and S.

$$w_f = \frac{lw_f}{\sum_{f=1}^{n} lw_f} \qquad \textbf{(6)}$$

Here, a *Local weight (lw)* is defined by experts, assumed to be a quantity reflecting importance of the corresponding feature, *Normalized weight (w)* is calculated by equation 6.

5.1 Fuzzy Similarity

A triangular membership function (*mf*) replaces a crisp input feature with a membership grade of 1 at the singleton. For instance, as shown in Figure 4 a current case has the lower and upper bounds 2.5 and 7.5 represented by the membership grade 0 and an input value 5 is represented by the membership grade of 1 (fuzzy set *m1*). Again an old case has the lower and upper bounds -1.5 and 4.5 represented by the membership grade of 0 and an input value 3 is represented by the membership grade of 1 (fuzzy set *m2*). In both cases, the width of the *mf* is fuzzified by 50% in each side. Then by applying fuzzy intersection between the two fuzzy sets *m1* and *m2* we get a new fuzzy set *om* which represents the overlapping area between *m1* and *m2.*

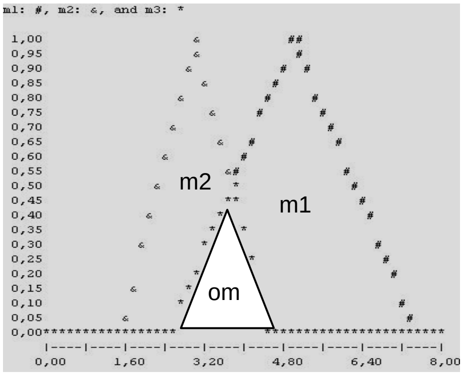


Fig. 4. Fuzzy similarity using triangular membership functions

Similarity between the old case and the new case is now calculated using equation 7 where area of each fuzzy set (*m1*, *m2* and *om*) is calculated. The similarity equation according to [10] is defined as-

$$sim(C_f, S_f) = s_f(m1, m2) = \max(om/m1, om/m2) \tag{7}$$

Where, $s_f\,(m1,\ m2)$ calculates the local similarity on feature f between the new and old cases. Clearly, when the overlapping area (*om*) is bigger the similarity on the feature will increase and for two identical fuzzy sets the similarity will reach unity.

5.2 Similarity Matching for Textual Part

The similarity between a stored case vector C_i and new case as a query vector Q is calculated using the cosine similarity function [24] [12] [32] where the cases deal with the textual information. This ratio is defined as the cosine of the angle between the vectors, within the values between 0 and 1 and can be calculated by equation 8.

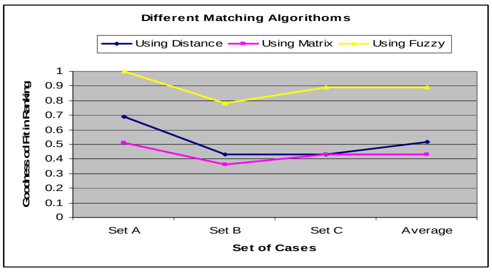
$$Cos\theta_{C_i} = Sim(Q, C_i) = \frac{Q \bullet C_i}{\|Q\|\|C_i\|} = \frac{\sum_j w_{q,j} w_{i,j}}{\sqrt{\sum_j w_{q,j}^2}\sqrt{\sum_j w_{i,j}^2}} \tag{8}$$

Where $Cos\theta_{C_i}$ is the *cosine of the angle* between a stored case and query case which is defined as the similarity function $Sim(Q,\ C_i)$. The dot product of a stored case and query case is $Q{\bullet}C_i$ where zero products are ignored; then vector lengths are calculated for a stored case and query case where $w_{i,j}$ and $w_{q,j}$ are weights calculated through equation 3 (zero terms are ignored).

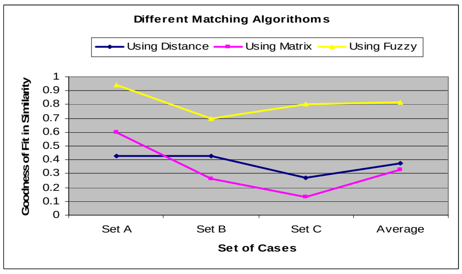
6. Evaluation

After implementing the proposed DSS, performance of the system has been evaluated where the evaluation is conducted on the similarity matching of the signal data and textual data respectively The accuracy of the matching algorithms on signal data as compared to the expert is calculated using a statistics index termed as *square of the correlation coefficient* or *Goodness-of-fit* (R^2) [8]. The performance of matching on textual data is evaluated by precision and recall of retrieval. The case base is initialized with 39 reference cases classified by the domain expert.

6.1 Similarity matching on signal data



a) R^2 in ranking value



b) R^2 in similarity value

Fig. 5. Comparison among three different matching algorithms.

We have discussed in the earlier section (section 5) about the three matching algorithms implemented in this system to choose the best one and now the performance of these algorithms is evaluated in this section. For the evaluation of matching algorithms on signal data we have chosen randomly three subsets of cases and three query cases, the subsets are as follows: 1) Set A: {7 cases} with query case id 4, 2) Set B: {11 cases} with query case id 16 and 3) Set C: {10 cases} with query case id 28. All the three sets have been sorted according to the similarity with the query case decided by a domain expert (human reasoning). The sorted cases are then converted to the rank numbers, i.e., the position of a case in the ranking. Likewise, the evaluation process is designed for the three algorithms including distance, matrix, and fuzzy matching, used in the system. Top six cases from each set according to the expert's ranking are used as standard for the evaluation process where both the similarity values and the ranking numbers are considered. Comparison charts of the three matching algorithms using the three sets according to their goodness-of-fit (R^2) are presented in Figure 5, where a) shows calculated R^2 for ranking values and b) shows R^2 for similarity values.

6.2 Similarity matching on textual data

The evaluation of the similarity matching method on textual data has been conducted in two phases. At first, each algorithm implemented in this system is tested according to their outcome that is, from the technical point of view, to check whether algorithms for pre-processing (i.e tokenization, stop-word removal and stemming), generating terms vector of cases (initial term weighting) and alternating the term vectors (using dictionary and user defined ontology) are functioning properly. Furthermore, functionalities such as case retrieval and case retain are verified through a web-interface, where the similarity value of two same cases is computed as 100% match. During retain, a case is successfully stored into the case base and the case base is then updated by an external service according to the case term vectors with corresponding term-weights. Although this initial phase is not that much significant for this paper it is necessary to discuss this because it works as a baseline for the evaluation.

We have evaluated the system performance in terms of precision and recall. Recall and precision are two common metrics used to estimate the efficiency of the information retrieval in a CBR system. Precision is the fraction of a searched output that is relevant to a particular query. It represents the proportion of the relevant retrieved cases to all the retrieved cases, i.e. the less irrelevant cases are retrieved the better the precision will be. So the calculation requires knowledge of the relevant and non-relevant hits in the evaluation set of cases. It is possible to calculate the precision of our implemented CBR system because the case base is artificially made from the medical domain. Recall on the other hand measures the ability of a retrieval system to obtain all or most of the relevant cases from a collection of cases (i.e. case base). It represents the proportion of relevant cases retrieved to all the relevant cases in the case base. The more relevant cases are retrieved the better the recall will be. Thus recall requires knowledge not just for the relevant and retrieved cases but also those are not retrieved yet relevant. There is no proper method for calculating absolute recall of such retrieval system as it is impossible to know the total number of relevant cases, but for our system we only concern the cases in our case base of moderate size so the recall is calculable.

Table 1. Experimental results comparing two methods in terms of precision and recall.

	Traditional VSM		Implemented method	
	Precision	Recall	Precision	Recall
problem1	68.7%	68.7%	77.23%	81.23%
problem2	63.1%	72.1%	84.45%	75.45%
problem3	65.3%	71.3%	73.1%	88.1%
problem4	69.3%	67.3%	80.34%	77.34%
problem5	67.23%	69.23%	80.7%	77.7%
Average	66.72%	69.72%	79.16%	79.96%

In the second phase, the evaluation has been done to judge the system performance on retrieving textual cases. The precision and recall are calculated comparing the text retrieval methods i.e. the conventional Vector Space Model (VSM) against our retrieval method enhanced with knowledge. For the evaluation, 5 new problem cases as query are created where each query case contains around 7 to 10 terms after removing stop-words. The comparison results between the two methods in terms of precision and recall are stated in Table 2 where 0.3 is considered as a threshold value. The results from Table 2 indicate that the average precision of five new problems for traditional vector space model is 67% whereas our enhanced method has better precision rate i.e. 79%. As can be seen from Table 2, the average recall of the five problems for our implemented method is 80% whereas the traditional vector space model has lower recall i.e. 70%. On the whole, the results suggest that the enhanced method performs better in terms of precision and recall in this CBR system.

5. Related research

Research work addressed in this paper for providing decision-support to clinicians in the psycho-physiological medicine is of great significance in applying CBR and other artificial intelligence techniques in medical domain.

5.1 CBR in psycho-physiological medicine

A procedure for diagnosing stress-related disorders has been put forward by Nilsson et al. [16] according to which stress-related disorders are 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. In our previous work [3], a stress diagnosing system using CBR has been designed based only on the variation of the finger temperature measurements, but this previous research did not explore whether any other subjective factors could also be used in diagnosing individual stress levels. In the earlier research [4] we have further demonstrated a system for classifying and diagnosing stress levels, exploiting finger temperature graphs and other features. This system relies on CBR as well as on fuzzy sets theory. The current paper presents a result of the evaluation of a computer-aided stress diagnosis system comparing with a domain expert/clinician. In this system CBR-retrieval works with fuzzy similarity matching for signal data and cosine similarity for textual information. In addition, the calibration phase is extented with a reliability test using a visual analogue scale and considers subjective features in a textual data format.

5.2 CBR in other medical domain

Some other related research works in the medical domain using CBR are: MNAOMIA [6] has been developed for the domain of psychiatry. CARE-PARTNER [7] is a decision support system developed in stem cell transplantation. Auguste [14] project has been developed for diagnosis and treatment planning in Alzheimer's disease. Montani et al. [15] has combined case-based reasoning, rule-based reasoning (RBR), and model-based reasoning to support therapy for diabetic patients. In [18] Perner has proposed a methodology for image segmentation using case-based reasoning in which information is extracted from digital medical images. Perner et al. [19] has proposed and evaluated a method to identify spores in digital microscopic images. BOLERO [13] is a successfully applied medical CBR diagnosis system in diagnosing pneumonias which applies fuzzy set theory for representing uncertain and imprecise values.

5.3 Related work in textual CBR

For the time being the majority of medical CBR systems are based upon results of measurements/tests in order to construct representations of cases. Various features (both numerical and symbolic) are extracted from sensed values, time-series signals, as well as images to acquire the conditions of patients under investigation. The advantage of using measurements for case indexing is objectiveness, which reduces vagueness and uncertainty in knowledge and information delivered. On the other hand, textual message presents another aspect of information available from digital records of patients stored in many hospitals. Textual case-based reasoning has been addressed for medical applications by recent works [20] [29] [30]. However, cases can be ill structured [31] [29] or have structures that do not match between cases, especially when digitalizing past cases or they may contain terminology that does not contain accordance to the clinical standard and building a CBR system for such context is quite challenging. A case retrieval framework has been described in [30] where the authors have applied textual CBR approach to acquire and elicit knowledge from structured documents. The authors in [32] have used feature vector generalization to form structural cases for retrieving textual cases, where it captures semantic relationships by the way of association. In [26], a vector space model-based retrieval system using cosine similarity and manual weighting for full text document search in MEDLINE has been presented. However in our system we use a domain specific ontology instead of manual weighting. The authors in [12] have showed that a modified cosine matching function performs better in retrieval compared with the Nearest-Neighbor in the electromechanical domain. In [22][11] authors have demonstrated the applicability of CBR-IR (information retrieval), a hybrid approach in dealing with the quality of retrieved documents in large case base. The advantages of combining CBR and IR methodologies have further been indicated by Bichindaritz [5] in memory organization to handle large scale case bases in biomedical domain. Vector space model (VSM) is a widely used information retrieval technique [9][2][1] and some of these applications also have taken advantage of ontology in retrieving useful textual cases.

6. Summary and conclusions

This paper presents a hybrid case-based reasoning system dealing with combined time series signals and unstructured textual documents for clinical decision support in stress medicine. We believe that time series measurements and textual data in documents capture different yet complementary aspects of the subject to be studied and they are desired to be tackled simultaneously for more comprehensive situation awareness and thereby more reliable diagnoses and decisions. The contribution of the paper is two-fold. First, a fuzzy matching function is proposed for evaluating the partial similarity of cases based on signals. This similarity function uses the theory of fuzzy sets to cope with imprecise attribute descriptions extracted from signals of finger temperatures, making judgments of similarity more robust against noises in sensor readings as well as closer to human thinking and reasoning. Second, certain knowledge models such as Wordnet and ontology are incorporated into the reasoning process with textual parts of cases. We have demonstrated that the domain knowledge and information encoded in these models (wordnet, ontology) can be made use of to refine weights of terms to enhance the cosine case matching on the textual dimension.

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