Hybrid Reasoning Framework for CARA Pervasive Healthcare

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Abstract. Pervasive computing has emerged as a viable solution capable of providing technology-driven assistive living for elderly. The pervasive healthcare system, *CARA*(Context Aware Real-time Assistant), is designed to provide personalized healthcare services for elderly in a timely and appropriate manner by adapting the healthcare technology to fit in with normal activities of the elderly and working practices of the caregivers. The work in this paper introduces a personalized, flexible and extensible hybrid reasoning framework for *CARA* system in a smart home environment which provides context-aware sensor data fusion as well as anomaly detection mechanisms that supports Activity of Daily Living(ADL) analysis and alert generation. We study how the incorporation of rule-based and case-based reasoning enables *CARA* to become more robust and to adapt to a changing environment by continuously retraining with new cases. Case study for evaluation of this hybrid reasoning framework is carried out under simulated but realistic smart home scenarios. The results indicate the feasibility of the framework for effective at-home monitoring.

Keywords: Pervasive Healthcare, CARA, Cased Based Reasoning (CBR), Fuzzy Rule Based Reasoning (FRBR), Activity of Daily Living(ADL), Anomaly Detection, Home Automation, Smart Home.

1 Introduction

With an increasingly ageing population profile, the provision of healthcare is undergoing a fundamental shift towards the exploitation of pervasive computing technologies to support independent living and avoid expensive hospital-based care [1]. Pervasive and context-aware applications [2] have been widely recognized as promising solutions for providing ADL analysis for the elderly, in particular those suffering from chronic disease, as well as for reducing long-term healthcare costs and improving quality of care [3].

The original CARA healthcare architecture has been shown to enable improved healthcare through the intelligent use of wireless remote monitoring of patient vital signs, supplemented by rich contextual information [4,5]. Important aspects of this application include: inter-visibility between patient and caregiver;

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real-time interactive medical consultation; and replay, review and annotation of the remote consultation by the medical professional. A rule-based reasoning engine is implemented in the CARA system by using fuzzy logic [6]. It allows a user to configure the fuzzy membership functions which represent the context model, and applies user designed fuzzy rules to make inferences about the context. The annotation of significant parts of the fuzzy-based reasoning provides the basis for the artificial intelligence of the CARA system. However, this system requires certain medical knowledge to structure fuzzy rules to perform the reasoning. It is limited by being domain specific and not so adaptable to a changing environment.

In this paper we present a novel approach that combines context awareness, case-based reasoning, and general domain knowledge in a healthcare reasoning framework. In combining these concepts the architecture of this system has the capability to handle uncertain knowledge and use context in order to analyse the situation and lead to an improved independent quality of life. The limitations of a single reasoning method are overcome by adapting the domain knowledge as rules in the process of reusing cases. Moreover, we introduce the idea of query-sensitive similarity measures in the case retrieval step which dynamically adjusts weights of contexts based on the output of the fuzzy-based rule engine.The context aware hybrid reasoning framework we proposed is flexible and extendible which can be applied to various domains. Especially in the medical field, the knowledge of experts does not only consist of rules, but of a mixture of explicit knowledge and experience. Therefore most medical knowledge based systems should contain two types of knowledge: objective knowledge, which can be found in textbooks, and subjective knowledge, which is limited in space and time and individual. Both sorts of knowledge can clearly be separated: objective knowledge can be represented in the form of rules, while subjective knowledge is contained in cases. The limitations of subjective knowledge can partly be solved by incrementally updating the cases [7]. The objective of this paper is to present a scalable and flexible infrastructure for the delivery, management and deployment of context-aware pervasive healthcare services to the elderly living independently.

2 Hybrid Reasoning Framework

2.1 Overall Design

A pervasive healthcare system is an ambient intelligence system that is able to (i) reason about gathered data providing a context-aware interpretation of their meaning, (ii) support understanding and decision and (iii) provide corresponding healthcare services. To achieve that in the CARA system, we adopted a context-aware hybrid reasoning framework by means of case-based reasoning and fuzzy rule-based analogy. The high-level interactions in the hybrid reasoning engine are presented in Figure 1. Raw data coming from sensors is processed and integrated with context knowledge by the context data fusion services, producing contexts for building case queries and fuzzy sets. After that, the case-based reasoning component starts running a standard CBR cycle(Retrieve, Reuse, Revise and

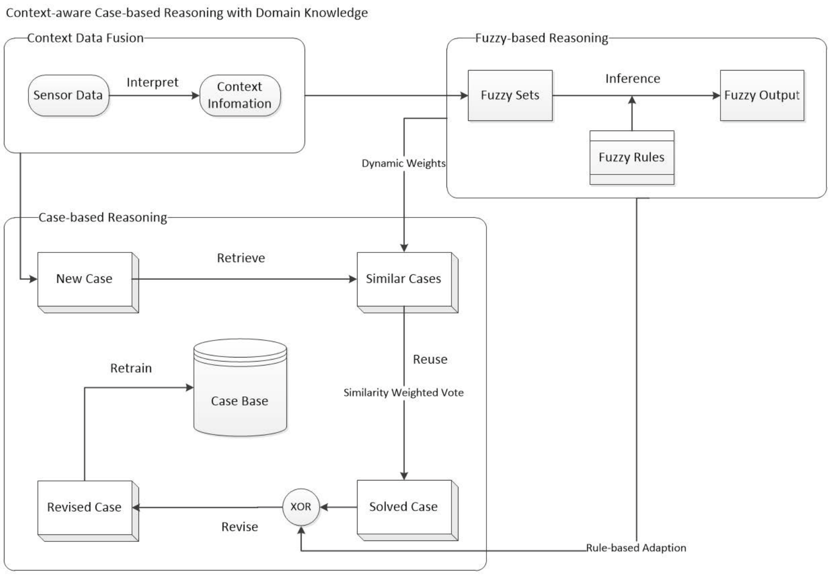


Fig. 1. The Structure of Context-aware Hybrid Reasoning Framework

Retain) to perform anomaly detection and home automation. Meanwhile, the fuzzy rule-based analogical component loads fuzzy rules from the inference rule database to generate higher level contexts(e.g. medical condition, and accident event) and further to identify current situation of the user (normal, abnormal or emergency). The result of the fuzzy output can be used to dynamically adjust weights of features or groups for case retrieval, and can also affect the adaptation of the retrieved solution to the new case. The case is revised according to the combination of retrieved similar cases and fuzzy outputs. Finally, if the detected situation is abnormal or an emergency, a notification or alarm is automatically sent to the remote monitoring server and an emergency service call can be triggered. The collected raw data and revised case are stored for enhancing the case base and subsequent additional analysis.

2.2 Context-Aware Query Sensitive

Case-based reasoning is recommended to build intelligent systems that are challenged to reduce the knowledge acquisition task, avoid repeating mistakes made in the past, reason in domains that have not been fully understood or modelled, learn over time, reason with incomplete or imprecise data and concepts, provide a means of explanation, and reflect human reasoning. However, the common k-nn (k nearest neighbour) algorithm for case retrieving has limitation as pointed out in [8], finding nearest neighbours in a high-dimensional space raises the following issues:

1. Lack of contrast: Two high-dimensional objects are unlikely to be very similar in all the dimensions.
2. Statistical sensitivity: The data is rarely uniformly distributed, and for a pair of objects there may be only relatively few coordinates that are statistically significant for comparing those objects.

To address these problems, we propose to construct, together with context awareness, a query sensitive mechanism for similarity or distance measure. The term *Query Sensitive* means that the distance measure changes depending on the current query object. In particular, the weights used for the features similarity measure automatically adjust to each query. Specifically, we apply fuzzy rules to the input query and use the crisp value of fuzzy output to dynamically adjust weights, which we expect to be significantly more accurate than the simple k-nn method associated with case retrieving. The query sensitive similarity measure function employed by our reasoning framework is shown in Equation 1.

$$Sim_g(Q,P) = \frac{\sum_{k=1}^{n} W_k Sim_l(Q_k, P_k)}{\sum_{k=1}^{n} W_k} \tag{1}$$

In this formula, Sim_g(Globe Similarity) of Q(Query) and P(Past Case) is calculated based on Sim_l(Local Similarity) of Q_k(Feature k of Query) and P_k(Feature k of Past Case) and the dynamic weight of the feature W_k. If k is the feature of a query, we use the term *weighted* to denote any function mapping W_k(weight of k) to the binary set 0,1. We can readily define the function using fuzzy logic. Given a query Q, and a block of fuzzy rules F_{rule}, we can define a weighted function $W_{Q,F_{rule}} \to \{0,1\}$as follows:

$$W_{Q,F_{rule}}(k) = \begin{cases} f(k) & if\ \forall k, k \in F_{rule} \\ 0 & otherwise \end{cases} \tag{2}$$

Where $f(k)$ is the degree of fuzzy membership function of feature k. For instance, we define the fuzzy membership function of Systolic Blood Pressure containing fuzzy sets {*very low, slightly low, normal, slightly high, very high*}, among them, *very high* is a left linear fuzzy set in the range of 140 to 200. If the Systolic Blood Pressure of a new case is 167mmHg, once the fuzzy rule "if (Activity is Sleeping or Activity is Resting or Activity is Watching TV or Activity is Toileting) and (Systolic Blood Pressure is High or Dynamic Blood Pressure is High) then Situation is Abnormal" is evaluated and triggered, the weight of Systolic Blood Pressure used for the similar case retrieval is set to 0.45 which is the fuzzy degree of *very high* fuzzy set of Systolic Blood Pressure. As the result, the final weight for each feature of the query is dynamically adjusted by the fuzzy outputs.

2.3 Similarity Weighted Vote

Similar cases are retrieved after the K Nearest Neighbour(K-NN) function is applied to similarity measurement. Normally, the possible solution for the given query can be predicted from the most similar case. In our case, for anomaly detection, the results of retrieved cases are supposed to be classified into *Normal, Abnormal, Emergency* categories. To determine the possible situation of the subject, a similarity weighted voting mechanism is considered to be used in the voting decision during prediction. Basically, every nearest neighbour has a different influence on the prediction according to its distance to the query. The principle of similarity weighted voting method is to use the similarity value of each retrieved case as the weight to vote for the most reasonable solution. It is achieved in following steps:

1. Classify K-NN retrieving result into different groups.
2. Calculate total similarity of all retrieved cases.
3. Get the sum of similarity of each group.
4. Use the group similarity to vote for prediction.
5. Calculate confidence value of the predicted result.

To distinguish the predicted result from past cases, we apply a threshold to the confidence value of the predicted solution which is used as a controller to balance the detection rate and false alarm rate of the rule engine. Let us remark that the threshold ε can be freely set by the user. If user chooses $\varepsilon = 0$, the rule engine takes into account all possible problems in P(Past Case), and the determination of the solution of a unique Q(Query) associated with given P lies in this case on the voting result. Otherwise, the threshold ε can be considered as a level of decidability: if there exists no P such that $Conf(Q, P) \geqslant \varepsilon$, then there is no already solved problem sufficiently similar to Q and no solution can be proposed. In this case we introduce the fuzzy adaptation model to deal with the uncertainty. The core competence of our reasoning framework is that domain knowledge, which is represented by fuzzy rules and fuzzy sets, is applied to both case retrieving and case adaptation.

2.4 Fuzzy Adaptation Model

We have developed an adaptation technique for case-based reasoning derived from fuzzy logic based analogical reasoning and modelling. Fuzzy logic imparts to case-based reasoning the perceptiveness and case discriminating ability of domain knowledge. Problems and solutions are, in many cases, described by means of linguistic terms or approximate values derived from expert knowledge. A convenient knowledge representation is thus fuzzy set based. The reason why we choose fuzzy logic is because it provides a simple way to arrive at a definite conclusion based upon ambiguous, imprecise, noisy, or missing input information. The steps to constructing the fuzzy adaptation model assisting CBR are:

1. Configure the fuzzy reasoning model.
2. Traverse the case base to find k-nn similar cases.
3. Make a prediction based on weighted median of similarity.
4. Apply the fuzzy adaptation if the confidence of the prediction is low.
5. Use the fuzzy output to revise the solution of the present case.

Step 1 is performed only once to configure the fuzzy membership function and register fuzzy rules. Step 2-4 are performed every time a CBR cycle starts. Note the fuzzy reasoning mechanism is applied if and only if the CBR method couldn't find a similar solution for the present query, the result of fuzzy output then uses as possible solution from the domain knowledge point of view to make up for the lack of experience. The principle of building a fuzzy framework is to design appropriate member functions which are also referred to as fuzzy sets. The fuzzy relations among these fuzzy sets indicate some of the rules in our reasoning engine. An example of anomaly detection rules are given in Table 1. Such rules can be specified by medical experts or a particular healthcare giver. They can also be modified by patient under supervision in case of individualization.

Table 1. Sample rules for anomaly detection in smart home environment

Medical Associated Rules
if Activity is not Exercising and HeartRate is VeryHigh then Situation is Abnormal
if SystolicBloodPressure is VeryHigh and DynamicBloodPressure is VeryHigh then Situation is Abnormal
Event Associated Rules
if Activity is Sleeping and (TV is ON or Cooker is ON or Lights is ON) then Situation is Abnormal
if Location is Outdoor and Time is Late Night then Situation is Abnormal

3 System Evaluation

It is difficult to evaluate the CARA system in its entirety without extensive field deployment and analysis. Issues including medical, ethical and practical make field experiments infeasible at present.

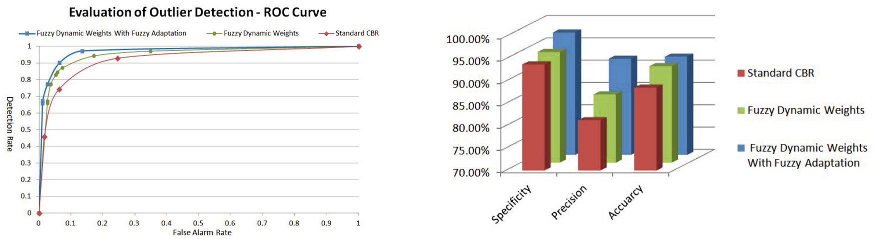
However, we have conducted realistic simulation experiments in our lab to test the correctness of the proposed context-aware hybrid reasoning framework in a pervasive healthcare environment and report the results in this section. In our testing scenario, we deploy the CARA system composed of Remote Healthcare Sever, Wearable Sensors and Client Applications in our lab. For this test stage, real-time vital signs of the patient are collected from wearable BioHarness sensors [9] while environmental sensing is simulated by an android application which we developed to reflect the change of the ambient environment. Biomedical parameters currently taken into account in the model are: heart rate frequency, pulse oxygen level, systolic and diastolic blood pressure, body temperature, and respiration rate while ambient contexts involves time, space and duration associated with a subject's activity, environmental sensing e.g. temperature, light, noise and humidity, device interactions e.g usage of TV, cooker, phone, and status of heater, window and lights.

Use case testing is underway with a trial in our lab. It is carried out to evaluate performance and acceptance of the implemented features. Since the test-bed for smart home environment is still under construction, we have to simulate the behaviour of a person living in a realistic home environment based on the daily routine of an elderly person, which provides us with *Activity Contexts*. We also simulate light, room temperature, sound and humidity changes during the test stage which gives us *Ambient Contexts*. *Physiology Contexts* and *Personal Contexts* are collected from the BAN and loaded from server database respectively.

All the contexts are used to build up the input query for CBR, they are also mapped into fuzzy sets and enforced by applying consistency rules which refers to the domain knowledge. The system then produces the final decision which indicates the current situation of the subject. To simplify the evaluation process for anomaly detection, here we only consider a two-class prediction problem (Normal or Abnormal), in which the outcomes are labelled either as positive or negative. The case base used for testing contains 262 cases, among them, 192 are normal cases and 70 are abnormal cases. We evaluated the proposed approach against the common CBR approach and evolving CBR approach using dynamic weights in case retrieval. Given the high variability among these trials, we are able to evaluate the accuracy of situation prediction over a wide range. The results are shown in Table 2. As we discussed in the previous section, we adjust the threshold for the confidence value to get a trade-off between Detection Rate and False Alarm Rate. We use receiver operating characteristic(ROC) in signal detection theory [10] to evaluate our reasoning framework. By calculating true positive rate and false positive rate, we are able to draw a ROC curve as shown in Figure 2 (a). Each prediction result or instance of a confusion matrix represents one point in the ROC space. The best possible prediction method would yield a point in the upper left corner at coordinate (0,1). So any point closer to that would be considered as a better approach. It is shown that the proposed approach is the best prediction method for anomaly detection. The best performance of each approach is compared and presented in Figure 2 (b),

Table 2. Results of Various CBR Approaches

Threshold	True Positive	False Positive	True Negative	False Negative	Accuracy
Common CBR					
0.9	65	47	145	5	80.15%
0.8	52	12	180	18	88.55%
0.7	32	3	189	38	84.35%
Improved CBR with Fuzzy Dynamic Weights					
0.9	68	67	125	2	73.66%
0.8	66	33	159	4	85.88%
0.7	54	7	185	16	91.22%
Proposed CBR with Fuzzy Dynamic Weights and Fuzzy Rules Adaptation					
0.9	68	26	166	2	89.31%
0.8	63	12	176	7	92.64%
0.7	54	5	187	16	91.98%



(a) ROC Space of Three Different Approaches for Anomaly Detection

(b) Best Performance of Three Different Approaches

Fig. 2. Use-case testing results

where the proposed approach gives 97.4% Specificity, 91.5% Precision and 92.6% Accuracy at Confidence Threshold value of 0.7 while the normal CBR approach only gives 93.7% Specificity, 81.2% Precision and 88.5% Accuracy at Confidence Threshold value of 0.8.

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