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].

A context-aware system is designed to use the context to provide relevant information and services to the user. To achieve pervasive healthcare for independent living [4], a context-aware system should be able to observe, interpret and reason about dynamic situations (both temporal and special) in a smart home environment. Although the straightforward rule based reasoning engine is a competent approach, it still has some unsatisfactory limitations. For example, specific rules may be easy to apply and are reliable, but only apply to a narrow range of adaptation problems; whereas more abstract rules span a broad range of potential adaptations but not provide domain-specific guidance. Case-based reasoning [5] is another approach targeting problem resolution in domains where structured domain knowledge is known, however it requires an accumulation of sufficient previous cases to accomplish the reasoning task.

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 [6]. 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.

The remainder of the paper is as follows. Related work about context-aware reasoning systems is summarized in section 2. This is followed by the presentation of an overview of the system structure. In section 4, our hybrid reasoning framework is incorporated into the CARA architecture for knowledge-intensive case-based reasoning. In section 5, the system is evaluated on simulated realistic scenarios to illustrate how pervasive healthcare can be supported by the proposed scheme. The final section presents a summary and conclusions.

2 Related Work

Making computer systems adaptable to the changes of their operating environment has been previously researched in the context of agent technologies [7]. An intelligent agent is a software system operating in an environment. It senses the changes of the environment, makes a decision in terms of its goal and domain knowledge, and takes actions accordingly.

Much work has been done on how to use reasoning mechanisms to achieve context awareness. W.Y. Lum et al. use decision trees to decide the optimal content for presentation, based on the specific context, such as intended target device capabilities, network conditions, and user preferences [8]. A. Ranganathan et al. propose a context model based on first-order predicate calculus [9]. M. Wallace et al. develop a context aware clustering algorithms for data mining a user's consumer interests of multimedia documents, based on user history [10]. Case-based reasoning is also a successful technique for context aware systems in many domains [11, 12],but less so for medical applications. The main problem for case-based reasoning is the adaptation task. Some more research is required on this topic; some formal adaptation models [13], but no general methods have been developed so far. In our work, a fuzzy logic based method for knowledge acquisition is developed and used for case retrieval and adaptation in a case-based reasoning system.

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 [14, 15]. Important aspects of this application include: inter-visibility between patient and caregiver; 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 [16]. 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. This paper describes case-based reasoning mechanisms incorporating fuzzy-based domain knowledge to compensate for the deficiencies of a single reasoning model.

3 System Overview

Advancements in internet technology have made possible innovative methods for the delivery of healthcare. Universal access and a networking infrastructure that can facilitate efficient and secure sharing of patient information and clinical data, make the internet an ideal tool for remote patient monitoring applications.

The overall design of the CARA pervasive healthcare system is shown in Figure 1. The patient's vital signs are monitored by different kinds of sensor within a wireless BAN(Body Area Network), and environmental sensors are deployed to monitor the home surroundings. All measurement data are transmitted to a gateway (often a PC or a smart phone) as raw data or lower level context. The gateway connects over the internet to the CARA cloud server which provides sensor data management and remote monitoring services. A Flash application

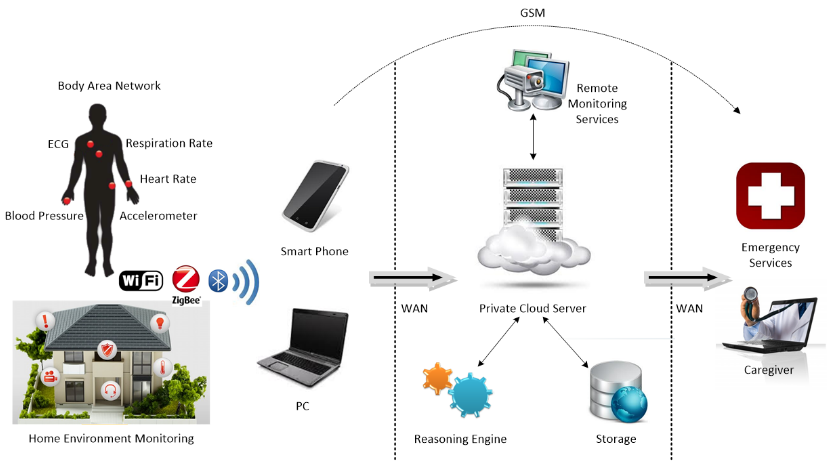


Fig. 1. CARA Pervasive Healthcare System Overview

running on the gateway publishes real-time sensor data along with live video streams to the CARA server so that the remote caregiver can communicate with the elderly throughout the monitoring. On the server side, data derived from the sensor data is stored in an implementation independent generic format (i.e. XML), and the contexts are stored as cases for CBR.

The reasoning engine plays a crucial role in the system both on the client and on the server side as an intelligent agent. It can be tailored with different rules for different applications (such as for in-clinic assessment or smart home monitoring), and it also executes in real-time and offers immediate notification of critical conditions. Some critical conditions may only be identified from correlating different sensor readings and trends in sensor readings accumulated over time. The CARA reasoning component is capable of performing the following reasoning tasks: (i) continuous contextualization of the physical state of a person, (ii) prediction of possibly risky situations and (iii) notification of emergency situations indicating a health risk. (iv) home automation or user prompting within a smart home environment.

Figure 2 illustrates the architecture of the CARA system. In the smart home healthcare scenario, BAN(Body Area Network) and various home environmental sensors are deployed to gather as much information about and around the person as possible. The system listens to all available sensor data via wireless communication protocols (i.e. bluetooth, zigbee). The raw numeric data is interpreted to construct the context for the monitored individual and environment. It can then be used by the intelligent reasoning components, which act as the brain of the system, to provide risk assessment and home monitoring. The real-time reasoning task is carried out with remote monitoring services and data mining services in parallel. In this paper, we focus on the hybrid reasoning framework which is a combination of case-based reasoning and fuzzy rule-based reasoning. It

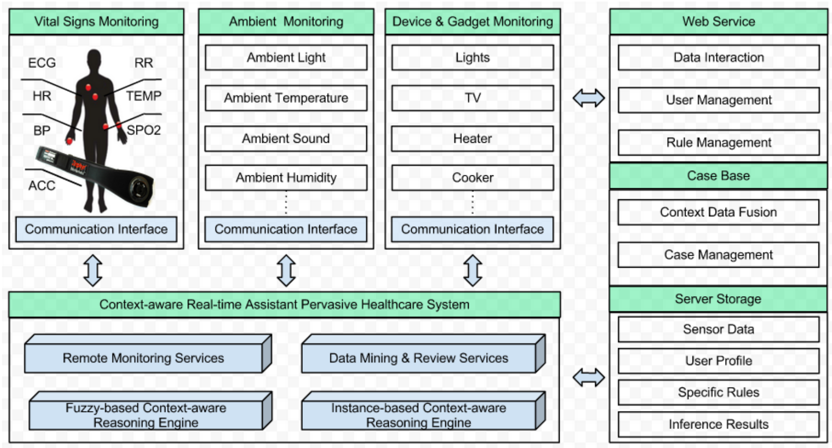


Fig. 2. Architecture of CARA System

is worth to mention that, although case-based reasoning has several advantages and perform good results in reasoning task, its efficiency suffers as the size of the case base grows. Especially for a mobile client with limited computing power, it seems a bit too expansive in term of efficiency to run the case-based reasoning applications. So our future work will focus on making use of the power of cloud computing to improve the performance of case retrieval in case-based reasoning. Eventually, the case-based reasoning component running on a private cloud environment should cooperate seamlessly with the light-weight fuzzy rule-based reasoning running on a PC or mobile client.

4 Hybrid Reasoning Framework

4.1 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 3. 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 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

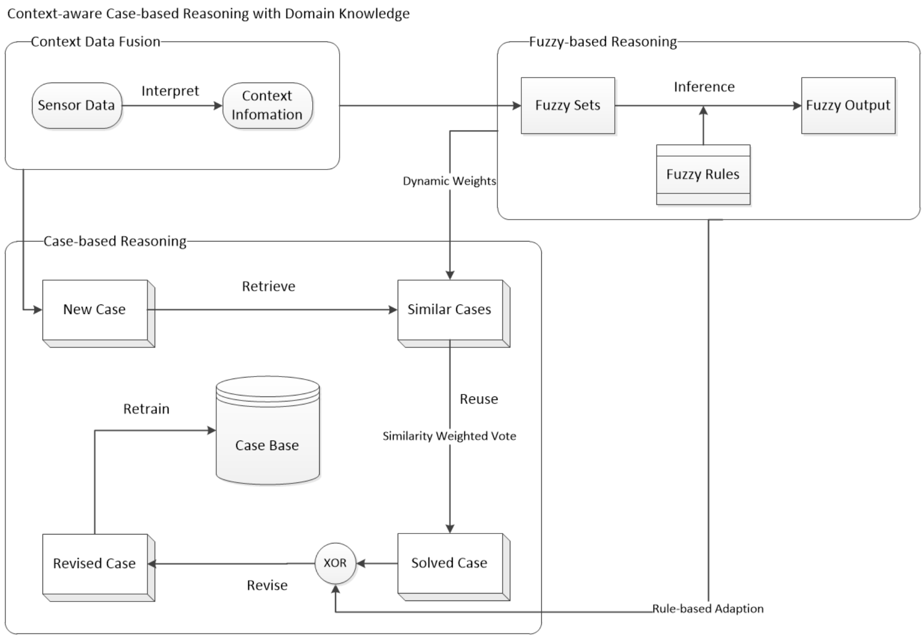


Fig. 3. The Structure of Context-aware Hybrid Reasoning Framework

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.

4.2 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 [19], 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.

4.3 Similarity Weighted Vote

K most 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, the elfevident, 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 (the details of the similarity weighted voting algorithm are shown is Algorithm 1).
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.

4.4 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, for instance "If the room temperature is very low and the season is not summer then turn on the heater". 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. It is an approach to control problems that mimics how a person would make decisions, only much faster. 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.

```
input  : Collection of cases from Retrieval Result
output: Predicted Solution
begin
    votes ⟵ New HashMap;
    counts ⟵ New HashMap;
    foreach case c of the retrieval result do
        solution = getSolution(c);
        similarity = getSimilarity(c);
        totalSim += similarity;
        if votes.containsKey(solution) then
            votes.put(solution, votes.get(solution) + similarity);
            counts.put(solution, counts.get(solution) + 1);
        else
            votes.put(solution, similarity);
            counts.put(solution, 1);
        end
        highestVoteSoFar ⟵ 0.0;
        predictedSolution ⟵ NULL;
        foreach entity e of votes do
            if e.getValue() ⩾ highestVoteSoFar then
                highestVoteSoFar = e.getValue();
                predictedSolution = e.getKey();
            end
            averageSim = highestVoteSoFar / counts;
            pow = highestVoteSoFar / totalSim;
            confidence = Math.pow(averageSim, pow);
            predictedSolution.setConfidence(confidence);
        end
    end
end
```

Algorithm 1: Similarity Weighted Voting for Prediction

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. A membership function is a representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, it defines functional overlap between inputs, and ultimately determines the output response [20]. The fuzzy relations among these fuzzy sets indicate some of the rules in our reasoning engine. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion. The inputs are combined logically using the logical operator to produce output response values for all expected inputs. The active conclusions are then combined into a logical sum for each membership function. Once the functions are inferred, scaled, and combined, they are defuzzified into a crisp output which gives the strength of each output membership function. An example of anomaly detection rules are given in Table 1. Such rules can be specified by medical

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

Medical Associated Rules
if Activity is not Exercising and (HeartRate is VeryHigh or RespirationRate is VeryHigh) then Situation is Abnormal
if SystolicBloodPressure is VeryHigh and DynamicBloodPressure is VeryHigh then Situation is Abnormal
if (Activity is Sleeping or Activity is Resting or Activity is WatchingTV or Activity is Toileting) and (SystolicBloodPressure is High and DynamicBloodPressure is High) 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
if (Activity is Eating or Activity is Cooking or Activity is Bathing or Activity is Exercising) and Time is Night and Lights is OFF then Situation is Abnormal

experts or a particular healthcare giver. They can also be modified by patient under supervision in case of individualization.

5 Implementation and 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 [22] 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. Figure 4 illustrates the screen shot of our protype application in a testing scenario.

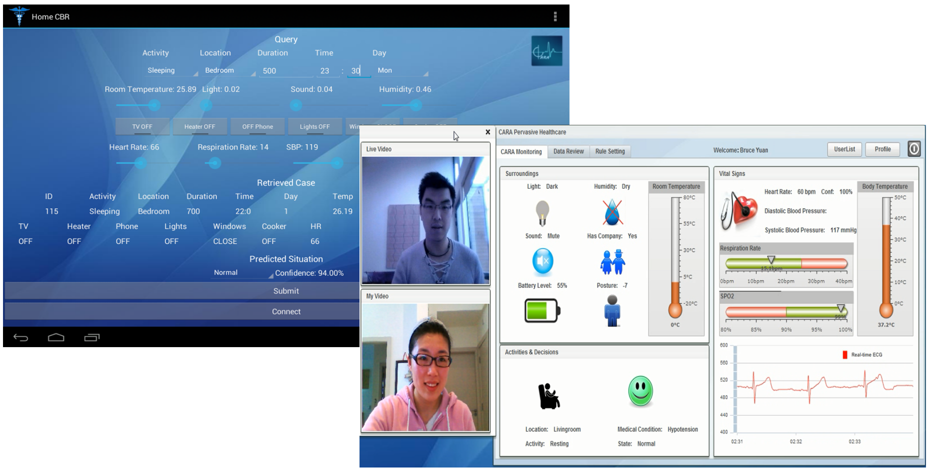


Fig. 4. Left is the Android application built for CBR in a smart home environment. Right is the demo of the CARA pervasive healthcare system showing context-aware reasoning and remote monitoring application

The remote monitoring and data review functions are previously implemented in CARA system as described in [14] [15]. Later, a fuzzy-based reasoning engine was integrated into the system which provides real-time intelligence for prediction in various healthcare situations [16]. We develop a context-aware hybrid reasoning framework which enhances the previous fuzzy rule-based reasoning engine with learning ability by adopting a novel case-based reasoning model. The approach is implemented based on jCOLIBRI:CBR Framework [21] and our previous work. It is implemented in Android and evaluated on an Android device(Motorola Xoom Tablet). Wireless connection between sensor network and client application is done using Bluetooth, and the application is also connected to the home gateway and remote healthcare server.

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 as shown in Figure 5, 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.

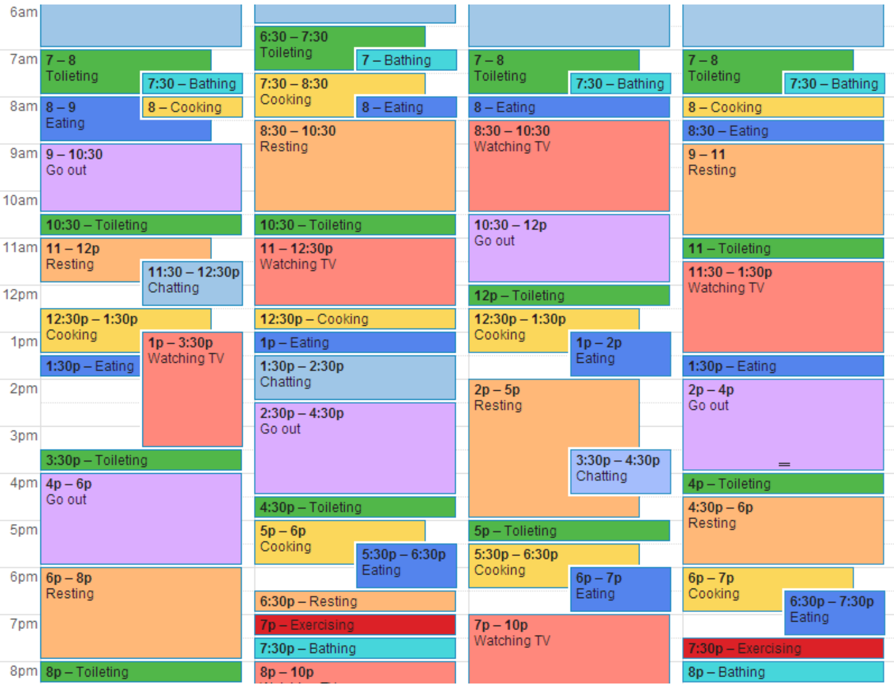


Fig. 5. Examples of Daily Routine of the Interviewee

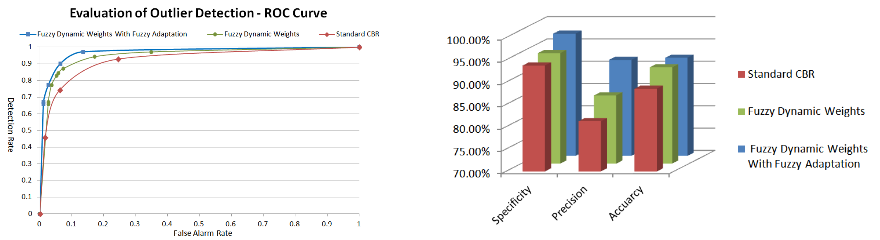
All the contexts are used to build up the input query for CBR, they are also mapped into fuzzy sets and enforced by applying consistency rules which refers to the domain knowledge. The system then produces the final decision which indicates the current situation of the subject. The case base used for 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. 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. If the outcome from a prediction is Abnormal and the actual situation is also Abnormal, then it is called a true positive (TP); however if the actual situation is Normal then it is said to be a false positive (FP). Conversely, a true negative (TN) has occurred when both the prediction outcome and the actual situation are Normal, and false negative (FN) is when

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%
0.6	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%
0.6	47	5	187	23	89.31%
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%
0.6	47	2	190	23	90.46%

the prediction outcome is Normal while the actual situation is Abnormal. 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. The contingency table above can derive several evaluation metrics e.g. true positive rate(Recall), false positive rate(Fall-out), true negative rate(Specificity), positive predictive value(Precision) [23]. It turns out that accuracy is not a sufficient metric for the evaluation of anomaly detection. Since most of the cases are normal, even if it predicts every situation as normal, the accuracy could still be very high. As a result, we introduce the idea of receiver operating characteristic(ROC) in signal detection theory [23] 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 6 (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), it is also called a perfect classification. 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 6 (b), 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.

To measure the performance of our approach, we added a time checking function. A start time is noted before calling a method, and then the finish time is noted after calling the method, providing a measure of the execution time for each task. We applied 10-fold cross-validation to several case bases with different amounts of Normal and Abnormal cases. The summarized test results are shown in Table 3.



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

(b) Best Performance of Three Different Approaches

Fig. 6. Use-case testing results.

Although the reasoning tasks mostly rely on the computational power of the client device, it is clear that the response time of our rule engine is in direct proportion to the amount of cases being checked and the complexity of rules. We notice that the CBR mechanism gets computationally extensive as the size of the case base increases. If we have the system running for weeks and months, producing many thousands of cases, then it would become unacceptable in terms of efficiency for the user. To relieve the problem, we are working on the following two approaches. Firstly, a regular maintenance scheme is essential to remove redundancy from the case base. Secondly, the underlying cloud computing could provide a reasonable solution for big data mining by sub-dividing the case bases and then allocating groups to different servers to allow parallel processing.

Table 3. Inference Performance for Various Case Bases

Total Amount of Cases	Normal	Abnormal	Time Per Cycle (ms)
262	192	70	1925
200	150	50	1256
100	72	28	507
50	39	11	182

6 Conclusion and Future Work

Case-based reasoning is a promising method for detecting unusual events that may correspond to the medical errors or unusual activities. In this paper, we have proposed a novel context-aware hybrid reasoning framework that integrates fuzzy rule-based reasoning with an instance-based model to achieve pervasive healthcare in smart home environment. The advantage of the approach is that it performs fully unsupervised learning and with the minimum input from the domain expert. The evaluation result shows that, comparing with other approaches(e.g. rule-based reasoning and common case-based reasoning), it significantly improves the performance of the reasoning engine in terms of efficiency, accuracy and flexibility. It achieves this by adopting context models for case representation, dynamic weights and hierarchic similarity for case retrieving, and intelligent rule validation for case adaptation. We believe the proposed reasoning framework makes the CARA system more robust and more adaptive to a changing environment.

Despite initial encouraging results, our current approach can be further refined and extended. The next phases of our work include recognizing user activities by tracking user movement and related context(e.g. location and duration), and then comparing them with recorded patterns. We are also working on building up a smart home lab by deploying wireless sensor networks, containing various environmental and device sensors, in a real home environment.

Another direction for future research we want to explore is to tie our findings back in to our earlier work on a design methodology for medical healthcare systems with a socio-technical perspective. Our research has shown that ambient intelligent systems can benefit from a clinical knowledge model, but we have not yet explored the relation to the different knowledge containers in detail. Additionally, we want to deploy our reasoning framework in a private cloud environment for data mining and more efficient case retrieving, since the current implementation is limited by the computing power of the device.

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