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Ambient Systems, Networks and Technologies (ANT-2012) Fuzzy CARA - A Fuzzy-Based Context Reasoning System For Pervasive Healthcare

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Abstract

Pervasive computing is allowing healthcare to move from care by professionals in hospital to self-care, mobile care, and at-home care. The pervasive healthcare system, *CARA*(Context Aware Real-time Assistant), is designed to provide personalized healthcare services for chronic patients 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. This paper presents a fuzzy-logic based context model and a related context-aware reasoning middleware that provides a personalized, flexible and extensible reasoning framework for *CARA*. It provides context-aware data fusion and representation as well as inference mechanisms that support remote patient monitoring and caregiver notification. Noteworthy about the work is the use of fuzzy-logic to deal with the imperfections of the data, and the use of both structure and hierarchy to control the application of rules in the context reasoning system. Results are shown for the evaluation of the fuzzy-logic based context reasoning middleware under simulated but realistic scenarios of patient monitoring. The results indicate the feasibility of the system for effective at-home monitoring.

Keywords: Pervasive Healthcare, CARA, Fuzzy Logic, Context-aware Reasoning

1. Introduction

In recent decades, developed countries have experienced an increase of average life-length with a consequent impact of chronic conditions on the population [1]. Pervasive and context-aware applications [2] have been widely recognized as promising solutions for improving quality of life of both patients suffering from chronic conditions and their relatives, as well as for reducing long-term healthcare costs and improving quality of care.

A pervasive system for independent living [3] should be able to (i) gather information about and around the patient through sensors, (ii) interpret sensor data to map them into a consistent assessment of the real situation, (iii) reason about available knowledge to support the patient's well being, (iv) perform actions and give feedback to the patient according to the results of the reasoning process.

In this paper we present the CARA pervasive healthcare architecture, with the focus on its fuzzy-based context modeling and reasoning framework. The main components of the CARA system are:

1. Wearable Wireless Sensors A key component of the system is a BAN (Body Area Network, i.e. a portable electronic device capable of monitoring and communicating patient vital signs), and this includes medical sensors such as the ECG, SpO2 meter, temperature sensor and mobility sensor.

2. Remote Monitoring System. This is responsible for remotely controlling the BAN and continuously measuring physiological signals of the elderly through the BAN and internet connection. A web camera is integrated into this application that may be used for monitoring and for interaction between the elderly and the caregiver.
3. Data & Video Review System. This is designed for a medical consultant or caregiver to review the data previously collected from the elderly in case s/he might not be available for real-time monitoring.
4. Healthcare Reasoning System. We assume the presence of an environmental monitoring system equipped with our pervasive sensor network and a non-monotonic reasoning engine. A rich set of sensors can be used for monitoring in home environments as well as a patient's vital signs. For this reason, we develop a logic-based context model for situation assessment combined with high level declarative feedback policy specification, and we apply medical rules appropriate for the individual to the high level context that is generated from the reasoning system. When certain conditions are met, alerts or notifications will be triggered so that the caregiver can take appropriate action.

In the case of context-aware services, it is really difficult to get an accurate and well defined context which we can classify as 'unambiguous' since the interpretation of sensed data as context is mostly imperfect and ambiguous. To alleviate this problem, a novel approach using fuzzy logic theory [4] as a reasoning mechanism for contexts is proposed. The fuzzy logic concept overlaps to some extent with other mathematical models developed to deal with vagueness and uncertainty. 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 independent living elders. Firstly, the overall structure of system are identified, then the context interpretation based on the model of context is described. Followed by the introduction of the fuzzy logic framework used for knowledge representation and reasoning. The fuzzy-based reasoning engine we used in CARA system is presented next. Finally, the system is evaluated on simulated realistic scenarios to illustrate how pervasive healthcare can be supported by the proposed scheme.

2. Related & Previous Work

There are a number of research projects related to pervasive healthcare and semantic modeling of context. Some are from a general point of view [12] [13] [20], Other attempts have focused on specific aspects, such as health status monitoring, alert and reminders based on scheduled activities, patient behavior and daily activities modeling. For instance, Jawbone UP is a personal-care system providing long-term monitoring of users activity profile, sleep pattern tracking and automatic alarm notification [7]. The Gaia project [8] developed at the University of Illinois is a distributed middleware infrastructure that provides support for context aware agents in smart spaces. CareMedia [9] uses multimedia information to track a person's activities. MITs PlaceLab [10] includes a proactive health care application based on wearable and environmental sensing. More relevant for context-aware pervasive healthcare for chronic conditions is H-SAUDE [11], which provides a decision-level data fusion technique for monitoring and reporting critical health conditions of a hypertensive patient at home.

Previously, we [5] [6] have shown the original CARA healthcare architecture enables improved healthcare through the intelligent use of wireless remote monitoring of patient vital signs, supplemented by rich contextual information. 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. This system lacks a sufficiently powerful context-aware modeling and reasoning mechanism, whereas this paper makes much use of symbolic reasoning using fuzzy-based knowledge.

We are aware of the fact that research efforts are converging toward the combination of statistical reasoning and ontology-based knowledge representation, many approaches have been proposed focusing on using semantic web languages with ontologies and rules to build reasoning system [14] [15] [16]. Our approach is similar to what we would obtain by using an ontology, with difference being fuzzy-based reasoning is more expressive, flexible and efficient in computation, since we allow rules to be editable by user with natural language rather than fixed machine understandable rules. Also our reasoning engine works off-line on the client handling rules loaded from the server and raw data collected from the WSN in real-time. In this paper we handle uncertainty in the reasoning process using fuzzy logic; there are other papers where uncertainty is handled in an abstraction layer, separate from the symbolic reasoning process as in [17].

3. System Overview

Advancements in internet technology have made possible innovative methods for the delivery of health-care. 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.

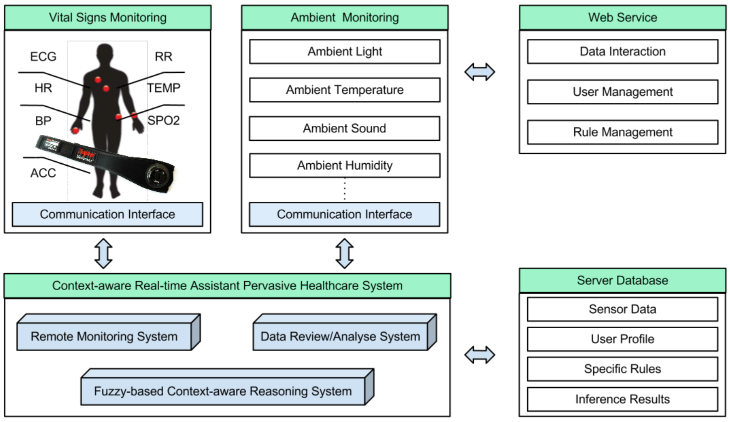


Fig. 1. CARA pervasive healthcare architecture

An overall architecture of the *CARA pervasive healthcare system* is shown in Figure 1. The patient's vital signs are monitored by different kinds of sensors within a wireless BAN, and environmental sensors are deployed to monitor the home surroundings. All measurement data are gathered by the base-station and are then transferred 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 server which provides sensor data management services. A Flash application running in the gateway publishes real-time sensor data along with live video streams to the CARA server. On the server side, data derived from the sensor data is stored in an implementation independent generic format (i.e. XML), and also kept in an embedded database.

The reasoning or rule engine plays a crucial role in the system both on the gateway 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 at-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 three main reasoning tasks: (i) continuous contextualization of physical state of a person, (ii) prediction of possibly risky situations and (iii) notification of emergency situations indicating a health risk.

4. Context Modeling

Context is any information that can be used to characterize the situation of an entity. And context-aware computing is the use of context to provide relevant information and/or services to the user, where relevancy depends on the particular task of the user [18]. Context modeling is a key feature in context-aware systems to provide context for intelligent services.

The main problem that we consider in this section is the following: given the current raw data, how can we model the context, e.g. the current values of relevant context parameters, and deal with data coming from multiple sources where part of the data might be erroneous or missing. Considering this context, we adopt a *Fuzzy Logic Model* [19] to represent the relevant variables and to build low level and high level context models. An overview of rhe Context Model is shown in Figure 2 where we structure the low level context according to the *Physiological Context*, *Personal Context* and *Environmental Context* and generate high level context consisting of *Activity Event* and *Medical Condition*. These are the contexts required in a ubiquitous context-aware environment.

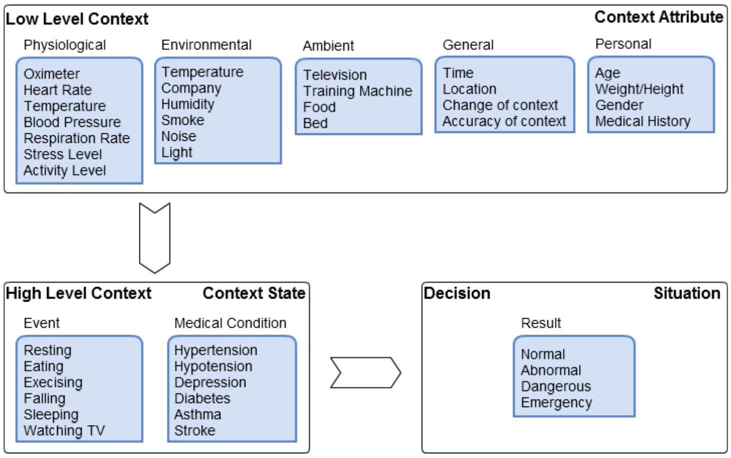


Fig. 2. Overview of context model

Previous studies of context models has indicated that there are certain entities in a context that, in practice, are more important than others for home monitoring. These are location, identity, activity and time [20]. In order to represent this information in our model we identify the following entities:

- *Person* entity to identify the person, his/her clinical profile and his/her movement.
- *Physiology* entity to identify vital signs of a person.
- *Area* entity to identify rooms and area in the environment.
- *Object* entity to identify objects or resources the person can interact with.

All pieces of information gathered by sensors can be indexed as attributes of the context entities. In our work, we map these attributes into individual *Fuzzy Set* in the Fuzzy Logic framework (see next section for preliminary notions). Some of the attributes associated with entities in our context model and their fuzzy sets are detailed in Table 1. These fuzzy sets can be used for high level context interpretation and further for decision inference.

Table 1. Fuzzy sets representing attributes about Person and Area entities

Fuzzy Set	**Attributes**	**Description**
Age	{young, middle-age, old}	Age of the person
Gender	{male, female}	Gender of the person
BMI	{low, normal, high}	Body Mass Index
Medical History	{hypertension...diabetes}	Has medical history
Temperature	{cold, worm, hot}	Room Temperature
Light	{dark, regular, bright}	Brightness
Sound	{mute, regular, noisy}	Noise level
Humidity	{dry, normal, wet}	Humidity level
Location	{bedroom...living room}	Current location

5. Fuzzy Logic Framework: Preliminary Notations

The declarative logical framework we use for knowledge representation and reasoning in CARA system is that of Fuzzy Logic, based on the fuzzy set theory proposed by Lotfi Zadeh [21] [22]. Fuzzy system become handy when someone intends to work with vague, ambiguous, imprecise, noisy or missing information. We can use it to control non-linear systems that are too tricky to model them mathematically in such case we adapt fuzzy logic into pervasive healthcare system. Before we describe our reasoning system in detail, we want to recall some basic Fuzzy Logic definitions. A Fuzzy Logic System consists of three main parts: fuzzy set, rules, and inference engine. These components and the general architecture is shown in Figure 3.

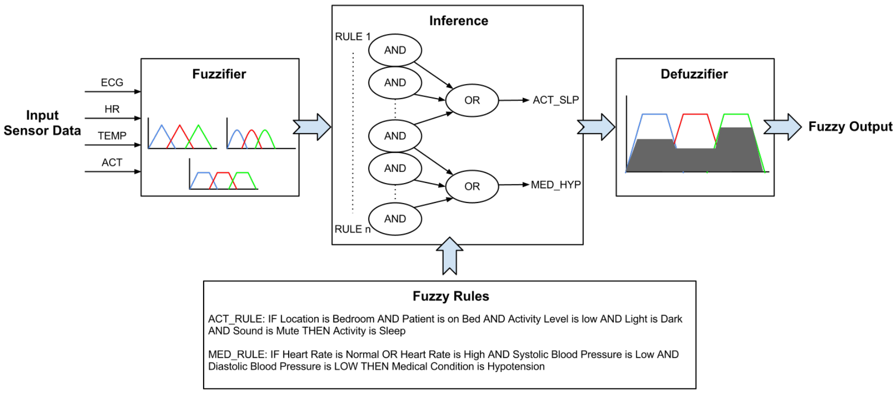


Fig. 3. A Fuzzy Logic System

The process of fuzzy logic is explained as following: Firstly, a crisp set of input data are gathered and converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms and membership functions. This step is known as fuzzication. Afterwards, an inference is made based on a set of rules. Lastly, the resulting fuzzy output is mapped to a crisp output using the membership functions in the defuzzification step.

The definition of a fuzzy set from Zadeh's paper is: Let X be a space of points, with a generic element of X denoted by x. Thus $X = x$. A fuzzy set A in X is characterized by a membership function $fA(x)$ which associates with each point in X a real number in the interval [0,1], with the values of $fA(x)$ at x representing the "grade of membership" of x in A. Thus, the nearer the value of $fA(x)$ to unity, the higher the grade of membership of x in A. Fuzzy set can be further divided based on type of membership function which describes them. Figure 4 lists the most common types triangular, trapezoidal, singleton and Gaussian shapes

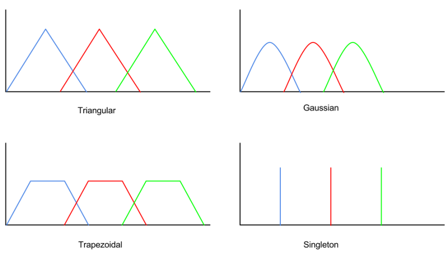


Fig. 4. Common types of Membership Functions

After the inference step, the overall result is a fuzzy value. This result should be defuzzied to obtain a final crisp output. Defuzzification is performed according to the membership function of the output variable. There are different algorithms for defuzzification too. The mostly-used algorithms are listed in Table 2, where U is result of defuzzification, u is output variable, min is lower limit for defuzzification, max is upper limit for defuzzification, inf is smallest value and sup is largest value.

Table 2. Defuzzification algorithms

Operation	**Formula**
Center of Gravity	$U = \frac{\int_{min}^{max} u\mu(u)\,du}{\int_{min}^{max} \mu(u)\,du}$
Left Most Maximum	$U = inf(u'), \mu(u') = sup(\mu(u))$
Right Most Maximum	$U = sup(u'), \mu(u') = sup(\mu(u))$

6. Fuzzy-based Reasoning Engine

We refer to an intelligent monitoring system as a monitoring system that is able to (i) reason about gathered data providing a context-aware interpretation of their meaning and (ii) support understanding and decision. To achieve that in the CARA system, we adopted a rule-based approach based on fuzzy logic for context reasoning. 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 [19].

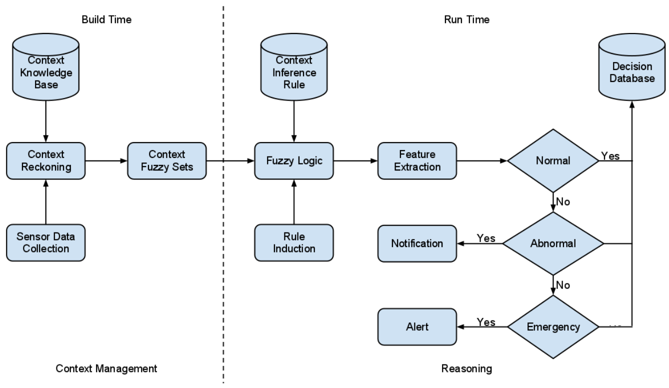


Fig. 5. The workflow of context-aware reasoning

The interactions in the reasoning engine are presented in Figure 5. Raw data coming from sensors and associated with context knowledge is processed by the context management services, producing Context Fuzzy Sets. After that, Fuzzy Rules loaded from the inference rule database are used to generate higher level context (e.g., medical condition, activity and accident event). Finally, the rule engine identifies the current state of the patient (normal, abnormal or emergency) based on the combination of high level context. This can be achieved in two steps: in the first step, the common rules are applied; in the second step, the personal profile further verifies the generated output. For example, if the patient has sort of medical history, an alert output can be consolidated as a normal situation. Only if the final output is abnormal or emergency, a notification or alarm is automatically sent to the remote monitoring server and an emergency service call can be triggered. The generated raw data is stored to assist other decisions making and for additional analysis.

The principle of building a fuzzy-based reasoning engine 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 [23].

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 generating a high-level context rules is given in Table 3.

Table 3. Sample rules for generating high level context

Medical Context Generating Rules
(Elderly ❘ Middle Age) & Very High Systolic Blood Pressure & Very High Diastolic Blood Pressure → Pre-Hypertension
Low Systolic Blood Pressure & Low Diastolic Blood Pressure → Hypotension
Event Context Generating Rules
On Bed & In Bedroom & Low Activity Level & Dark & Mute → Sleep
TV On & In Living Room & Low Activity Level ❘ Normal Activity Level & Regular Noise ❘ Loud Noise → Watching TV
Has Smoke & High Temperature & Dry & Bright & !In Kitchen → On Fire

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.

7. Laboratory Evaluation

It is difficult to evaluate the CARA system in its entirety without extensive field deployment and analysis. We are working towards this goal but do not have good results from field experiments which are diverse enough to yield scientific significance.

However, we conducted simulation experiments in our lab to test the correctness of the proposed fuzzy-based reasoning framework in a pervasive healthcare environment and report the results in this section. In our test 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 while environmental sensing is simulated by an android application so we can remotely control the change of ambient. Biomedical parameters currently taken into account in the model are: heart rate frequency, pulse oxymetry, systolic and diastolic blood pressure , body temperature, and respiration rate. Figure 6 illustrates the screen shot of our demo application and the BAN used in test scenario.

Fig. 6. Left is the snapshot of the CARA pervasive healthcare system showing context-aware reasoning and remote monitoring application. Right is ’patient’ wearing Zephyr BioHarness Sensor

The monitoring and data review functions are previously developed in CARA system as described in [5] [6]. In this work, we integrated the fuzzy-based reasoning engine into the system which provides real-time intelligence for prediction in various healthcare situations. To measure the physical performance of our approach, we added a time check function. We checked a start time before calling the method, and then we also checked a finish time after calling the method. So we can get the execution time of each task. We applied different amounts of fuzzy rules and tested them with several data sets input. Summarized test result is shown in Figure 7. Although the reasoning tasks mostly rely on the computational power of the client machine, it is obviously discovered that the response time of our rule engine is in direct proportion to the amount of contexts taken into account and the complexity of rules.

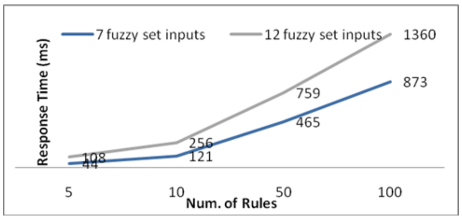
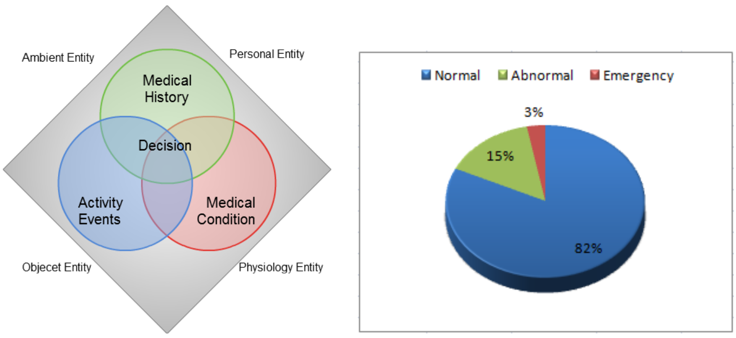


Fig. 7. Inference performance for various rules and inputs

Use-case testing is underway with a trial in our lab. It is carried out to evaluate health operators acceptance of implemented features. To do that, we use an Android tablet to simulate the behaviour of a person living in a realistic home environment which provides us *Activity Contexts*, we also simulate light, room temperature, sound and humidity evolutions during the test period which gives us *Ambient Contexts*. *Physiology Contexts* and *Personal Contexts* are collected from BAN and loaded from server database simultaneously. All the contexts are mapped into *Fuzzy Sets* and enforced by applying consistency rules which refers to the fuzzy relations shown in Figure 8(a), the system then produces the final decision which indicates the current status of the 'patient'. Given the high variability among five trials, we are able to draw the picture of the scale of situation prediction. The result is represented in Figure 8(b).



(a) Abstract view of fuzzy relations (b) Scale of situation prediction

Fig. 8. Use-case testing results a) An abstract view of all the member functions or fuzzy sets that are designed for our fuzzy-based reasoning engine with their relations b) The state of the patient is defined as Normal, Abnormal and Emergency which can be predicted from the inference result of our reasoning engine. The pie chart shows the scale of each state summarized from this trail test. Most of the case are Normal while over 10% situations are Abnormal and round 3% are considered as Emergency with the confidence vary from 70% to 100%.

8. Conclusions

All available sources of information including patient medical sensor data, patient behaviour data, environmental data, and patient profile are relevant for a pervasive healthcare application. To effectively and safely combine these sources of information requires a careful approach that deals with any imprecision or uncertainty in the data but that allows valid inference of the patient's condition. The approach taken is to use a fuzzy-logic based reasoning framework where the rule sets have been structured and organized as a hierarchy. This provides both a more computationally efficient solution, as well as a solution where the inspection of rule sets by domain experts is made easier by the structuring and hierarchy of the rules.

The fuzzy-logic based reasoning framework is presented in the context of the overall CARA healthcare architecture. The reasoning component, fusing, physiological, behavioural and environmental information, enables effective home healthcare monitoring in CARA. In particular it can provide a means for more accurate emergency situation detection due to the incorporation of real-world environmental data to supplement the medical sensor data. The results of the experiments using typical scenarios indicate that the performance of the reasoning framework is more than adequate for effective use.

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