A Fuzzy-based Context Modeling and Reasoning Framework for CARA 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.

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.

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, 2)Remote Monitoring, 3) Data & Video Review System, 4)Healthcare Reasoning System. 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 set theory as a discovery mechanism for contexts is proposed. 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.

2 System Overview

An overall architecture of the *CARA pervasive healthcare system* is shown in Figure 1.

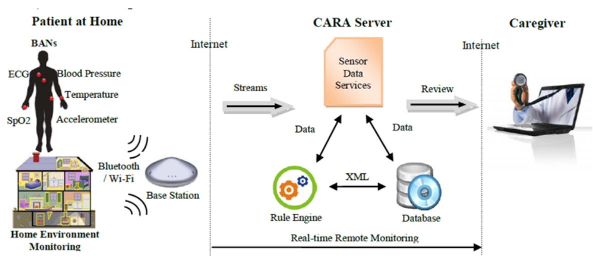


Fig. 1. CARA healthcare architecture

The reasoning 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.

3 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 or services to the user [3]. 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, we adopt a *Fuzzy Logic Model* to represent the relevant variables and to structure low level and high level context models. All pieces of information gathered by sensors can be indexed as attributes of the context entities. In our work, we represent these attributes as individual *Fuzzy Sets*. 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 also for decision inference which we will discuss in the next section.

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

Fuzzy Set	**Attributes**	**Description**
Age	{young, middle-age, old}	Age of the person
Medical History	{hypertension...diabetes}	Has medical history
Temperature	{cold, worm, hot}	Room Temperature
Light	{dark, regular, bright}	Brightness
Sound	{mute, regular, noisy}	Noise level
Location	{bedroom...living room}	Current location

4 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 interactions in the reasoning engine are presented here. 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. 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. 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. 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.

5 Deployment In A Real Application Scenario

We conducted simulation experiments to evaluate the performance of the proposed fuzzy-based reasoning framework in a pervasive healthcare environment and report the results in this section. Figure 2 illustrates the screen shot of our demo application. The monitoring and data review functions are previously developed in CARA system as described in [4]. In this work, we integrated the

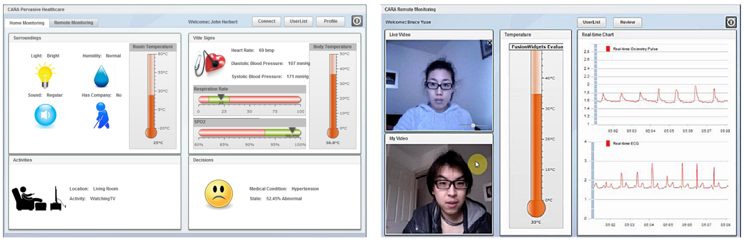
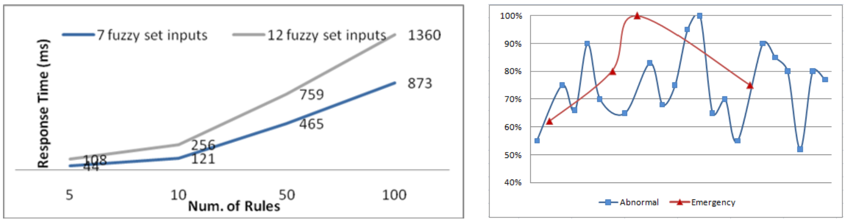


Fig. 2. Snapshot of the CARA pervasive healthcare system. Left is Fuzzy-based context-aware reasoning application. Right is Real-time remote monitoring application

fuzzy-based reasoning engine into the system which provides real-time intelligence for prediction and prevention in various healthcare situations. To measure the 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. Some of the test results are shown in Figure 3.



(a) Inference performance (b) confidence of prediction

Fig. 3. Use-case testing results a)Different amounts of fuzzy rules are applied and tested with several data sets input. b)The confidence is generated from the crisp output of fuzzy-based rule engine. The confidence value is changed in the range of 52% to 100%.

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