Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 141 (2018) 421–427
Procedia Computer Science
www.elsevier.com/locate/procedia

The 8th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH 2018)

A Fuzzy based Diagnostic Agent for Context Aware Patient Monitoring

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Abstract

It is widely known that Remote healthcare monitoring can be a solution to provide an alternative healthcare service that can reduce the amount of strain that the current health care systems experience with the ever increasing demand of health care services world wide. However monitoring a patient remotely requires an accurate interpretation of the data regarding the patients condition. This position paper presents a Fuzzy expert system used to reason medical contexts from a Body Area Network consisting of several sensors monitoring vital healthcare indicators. Fuzzy Logic is used to aggregate the data from the sensors and handle the reasoning required to abstract high-level context information from the low-level context from the sensors and determine the patients condition.

Keywords: Remote healthcare; Fuzzy Reasoning; Context awareness;

1. Introduction

Remote monitoring for health-care purposes is one of the most motivating applications of pervasive computing and Ambient Intelligent systems. With the ever increasing number of patients with chronic illnesses in both first world and third world countries it is important to find alternative ways of providing health-care services. In South Africa as reported by the South African Health Research Council the increase in chronic illnesses combined with the increase of HIV amongst the population creates a huge burden for the current health-care system[1]. Pervasive computing is seen by many researchers as one way of providing ubiquitous health-care and reducing the health-care costs that patients would incur when consulting regularly whilst at the same time improving their quality of life [2, 3, 4].

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1877-0509
10.1016/j.procs.2018.10.174

A Pervasive health care system is defined as a system which is able to provide healthcare services any-time anywhere[3]. A pervasive health-care system can provide various services such as health status monitoring for both short term and long term monitoring, emergency alert, assisted living for the disabled and aged[2, 4, 5]. One common key component in most health monitoring systems is a Body Area Network or commonly called BAN which continuously acquires physiological data from various sensors placed on the subjects body which is made possible through unobtrusive wearable sensors. This Body Area Network would then connect to a gateway that will transmit the information to the cloud where it can be analysed or monitored by a medical expert. Some systems will have added sensors in the environment such as video cameras and sensors around the patients house to increase the quality of the information about the patients situation however this will be limited to a specific location. This information about an entity's or in this case a patient's situation is known as context awareness. In this paper we provide an agent that uses a fuzzy based context reasoning approach for remote healthcare monitoring, assisted living for the elderly and patients with chronic illnesses. The paper is organized as follows. Section 2. gives background and literature review on Context awareness and Healthcare Monitoring. Section 3. discusses our context model. Section 4. gives a discussion on our fuzzy Reasoning engine. Section 5. is a discussion of the implementation and simulation and Section 6. concludes the paper.

2. Background

Context can be formally defined as any information or data that can be used to characterize an entities situation [6]. A context Aware system needs to be able to reason about the information and provide an appropriate prediction on the patients/entities context. To achieve Context Awareness a system needs to have an appropriate context model and a suitable reasoning method. The challenge with context aware services is that there is almost always a degree of uncertainty/ambiguity which makes it difficult to make an accurate context prediction to allow for a perfect interpretation of the context data from the sensors [7].

There are several projects on Context awareness for the purpose of monitoring healthcare. Some of these are generic while others are specific to certain conditions[8, 2] Yuan and Herbert in [2] provide a list of existing projects e.g the Gaia project[9], Jawbone project and MIT Placelab project[10] including their own CARA project[11]. Most of the work makes use of smart spaces and multimedia techniques to determine the context whereas others are tele-medicine applications. The problem with such an approach is that they would be limited to a specific location to provide context awareness which can be detrimental to patient the if something should occur whilst the patient is away from the smart space.

One of the key issues involved when dealing with context awareness especially when not using any multimedia information(image processing etc.) is the issue of uncertainty and how to deal with it [12]. There are several methods used to deal with uncertainty namely probabilistic logic, Bayesian Networks, Hidden Markov Models, Dempster-Shafer theory, and Fuzzy logic [13, 14]. Most of the literature makes use of Statistical reasoning and ontological based reasoning methods to build context reasoning systems[15] however as done by Yuan et al in [2] we make use of Fuzzy logic to obtain an ontology equivalent approach, reason being that data from body sensors is often vague, noisy and imprecise and fuzzy logic is able to deal such data without complex modelling as compared to the other methods mentioned above which are much more susceptible to noise. Fuzzy logic is also very useful for multi-sensor fusion and describing subjective contexts[7] and allows a medical expert to edit the rules easily making the system highly flexible and is computationally efficient for real time operations.

3. Context Model

As explained in the previous section a context aware system should have an appropriate context model that will allow the system to interpret the data from the sensors as accurately as possible. The low level context data from the sensors on its own is often not meaningful and ambiguous therefore it is important for our model to be able to abstract high level context information from the low level context data from the sensors. To achieve this we create a two layer model with the first layer being the raw sensor data from the BAN and the second layer being the high level context layer which interprets the low level context information from the sensors into meaningful high level context information. Our model makes use of Fuzzy logic to abstract the low level context from the BAN into meaningful high level context which is a different approach from the more commonly used approaches that are ontology based and statistically based[13, 16, 12].

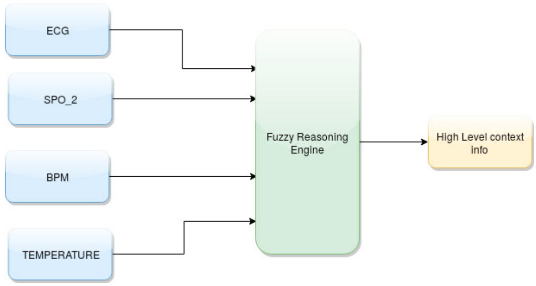

Fig. 1. An overview of the context model

The low level context data is fuzzified into various fuzzy sets which are inputs to our fuzzy reasoning engine(Fuzzy expert system) which will then abstract the input into meaningful high level context information and make inferences on the patients status based on our knowledge base.

4. Fuzzy Reasoning Engine

A fuzzy reasoning system consists of the 4 stages fuzzification, a knowledge base, a defuzzification and a decision making unit [17, 18]. The fuzzification stage maps the crisp input into degrees of membership using linguistic variables e.g(temperature of 23 could be 80% normal and 20% high). The knowledge base consists of a database and a rule base, the database contains the expert information in the form of membership functions whereas the rule base contains a set of antecedents and consequent rules (If-then rules) which the Decision-making unit uses to make the necessary inferences. The defuzzification produces a crisp aggregate result from the fuzzy inference process.

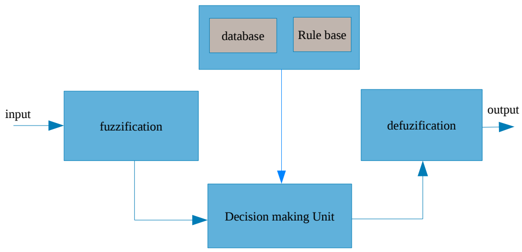

Fig. 2. Fuzzy inference system

4.1. The Fuzzification Process

The process of fuzzification involves the mapping of the input values into degrees of memberships using the membership functions. The input values are grouped into fuzzy sets whereby membership functions will give a degree of membership of each crisp value within the fuzzy set. Let X be a set of space of Real numbers where a generic element is given by x then $X = \{x\}$, a fuzzy set A in X is characterised by a membership function $F_A(x)$ which maps each point in X within the interval $[0, 1]$ which gives each x a degree of membership [18]. In our system we have 5 fuzzy inputs ECG, body temperature, blood oxygen(SPO_2), Pulse rate(bpm), airflow. Each sensor is an input that is fuzzified into the relevant linguistic variables as displayed in Table1. The creation of the membership functions for temperature is given below.

Table 1. Fuzzy inputs and linguistic variables

Input	Linguistic Variable
Temperature	low,Normal, high
SPO_2	low, Normal
Bpm	low, Normal, High
GSR	low, Normal, high
ECG (artrial rhythm)	low, Normal, High
ECG (ventricular rhythm)	low, Normal, High

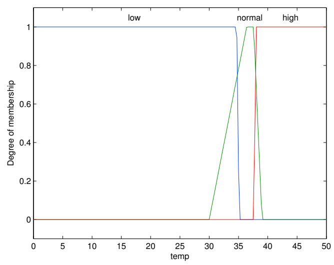

Fig. 3. Temperature member function

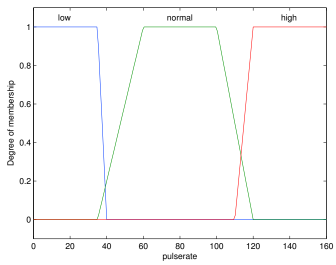

Fig. 4. pulserate member function

$$\mu_{low}(t)=\begin{cases} 1 & 0 < t < 35 \\ \frac{35-t}{1} & 34 < t < 35 \\ 0 & t > 35 \end{cases} \mu_{Normal}(t)=\begin{cases} 0 & t < 35 \\ \frac{t-35}{25} & 35 < t < 60 \\ 1 & 36.4 < t < 37.6 \\ \frac{120-t}{20} & 120 < t < 100 \\ 0 & t > 26 \end{cases} \mu_{high}(t)=\begin{cases} 0 & t < 37.6 \\ \frac{t-37.9}{0.3} & 37.6 < t < 37.9 \\ 1 & t > 37.6 \end{cases} \quad (1)$$

The member function for Blood pulse rate (Bpm) is given by the following:

$$\mu_{low}(b)=\begin{cases} 1 & p < 35 \\ \frac{40-p}{5} & 35 < p < 40 \\ 0 & p > 40 \end{cases} \mu_{Normal}(b)=\begin{cases} 0 & p < 35 \\ \frac{p-60}{25} & 35 < p < 60 \\ \frac{120-p}{20} & 100 < p < 120 \\ 0 & p > 120 \end{cases} \mu_{high}(b)=\begin{cases} 0 & p < 110 \\ \frac{p-120}{10} & 110 < p < 120 \\ 1 & p > 120 \end{cases} \quad (2)$$

The member function for Blood oxygen percentage (SPO_2) is given by the following:

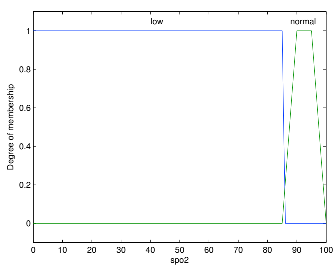

Fig. 5. blood oxygen member function

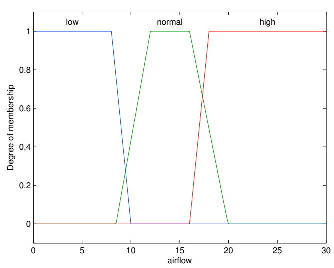

Fig. 6. breathing member function

$$\mu_{Normal}(b)=\begin{cases} 1 & spo_2 < 85 \\ \frac{85-s}{5} & 85 < spo_2 < 86 \\ 0 & spo_2 > 86 \end{cases} \mu_{high}(b)=\begin{cases} 0 & spo_2 < 85 \\ \frac{s-90}{5} & 85 < spo_2 < 90 \\ \frac{100-s}{5} & 95 < spo_2 < 100 \\ 0 & spo_2 > 100 \end{cases} \quad (3)$$

The member function for respiration airflow (breathing) is given by the

$$\mu_{low}(t)=\begin{cases} 1 & a<8 \\ \frac{a-10}{2} & 8<t<10 \\ 0 & a>0 \end{cases} \mu_{Normal}(t)=\begin{cases} 0 & a<0 \\ \frac{a-12}{4} & 8<a<12 \\ \frac{a-12}{4} & 12<a<16 \\ 0 & t>26 \end{cases} \mu_{high}(a)=\begin{cases} 0 & a<16 \\ \frac{a-18}{2} & 16<t<18 \\ 1 & t>18 \end{cases} \tag{4}$$

4.2. Fuzzy Rules

The fuzzy rules allow for the fusion of various sensors to enable the generation of better medical context data which can be extended to include environmental sensors in a pervasive computing environment to increase the quality of the context information. In our case we aggregate the rules using the AND operator. An example of the fuzzy rules used in this Fuzzy inference system are presented in Table 2

Table 2. sample of Fuzzy Rules for generating medical context from Body Area Network

RULES FOR MEDICAL CONTEXT
if Temperature is *Low* **AND** airflow is *Low* **THEN** Hypothermia is *High*
if SPO_2 is *Low* **AND** airflow is *Low* **AND** BPM is *Low* **THEN** Anaemia is *High*
if *BPM* is *Low* **AND** airflow is *Low* **THEN** Hypotension is *High*
if SPO_2 is *Low* **AND** airflow is *Low* **THEN** hypertension is *High*
if SPO_2 is *Low* **AND** airflow is *Low* **THEN** depression is *High*

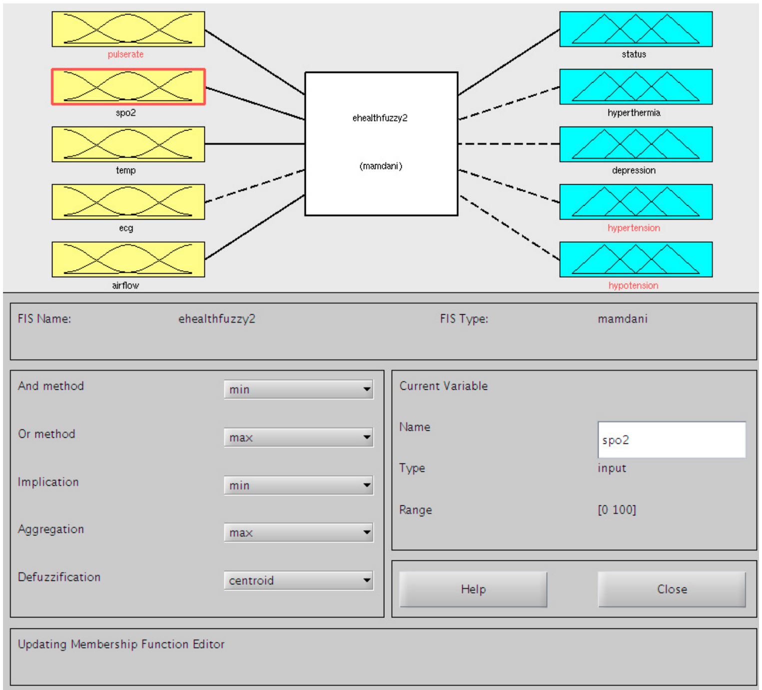

Fig. 7. Fuzzy Inference system using MATLAB

5. Simulation

In our evaluation we deploy a BAN based on the e-health platform by cooking-hacks which consists of various vital sensors such as ECG, Body temperature sensor, Pulse Oxymetry, blood pressure, body position sensor which is attached to a raspberry pi [19]. In our test we made use of the e-health platform with the following sensors attached: Pulse Oxymetry sensor, ECG, body temperature sensor and the electro-dermal sensor(galvanic skin response sensor). A database stores the data from the sensors where our fuzzy reasoning engine has access to the data and makes the necessary inferences. The data set acquired from the body area network was used to as inputs for our fuzzy reasoning engine a sample of the dataset is given in Table 3. The data set was then used to supply the input to our fuzzy reasoning engine in Matlab.

Table 3. Sample of Data from BAN.

ECG	BPM (p)	SPO_2(%)	Temp	GSR
1.86217	74	99	38	0.474
1.85728	74	99	38	0.474
1.88172	73	98	38	0.474
1.88172	73	98	38	0.474
1.92082	73	98	38	0.474
1.83773	72	98	38	0.474
1.85728	72	98	38	0.474
4.1349	72	98	38	0.479
1.72043	71	98	38	0.489
1.42717	71	98	38	0.489
1.62757	71	98	38	0.479
1.83773	70	98	38	0.484
2.13587	68	98	38	0.484
2.37048	68	98	38	0.484
1.56892	66	98	38	0.484
1.46628	66	98	38	0.484

6. Conclusion

In this paper a fuzzy inference engine for abstracting low level context data from various sensors to high level context information is provided. The fuzzy inference engine can personalized for a patient based on the patients condition e.g. diabetic, asthmatic etc. It can further be used to incorporate context information from ambient sensors in the environment to increase the quality of the context information

7. Future work

A communication system is a necessary component for a Remote health monitoring system therefore in the future work we will look into implementing an M2M system to handle the communication of the Remote health monitoring system and further look into adding other agents to handle the various context providers together in a pervasive computing environment and manage the communication between the gateway and health server.

8. Acknowledgement

This work is funded by Tshwane University of Technology in collaboration FSATI and LISSI laboratory UPEC.

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