Closing the loop from continuous M-health monitoring to fuzzy logic-based optimized recommendations

Abdelghani Benharref - IEEE Member, Mohamed Adel Serhani, and Al Ramzana Nujum

Abstract — **Continuous sensing of health metrics might generate a massive amount of data. Generating clinically validated recommendations, out of these data, to patients under monitoring is of prime importance to protect them from risk of falling into severe health degradation. Physicians also can be supported with automated recommendations that gain from historical data and increasing learning cycles. In this paper, we propose a Fuzzy Expert System that relies on data collected from continuous monitoring. The monitoring scheme implements pre-processing of data for better data analytics. However, data analytics implements the loopback feature in order to constantly improve fuzzy rules, knowledge base, and generated recommendations. Both techniques reduced data quantity, improved data quality and proposed recommendations. We evaluate our solution through a series of experiments and the results we have obtained proved that our fuzzy expert system combined with the intelligent monitoring and analytic techniques provide a high accuracy of collected data and valid advices.**

I. Introduction and Related Work

The tremendous development of biosensors and the emergence of sophisticated mobile devices are offering a golden opportunity for chronic disease patients who would like or rather have to be continuously monitored even when they are out of hospitals. Off-hospitals monitoring of such patients is being seriously considered as an efficient and cost-effective approach to reduce the burden on patients as well as on health authorities. Body sensors usually collect a considerable amount of data at relatively high frequencies, which present many challenges including data acquisition, data processing, data analytics and visualization.

There have been many works addressing independently each of the challenges listed above and trying to come up with appropriate M-health monitoring approaches. In data analytics, which is the purpose of this paper, the authors in [1] present a decision support system where decisions are taken using decision trees, rules, and transformation of rules into fuzzy logic. In [2], the authors present another decision support system that tries to compute, for each patient, a health score. This health score is a reflection of the analysis, by the expert system's engine, of different readings coming from various clinical measurements. The final score, categorized as high, average, or low priority, is then presented to medical staff for further assessments so they can take necessary actions if required. A server-based solution is presented in [3] where a remote server takes as input health data and their timestamps and then offers automated clinical support decision to help medical staff decisions.

Two fuzzy expert systems for blood pressure and hypertension are proposed in [4] and [5] respectively while [6] presents a design for an expert system for heart diseases monitoring. Authors in [7] propose a system to help doctors and patients determine their appropriate diets plans. [8] present a case and rule based reasoning system for combined therapies where the knowledge base is made up using fuzzified input values. Those input values are then defazified after reasoning to produce concise outputs. Another use of fuzzy logic in health-related diagnosis is presented in [9] for the diagnosis of heart and blood pressure measurements.

The authors in [10] aim at the development of a cloud-based decision support system for the risk assessment of coronary heart disease by leveraging the techniques of fuzzy expert system. The authors in [11] and [12] present two fuzzy logic-based expert systems to help in decision taking for diabetes while authors in [13] present a fuzzy expert system for hypoglglycaemia of diabtes patients.

Although the works cited above are interesting, they have some substantial limitations. The most serious is the lack of consideration of streams of data. In fact, most of the above works do not cope with continuous monitoring activities generating a high volume of data which makes it very challenging in retrieving accurate and useful data, processing data, and generating validated clinical decisions. The aim of this paper is to address some of the above challenges by providing an end-to-end solution that implements the following:

- Intelligent Mobile sensing scheme that cope with continuous data collection and processing.
- An enhanced fuzzy expert system that learns from the continuous data streams and adjusts accordingly.
- Optimized recommendations supporting physicians and patients for better health control.

II. Architecture

A. Overview

Figure 1 illustrates the overall M-health monitoring lifecycle scheme that starts with collecting data using sensors and mobile applications. These data, in addition to extra data (e.g. lab tests, historical data), are then used as input to the *Fuzzy Expert System* (FES), which maps these data on a set of

Research supported by UAE NRF Grant Number 20951.
Dr. Mohamed Adel Serhani and Al Ramzana Nujum are with the College of Information Technology, UAE University, U.A.E (phone: +971-3-713 5572; fax: +971-3 -713 6901; e-mail: serhanim@uaeu.ac.ae, ramzana@uaeu.ac.ae).

Dr. Abdelghani Benharref is with University of Wollongong in Dubai (e-mail: AbdelghaniBenharref@uowdubai.ac.ae).

rules that are already validated by human medical experts. The generated output is mapped to a set of *recommendations* stored in a database and *visualized* by patients and physicians. The physicians have the right to validate/update/extend these advices through the visualization interface then stored into the knowledge base database. Finally, the knowledge retrieved from physician's recommendations is used by the *learning module* to enrich the set of rules with new rules, and/or update existing rules.

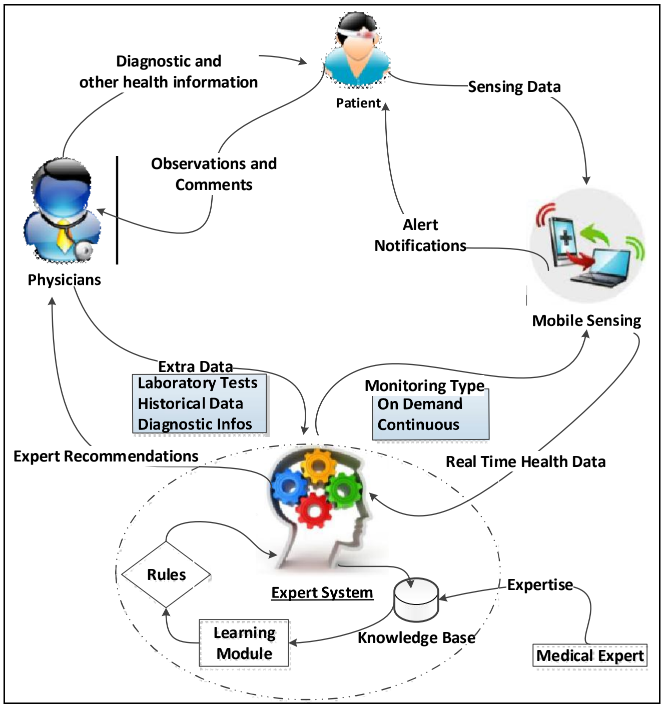

Figure 1. Monitoring Overview

B. *Fuzzy Rules*

The table below provides a sample for each category of these rules.

TABLE 1. SAMPLES OF FUZZY RULES DESCRIPTION

Rules	Description
Age & Max Heart Rate	1. IF (**Age** is Very Young) and (MaxHeartRate is High) **THEN** (**FoodIntake** is *Normal*) **AND** (**Lifestyle & Exercise** is Regular) **AND** (**Medication** *No Change*) 2. ...
Cholesterol	1. IF (**Cholesterol** is *optimal*) **THEN** (**FoodIntake** is *normal*) **AND** (**Lifestyle & Exercise** is *Regular)* **AND** (**Medication** *Slight Change*) 2. ...
Blood Sugar (BS)	**IF (Fasting B*loodSugar* is** *Normal)* ***THEN (FoodIntake*** *is normal)* ***AND (Lifestyle & Exercise*** is *Regular*) **AND** (**Medication** *is No Change*) 2. ...
Blood Pressure (BP)	1. **IF** (**SYSTOLIC is** *low*) **AND** (**DIASTOLIC is** *low*) **THEN** (***FoodIntake*** *is strict) **AND (Lifestyle & Exercise*** is *Stop*) **AND** (**Medication** *is Consult & Change*) 2. ....

C. *Data acquisition based Mobile application*

Data are collected using sensors and then transmitted to a mobile device using a communication protocol (e.g. Bluetooth, Wi-Fi). Mobile application implements some intelligent features to cope with continuous streams reception. These features include for instance pre-processing of data including data filtering and cleansing. These intelligent features will considerably reduce the volume of data and will insure a better data accuracy.

D. *Fuzzy Expert System*

Figure 2 describes main steps in the fuzzy inference process and includes the following: fuzzification of the input variables (e.g. Blood Pressure (BP), Heart Rate (HR), Blood Sugar (BS)), inference, and defuzzification. The process is described in the following steps.

The fuzzy expert system is continuously improved as new data are used and the knowledge base is augmented. This reflects on the fuzzy rules and the upcoming generated recommendations.

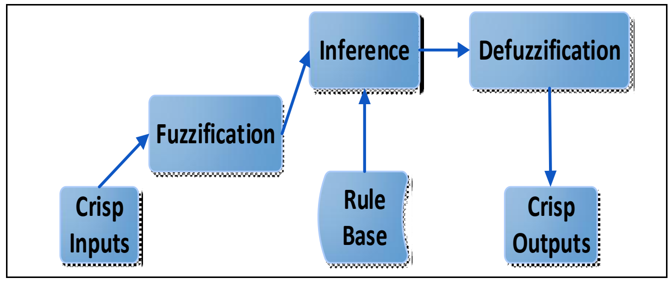

Figure 2. Fuzzy Inference Process

E. *Recommendations*

The FES automatically generates three categories of recommendations that are related to food-intake, medications, and lifestyle. These recommendations are validated by medical human expert through a visualization interface and then stored into a database. Further validations are done to check if the advices have adjusted the level of BS, BP and HR readings collected in the following monitoring cycle(s).

III. IMPLEMENTATION

A. *Experimental setup*

The following is the implementation details of the main components involved in the end-to-end monitoring:

- Sensors: we have used a couple of sensors to sense the vital signs we used in our experiments. These include Zephyr BioHarness-3 and iBGStar® Blood Glucose Meter for iPhone.
- Mobile devices: iPhone 4S running iOS 7, Android tablet running Android KitKat 4.4.2.
- Database server: MySQL server.
- MATLAB 2012 Fuzzy Logic Toolbox.

B. *Dataset*

We used readings collected from continuous monitoring of BS, BP, and HR. Readings were collected for a monitoring cycle of three (3) months. The BP has two values (Systolic and Diastolic) and the BS has five readings that are: fasting, pre-prandial, after meal, bedtime, and random. The HR considers maximum HR and considers also the age.

C. *Implemented Components*

We have implemented a couple of components that include a couple of Restful Web services, Fuzzy Expert System, and visualization module. Restful Web Services provide an interface with a set of operations to create, read, update, and delete BP, BS, and HR reading, which helps in the pre-processing of collected readings. The Fuzzy Expert System

Web service provides an interface to the visualization module to retrieve readings from the database. It is developed using Mamdani Inference method ([14]) and designed in MATLAB 2012. The visualization interface offers advices as read-only for patients while physicians can edit and update these advices.

D. Fuzzy Expert System

1) Step 1. Fuzzification

The fuzzification process includes two steps: (1) fuzzifying inputs and building their membership functions, and (2) fuzzifying outputs and build their related membership functions.

The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions.The inputs we used for the model are Blood Sugar, Blood Pressure (Diastolic, Systolic) and Heart Rate.

TABLE 2. FUZZY SETS OF BLOOD SUGAR, BLOOD PRESSURE

INPUT FIELD	RANGE		FUZZY SETS
Blood Sugar	>=200		vhigh
	>=125		high
	>=70		normal
	<50		vlow
	50 – 70		low
INPUT FIELD	**Systolic (mmHg)**	**Diastolic (mmHg)**	**FUZZY SETS**
Blood Pressure	<90	<60	Low
	90 – 120	60 – 80	Normal
	120 – 139	80 – 90	PreHigh
	140 – 160	90 – 100	Stage1High
	>160	>100	Stage2High

The following are the membership functions we used for all inputs (BS and BP). Blood Sugar Membership functions are included below.

$$\mu_{vhigh}(x) = \begin{cases} 1 & x \geq 400 \\ (x - 200)/200 & 200 \leq x \leq 400 \end{cases}$$

$$\mu_{high}(x) = \begin{cases} 1 & x = 140 \\ (140 - x)/15 & 125 \leq x < 140 \\ (200 - x)/60 & 140 < x \leq 200 \end{cases}$$

$$\mu_{normal}(x) = \begin{cases} 1 & x = 70 \\ (130 - x)/60 & 70 < x < 130 \end{cases}$$

$$\mu_{low}(x) = \begin{cases} 1 & x = 60 \\ (50 - x)/10 & 50 \leq x < 60 \\ (70 - x)/10 & 60 < x < 70 \end{cases}$$

$$\mu_{vlow}(x) = \begin{cases} 1 & x \leq 35 \\ (50 - x)/15 & 35 \leq x < 50 \end{cases}$$

Figure 3. Membership Functions of Blood Sugar

The outputs Medication, LifeStyle & Exercise and Diet are fuzzified.

TABLE 3. FUZZY SETS OF LIFESTYLE & EXERCISE

OUTPUT FIELD	RANGE [1 – 10]	FUZZY SETS
Lifestyle & Exercise	< 2	Stop
	2 – 4	Light
	4 – 6	Moderate
	6- 8	Regular
	>8	Heavy

Similarly to the input membership functions, output membership functions are derived. Output membership functions for LifeStyle & Exercise are given in Figure 4.

$$\mu_{stop}(x) = \begin{cases} 1 & x = 1 \\ (2 - x)/1 & x < 2 \end{cases}$$

$$\mu_{light}(x) = \begin{cases} 1 & x = 3 \\ (4 - x)/1 & 2 \leq x \leq 4 \end{cases}$$

$$\mu_{moderate}(x) = \begin{cases} 1 & x = 5 \\ (5 - x)/1 & 4 \leq x \leq 6 \end{cases}$$

$$\mu_{regular}(x) = \begin{cases} 1 & x = 7 \\ (8 - x)/1 & 6 \leq x \leq 8 \end{cases}$$

$$\mu_{heavy}(x) = \begin{cases} (x - 8)/2 & 8 \leq x \leq 10 \\ 1 & x \geq 10 \end{cases}$$

Figure 4. Membership Functions of Lifestyle & Exercise

Figure 5 shows the Membership function of the output variable LiveStyle & Exercise as explained in table 3.

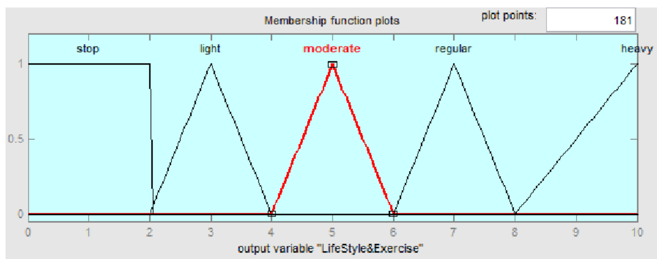

Figure 5. Membership Function - LifeStyle & Exercise

2) Step 2. Fuzzify Inference

In the fuzzy inference process, the membership functions are combined with the control fuzzy rules as shown is table 1 to derive the control output and arrange those outputs into a table called the lookup table.

3) Step 3. Defuzzification

The conclusion derived from the combination of input, output membership functions, and fuzzy rules is still a vague or fuzzy element, which is defuzzified. We have used the most popular defuzzification method i.e. the centroid calculation ([15]), which returns the center of area under the curve.

E. Automated Recommendations

Automated recommendations are generated and visualized by both physicians and patients to include the following information: recommendation theme, Lifestyle, medication, food in take, exercises advices, short term risks, long terms risks, and action(s) to be taken.

IV. RESULTS

Figure 6, Figure 7, and Figure 8 illustrate the surface view of Diastolic and Systolic inputs against the three outputs namely FoodIntake, LifeStyle & Exercise, and Medication. The results showed in the graphs prove the accuracy of the fuzzy inference system along with the used fuzzy rules. For example and according to Figure 8, if systolic and diastolic are high medications should be adjusted. Also, according to Figure 6, if systolic and diastolic are normal the foodintake infer no changes. The same applies to lifestyle & exercises that should be stoped if input values of systolic and diastolic are very high.

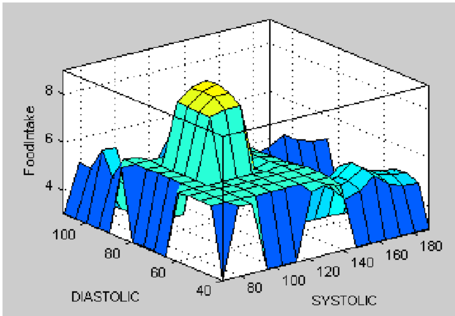

Figure 6. Surface View of Diastolic, Systolic and FoodIntake

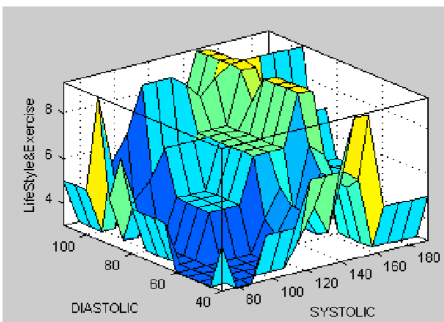

Figure 7. Surface View of Diastolic, Systolic and LifeStyle & Exercise

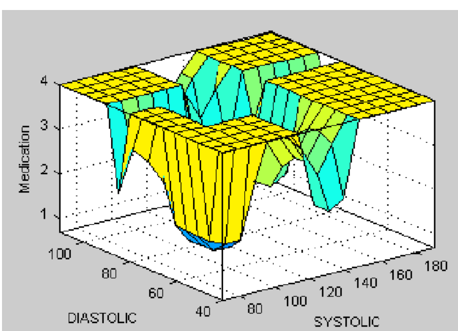

Figure 8. Surface View of Diastolic, Systolic and Medication

V. CONCLUSION

Mitigating and controlling the elicited risks of chronic diseases necessitate a continuous monitoring to produce accurate recommendations for both patients and physicians. In this paper, we proposed an adaptive fuzzy expert system that relied, not only on a set of rules validated by experts but also linked to an intelligent continuous monitoring scheme that coped with continuous data streams and implemented smart sensing and pre-processing of data. In addition, we implemented an iterative data analytic technique that learns from the past FES experience to continuously improve clinical decision-making and automatically generate validated advices. These advices are visualized via an application interface. The experiments we have conducted proved that our FES combined with the intelligent monitoring and analytic techniques provided a high accuracy of collected data and valid advices.

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