
Artificial intelligence application to design smart portable intensive care unit

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ABSTRACT

Controlling of vital signs is crucial for patients in an intensive care unit (ICU) who need safe diagnostic and restorative intrusion. The goal of personalized medicine in the ICU is to predict which diagnostic tests, monitoring interventions and treatments are necessary. The devices used in ICU should ensure accuracy, reliability and safety of needed alarms. In this study, we propose an intelligent approach based on fuzzy logic able to automatically learn the features of a patient and consequently send the required alarms. Vital Signs in ICU Patients (Blood Pressure systolic/ diastolic), Heart Rate, Respiration Rate, and Body Temperature are considered in this research work. Multisensor data synthesis (MSDS) is used to collect patient vital signs data. A Fuzzy approach is to be used to process the read data and give results in sending alarm about the case, or not to send depending on the processed readings of patient vital signs. The new addressed issue in this research is considering parameters of: Patient age, gender, and previous medical status that could affect the range of normal or accepted readings. This alarm is to be sent and broadcasting, together with patient' readings in case of jeopardy, using wireless communication to neighborhood medical centers or hospitals for back response or sending ambulance. These in turn should broadcast an acknowledgment to others that it got the case.

Key words: vital signs; fuzzy logic; wireless communications

Introduction

Health care, especially critical care medicine is complex and expensive both in terms of money and human terms. Great and satisfying medical decision making are done depending on the knowledge of the patient's medical record history and having accurate current clinical information. In a financially restrained environment, the cost of intensive care is expensive and not all the patients' families can afford to pay. In other words, the cost is main idea of making Smart Portable Intensive Care Units (SPICU) inevitable especially with the simplest techniques that can be efficient, understandable, and at the same time affordable to wide range of people. They then can take care of their patients at home, monitoring their biological functions. Vital signs are measurements that provide physiological data indicating the health conditions of the person, demonstrating the functioning and changes in body function. Thus, the vital signs guide the initial diagnosis and the monitoring of patients' clinical evolution. So, their main objective is to help in the health assessment of the person, as well as equip the decision making process related to specific interventions. The most decisive vital signs monitored that help the medical diagnosis are: Systolic blood pressure, diastolic blood pressure (mean arterial

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pressure), heart rate, respiratory rate, and body temperature. The accurate measurement of vital signs is enormously essential for the clinical assessment of patients that are, in this work scope, in the ICU. The importance of idea of maintaining the electronic vital data record is to analyze the individual's trends, range, history and known health issues; overall the record also helps to understand how an individual patient responds to care. This raise the need for a smart portable ICU that has the ability of monitoring the patient's vital signs that can also help in detecting of his biological status and also broadcast his status to medical center, hospital, or his doctor or physician. The less complete the information the greater the potential for error and waste. This is also true of decision making within a health care system. The data should be chosen based upon: reliability, usefulness and feasibility, action enabling, representing a mixture of outcomes, processes and cost, and reflecting present performance. Much research work has been carried on to use artificial intelligence techniques to monitor and process patient's vital signs (Umoh and Nyoho, 2015; Dadashi *et al.*, 2015; Sadrawiand *et al.*, 2015; Cecilia *et al.*, 2015; Kim van Loon, 2017 and Dutta, 2013). Much of the work in the ICU revolves around information that is recorded by electronic devices. Such devices typically incorporate simple alarm functions that trigger when a value exceeds or falls down pre-defined limits (normal). The high rate of false alarms is not only a nuisance for patients and caregivers, but can also compromise patient safety and effectiveness of care. The development of alarm systems has lagged behind the technological advances of medical devices over the last years. The idea is that in order for an alarming scheme to be efficient, the definitions of normal, abnormal and intermediate state have to be changed many times on an hour to hour basis, since in ICU the patient state can change dramatically from day to day. In a study 2176 alarms events were recorded, 68% were false, 5.5% were significant, and 26.5% were induced by interventions. Concluded that 94% of alarms events were clinically insignificant. The goal of personalized medicine in the ICU is to predict which diagnostic tests, monitoring interventions and treatments translate to improved outcomes given the variation between patients.

The main objective of this research work is to design Smart Portable Intensive intelligent systems techniques combined with technologies that integrate mobility and portability in accessing processed information Care Unit (SPICU) foreseeable model for medical decision support using. A Fuzzy approach is used to give results in sending alarm about the case, or not to send depending on the processed readings of patient vital signs (blood pressure, heart beats, body temperature, and respiration rate) considering patient age, gender, and previous medical status (not addressed in previous related work). This alarm is to be sent using wireless communication to medical center or hospital for back response. The effects of this architecture can be significant, allowing a better interface, especially in the aspect of expert knowledge, communication and usability, important features for applications in medicine. Thus, the specification of the application architecture considered environments with heterogeneous architectures and was based on: the acquisition of data from patient's vital signs monitoring; the use of intelligent systems techniques, especially fuzzy logic; information processing; and sending alerts through mobile devices. The monitored environment, entitled Intelligent System for Monitoring Patients.

A. Steps of achievement

First is to use multisensory devices that read five patient vital signs: heart rate, blood pressure systolic, blood pressure diastolic, respiration rate, and body temperature. Fuzzy logic is used for processing these data. This is used to deal with the problem of different physical or normal readings when considering patient age, gender, and previous medical status (not addressed in previous related work). A fuzzy model is built for each level of ages as well as if the patient is male or female. Upon the previously mentioned steps, such SPICU can alert the hospital or medical center if anything goes wrong or any deviation from normal level happens. The SPICU consists of: acquisition of data through a network of sensors attached to the patient; data processing and classification using fuzzy logic; data post-processing and preparation for sending alerts if any abnormality was detected; the information is sent to mobile devices that are registered in the environment, to support medical staff in decision making and implementation of relevant actions. (Fig.1). Also, such SPICU should alert the hospital or medical center if anything goes wrong or any deviation from normal level happens. Examples of patients that can benefits from such devices are: People have heart or blood vessels problem (for example very low very high blood pressure, a heart attack, or unstable heart rhythm). People who have serious infections

in their bodies or having imbalance in the level of chemicals, having salt, or minerals in their blood. Such people need continuous reading of their vital signs.

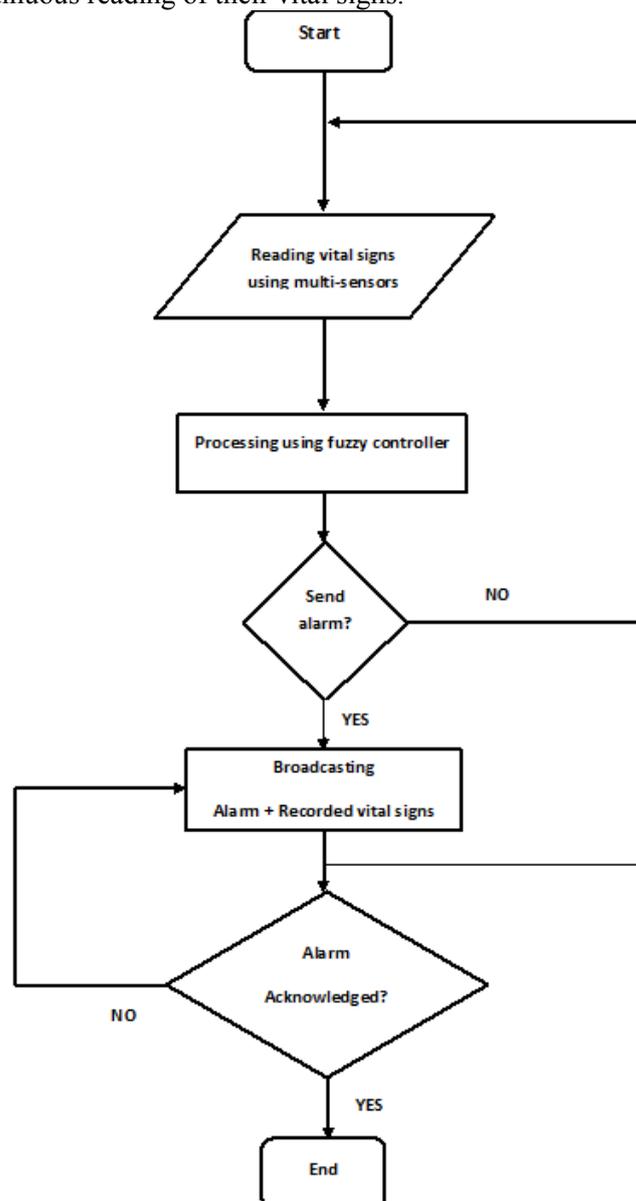


Fig. 1: Activity diagram of SPICU cycle.

2. Vital Signs

Vital signs are measurements of the body's mainly basic functions. Patient health status can be estimated and determined upon the acquisition of basic physiological vital signs. The four main vital signs monitored consistently include the following: Heart Pulse rate, Blood pressure (Systolic/Diastolic), Body temperature, and Respiration rate (rate of breathing). Vital signs are essential components of monitoring the patient's progress during hospitalization. Credits to the wide technological advances in data wireless communication systems in the last decade, the claim of wireless-based vital sign monitoring devices for patient monitoring gained an escalating attention in the clinical field. These could be monitored by using wearable medical body sensor devices placed on the patient's body. The vital signs are measured, observed and monitored to check level of physical functioning. Normal vital signs defers and changes with gender, age, weight and overall health (Jauch *et al.*, 2010). Normal vital sign ranges for the regular healthy adult while resting, implemented in this research paper, are:

- Blood pressure: 90/60 mm/Hg to 120/80 mm/Hg
- Pulse: 60 to 100 beats per minute

- Temperature: 97.8°F to 99.1°F (36.5°C to 37.3°C), average 98.6°F (37°C)
- Breathing: 12 to 18 breaths per minute

A. Blood Pressure

The blood pressure measurement unit is mm Hg (millimetres of mercury). There are two numbers recorded when blood pressure is measured. The higher number present's systolic pressure. This shows the pressure inside the artery when the heart contracts and pumps blood through the body. The lower number or diastolic pressure presents the diastolic pressure which is the pressure inside the artery when the heart is at rest and is filled with blood. Boso-medicus prestige blood pressure monitor is an example of a wireless blood pressure sensor as it is a wireless Bluetooth device and can be used to detect the blood pressure (systolic and diastolic) of the patient (Blood-Pressure, 2017).

B. Heart rate Sign (resting pulse rate)

The measurement unit of heart pulse rate is: beats per minute. Heart beat rate is one of the vital signs consistently measured in clinical observation (National Library of Medicine, 2017).

C. Body temperature

The normal body temperature of a person varies depending on sex, food, recent activity, time of day, fluid consumption. In women additionally it varies with the stage of the menstrual cycle. Normal body temperature ranges from 97.8 degrees F (or Fahrenheit, equivalent to 36.5 degrees C, or Celsius) to 99 degrees F (37.2 degrees C) for a healthy adult. G-plus wireless remote body thermometer is a wireless continuous body temperature sensor device that can be used.

D. Respiratory Rate

The respiratory rate is the rate at which breathing occurs. This is usually measured in breaths per minute. The respiratory rate is measured when a person is at rest and involves counting the number of breaths for one minute, thesis done by counting how many times the chest rises. *Pulse oximeter*: Nonin's Onyx II finger clip oximeter is a wireless Bluetooth device which records oxygen saturation and heart rate continuously (Respiratory_Minute_Volume, 2017).

3. Design Criteria and Constraints

A fuzzy logic model is designed for vital signs monitoring and its process. The model has five main fuzzy input variables: Blood pressure systolic, Blood pressure diastolic, Heart Pulse rate Body temperature, and Respiration rate. These input variables are the readings outputs of multisensor device attached to the patient. The output fuzzy variable would be constancy degree of patient. The following assumptions are made: whether the patient is stable, semi-stable or unstable. The fuzzy controller design steps are:

A- Definition of fuzzy medical system

Where vital signs investigation is held, including the consideration of the parameters of ordinariness and the defined fuzzy rules base, inferences in vital signs are made resulting in generating alarms from pre-diagnosis indicating abnormalities.

B- Obtain information from one or more specialists

In this step, the role of a specialist in the application is to be modeled and this gives the fundamental importance to collaborate in the construction of membership (relevant) functions for the entries description.

C-Fuzzification

This step includes the definition of the fuzzy sets or, membership functions. In this step, each input variable is indentified to which fuzzy set(s) it can belong to by assigning the relevant degree to each fuzzy set. Before the creation of fuzzy system, it is obligatory to assemble the fuzzy sets (relevance functions) to be used in both fuzzification and defuzzification steps.

D- The inference mechanism

The fuzzy logic technology is associated with artificial intelligence. As humans automatically use rules in implementing their actions, the inference process uses a number of rules concurrently. This process is a combination of four sub processes that are: fuzzification, inference, composition, and defuzzification.

E- Reporting the comments to the fuzzy sets – Inference

In this step, the inputs are analyzed to generate the output fuzzy set with its relevant degree of compatibility. In the fuzzy ICU system, the controller model proposed by Mamdani (1974) is used, where the activation function of each rule is set in and the inference system determines the degree of compatibility with the premise of the rules contained in the rules base. After that, activated rules are determined and the relevance output function is applied, joining all activated output fuzzy sets and their degrees of compatibility in a single output set. This represents all acceptable actions to the input set, each one with their level of compatibility.

4. Fuzzy Logic Controller (FLC)

A- Fuzzy input and output variables

The inputs of fuzzy system here are the main vital signs (Blood Pressure systolic, Blood Pressure diastolic Rate, Body Temperature, Heart Pulse and Respiration Rate). These are shown in Table I. Note that notations are used to shorten these variables.

Table 1: Fuzzy Variables Inputs and Outputs

Fuzzy Inputs										Fuzzy Output	
BP _s		BP _d		HR		TB		RR		Stability	
Low <85	L	Low <55	L	Low <50	L	Low <36	L	Low <10	L	Low	Unstable_L
LowNormal 85-95	LN	LowNormal 55-60	LN	LowNormal 50-59	LN	LowNormal 36-36.5	LN	LowNormal 10-11	LN	LowNormal	LS
Normal 96-130	N	Normal 61 - 80	N	Normal 60-110	N	Normal 36.6 – 37°	N	Normal 12 to 18	N	Stable	S
HighNormal 131-140	HN	HighNormal 81-85	HN	HighNormal 111-125	HN	HighNormal 37.1-37.3	HN	HighNormal 19-20	HN	HighNormal	HS
High >140	H	High >85	H	High >125	H	High >37.3	H	High >20	H	High	Unstable_H

B- Fuzzification- Membership functions

Fuzzification is a process to match the input variables with the linguistic terms. It converts an input value into degrees of membership for each input variable. Fuzzification works with membership functions (MF) for each input variable used in the fuzzy set. The number of membership functions can be varied from three to more. Each membership function has to be defined in a different category, for example LOW, NORMAL and HIGH. The shape of these functions can be represented in different forms (e.g. triangle, trapezoid etc.) Sometimes Gaussian functions are also used to represent the membership functions. In this research work, the trapezoid shaped membership functions are used in defining the basic concepts of fuzzy logic system and the synthetic data validation.. For the vital signs fuzzy model, there are three membership functions for each of the input and output fuzzy variables. The

membership functions for each fuzzy linguistic variable together with its graphical representation is illustrated in Fig. 2, 3, 4,5, and 6. For the input fuzzy variables the universe of discourse (the x-axis) is the quantized value of each of vital sign. For the output fuzzy variable the universe of discourse is the priority degree of the given approach.

1) *Blood Pressure systolic (BP_s) Membership Function*: BP_{s,n} normal (BP_{s,n})=120, considering a domain (95-130), by the linguistic terms low (L), normal (N) and high (H), respectively representing the bands, as illustrated in Fig. 2:

$$\text{high (BP}_s) = \left\{ \begin{array}{ll} 0, & \text{if BP}_s < 130, \\ (\text{BP}_s-130)/10, & \text{if } 130 \leq \text{BP}_s \leq 140, \\ 1, & \text{if BP}_s > 140 \end{array} \right\} \quad (1)$$

Fuzzy set of BP_s:

$$F(\text{BP}_s, 85, 95, 130, 140) = \left\{ \begin{array}{ll} 0, & \text{BP}_s \leq 85 \\ (\text{BP}_s - 85)/(95-85) & 85 < \text{BP}_s \leq 95 \\ 1, & 95 < \text{BP}_s \leq 130 \\ (140 - \text{BP}_s)/(140-130) & 130 < \text{BP}_s \leq 140 \\ 0, & 140 < \text{BP}_s \end{array} \right\}$$

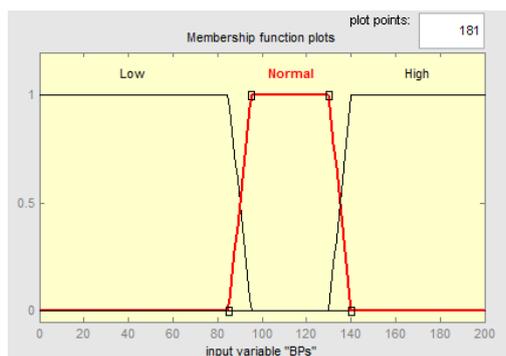


Fig. 2: Membership function of BP_s. – the first input of FLC

2) *Mean Blood Pressure diastolic (BP_d) Membership Function*: BP_d normal (NBP_d) considering a domain (60-80), by the linguistic terms low (L), normal (N) and high (H), respectively representing the bands, illustrated in Fig.3:

$$\text{high (BP}_d) = \left\{ \begin{array}{ll} 0, & \text{if BP}_d < 80, \\ (\text{BP}_d-80) / 8, & \text{if } 76 \leq \text{BP}_d \leq 84, \\ 1, & \text{if BP}_d > 85 \end{array} \right\} \quad (2)$$

$$f(\text{BP}_d, 55, 60, 80, 85) = \left\{ \begin{array}{ll} 0, & \text{BP}_d \leq 55 \\ (\text{BP}_d - 55)/(60-55) & 55 < \text{BP}_d \leq 60 \\ 1, & 60 < \text{BP}_d \leq 80 \\ (85 - \text{BP}_d)/(85 - 80) & 80 < \text{BP}_d \leq 85 \\ 0, & 85 < \text{BP}_d \end{array} \right\}$$

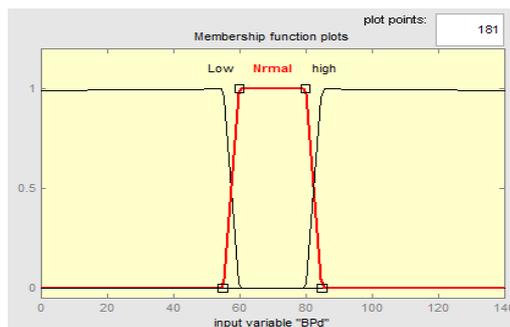


Fig. 3: Membership function of BPD– Second input of FLC

3) *Heart Beats (Pulse rate HR) Membership Function:* HR normal (NHR) considering a domain (60-100), by the linguistic terms low (L), normal (N) and high (H), respectively representing the bands, as illustrated in Fig. 4:

$$\text{high (HR)} = \begin{cases} 0, & \text{if } HR < 100, \\ (HR-60)/40, & \text{if } 60 \leq HR \leq 100, \\ 1, & \text{if } HR > 100 \end{cases} \quad (3)$$

$$f(\text{HR}, 50, 60, 110, 125) = \left\{ \begin{array}{ll} 0, & \text{HR} \leq 50 \\ (\text{HR} - 50)/(60-50) & 50 < \text{HR} \leq 60 \\ 1, & 60 < \text{HR} \leq 110 \\ (125 - \text{HR})/(125-110) & 110 < \text{HR} \leq 125 \\ 0, & 125 < \text{HR} \end{array} \right\}$$

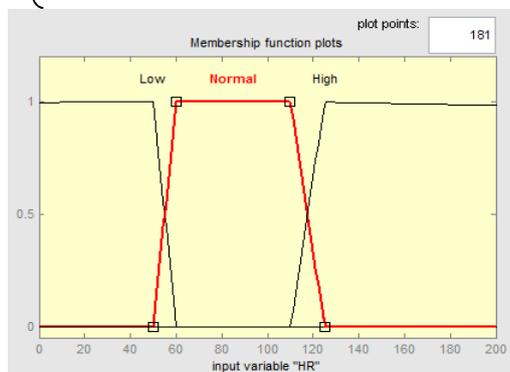


Fig. 4: Membership function of HB. – Third input of FLC

4) *Body temperature (TB) Membership Function:* TB normal (NTB) considering a domain (36.5°C to 37.3°C), by the linguistic terms low (L), normal (N) and high (H), respectively representing the bands, as illustrated in Fig. 5:

$$\text{high (TB)} = \begin{cases} 0, & \text{if TB} < 36.5, \\ (TB-36.5)/0.8, & \text{if } 36.5 \leq \text{TB} \leq 37.3, \\ 1, & \text{if TB} > 37.3 \end{cases} \quad (4)$$

$$f(\text{TB}, 36, 36.5, 37, 37.3) = \begin{cases} 0, & \text{TB} \leq 36 \\ (TB - 36)/(36.5 - 36) & 36 < \text{TB} \leq 36.5 \\ 1, & 36.5 < \text{TB} \leq 37 \\ (37.3 - \text{TB})/(37.3 - 37) & 37 < \text{TB} \leq 37.3 \\ 0, & 37.3 < \text{TB} \end{cases}$$

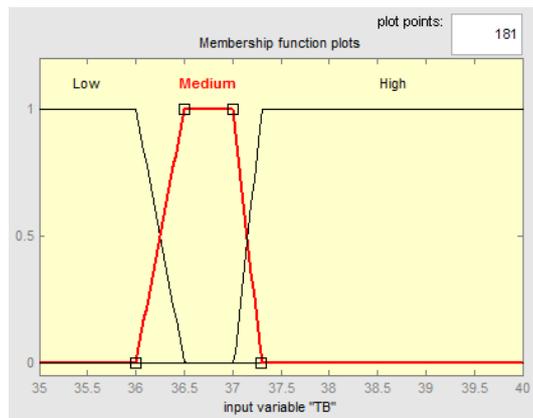


Fig. 5. Membership function of TB.– fourth input of FLC

5) *Respiration rate (RR) Membership Function*: RR normal (NRR) considering a domain (12 to 18), by the linguistic terms low (L), normal (N) and high (H), respectively representing the bands, as illustrated in Fig. 6:

$$\text{high (RR)} = \begin{cases} 0, & \text{if RR} < 12, \\ (RR-12)/18 & \text{if } 12 \leq \text{RR} \leq 18, \\ 1, & \text{if RR} > 18 \end{cases} \quad (5)$$

$$f(\text{RR}, 10, 12, 18, 20) = \begin{cases} 0, & \text{RR} \leq 10 \\ (RR - 10)/(12 - 10) & 10 < \text{RR} \leq 12 \\ 1, & 12 < \text{RR} \leq 18 \\ (20 - \text{RR})/(20 - 18) & 18 < \text{RR} \leq 20 \\ 0, & 20 < \text{RR} \end{cases}$$

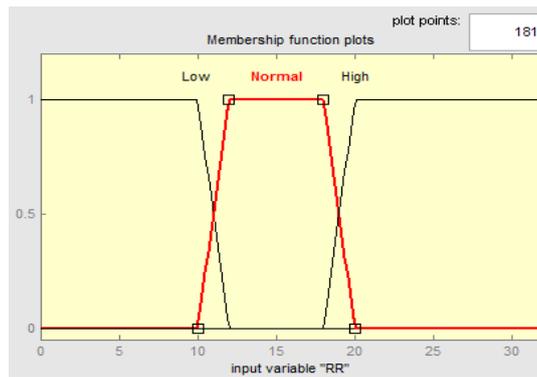


Fig. 6. Membership function of RR. – fifth input of FLC

6) Fuzzy Output S (Stability) Membership Function: S normal (NS) considering a domain (12 to 18), by the linguistic terms low (L), normal (N) and high (H), respectively representing the bands, as illustrated in Fig. 7:

$$\text{high}(S) = \begin{cases} 0, & \text{if } S < 6, \\ (S-6) & \text{if } 6 \leq S \leq 7, \\ 1, & \text{if } S > 7 \end{cases} \quad (6)$$

$$f(S, 3, 4, 6, 7) = \left\{ \begin{array}{ll} 0, & S \leq 3 \\ (S-3)/(4-3) & 3 < S \leq 4 \\ 1, & 4 < S \leq 6 \\ (7-S)/(7-6) & 6 < S \leq 7 \\ 0, & 7 < S \end{array} \right.$$

The objective here is to classify the patient condition, in real time, for indicating whether a normal (i.e., vital signs with normal values), a semi-stable (i.e., vital signs with values close to normal), or an unstable situation (i.e., vital sign values fairly abnormal).

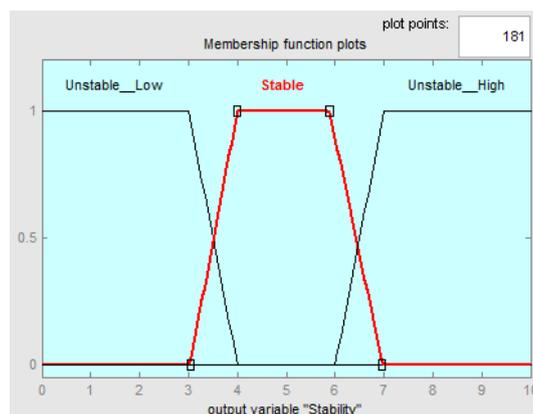


Fig. 7: Membership function of Stability. – Output of FLC

A. Rules- Rule Base

Fuzzy rules definition (Rules Base): When the input variables and membership functions are defined, then we next have to establish linguistic rules, which are represented or assembled with the following structure, as

IF <premises or antecedents> THEN <conclusions or statements >

The number of rules increases rapidly with the addition of more variables. If the number of fuzzy input variables is 6 and Number of Terms per Variable is 5 then Number of Rules is 15,625. A part of the Rule base used in this research is shown in Fig. 8.

At this stage it is important that the amount of rules defined can cover all possible combinations of inputs and outputs of the problem proposed and that the consistency of the rules is reviewed to avoid contradictions. The rules base was developed from several meetings, discussions and interviews with the Promoter hospital medical staff.

B. Inference

The input values provided in the fuzzification step have to be processed by these rules to generate an output value. This processing is done by applying inference, using different linguistic rules in the following three steps: Aggregation, activation, and accumulation.

1. If (BPd is Low) or (BPd is Low) or (HR is Low) or (TB is Low) or (RR is Low) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
2. If (BPd is High) or (BPd is High) or (HR is High) or (TB is High) or (RR is High) then (Stability is Unstable__High)(Diagnosis is AlarmHigh) (1)
3. If (BPd is Normal) and (BPd is Normal) and (HR is Normal) and (TB is Normal) and (RR is Normal) then (Stability is Stable)(Diagnosis is NoAlarm) (1)
4. If (BPd is Low) and (BPd is Normal) and (HR is Normal) and (TB is Normal) and (RR is Normal) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
5. If (BPd is Normal) and (BPd is Low) and (HR is Normal) and (TB is Normal) and (RR is Normal) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
6. If (BPd is Normal) and (BPd is Normal) and (HR is Low) and (TB is Normal) and (RR is Normal) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
7. If (BPd is Normal) and (BPd is Normal) and (HR is Normal) and (TB is Low) and (RR is Normal) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
8. If (BPd is Normal) and (BPd is Normal) and (HR is Normal) and (TB is Normal) and (RR is Low) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
9. If (BPd is High) and (BPd is Normal) and (HR is Normal) and (TB is Normal) and (RR is Normal) then (Stability is Unstable__High)(Diagnosis is AlarmHigh) (1)
10. If (BPd is Normal) and (BPd is High) and (HR is Normal) and (TB is Normal) and (RR is Normal) then (Stability is Unstable__High)(Diagnosis is AlarmHigh) (1)
11. If (BPd is Normal) and (BPd is Normal) and (HR is High) and (TB is Normal) and (RR is Normal) then (Stability is Unstable__High)(Diagnosis is AlarmHigh) (1)
12. If (BPd is Normal) and (BPd is Normal) and (HR is Normal) and (TB is High) and (RR is Normal) then (Stability is Unstable__High)(Diagnosis is AlarmHigh) (1)
13. If (BPd is Normal) and (BPd is Normal) and (HR is Normal) and (TB is Normal) and (RR is High) then (Stability is Unstable__High)(Diagnosis is AlarmHigh) (1)
14. If (BPd is Low) and (BPd is Low) and (HR is Normal) and (TB is Normal) and (RR is High) then (Stability is Unstable__Low)(Diagnosis is AlarmHigh) (1)
15. If (BPd is Low) and (BPd is Low) and (HR is Low) and (TB is Normal) and (RR is High) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
16. If (BPd is Low) and (BPd is Low) and (HR is Low) and (TB is Low) and (RR is High) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
17. If (BPd is Low) and (BPd is Low) and (HR is Low) and (TB is Low) and (RR is Low) then (Stability is Unstable__Low)(Diagnosis is AlarmLow) (1)
18. If (BPd is High) and (BPd is High) and (HR is Normal) and (TB is Normal) and (RR is Normal) then (Stability is Unstable__High)(Diagnosis is AlarmHigh) (1)

Fig. 8: Part of Rules Base.

1. Aggregation

Aggregation is used to determine the degree of success, which is a single output value combining the degree of membership functions of all the subconditions used in a rule. It considers the degree of membership of each subcondition in a rule. If the condition consists of a combination of more than one subcondition then the degree of accomplishment has to be calculated considering each individual value of each subcondition. Aggregation works with two operators: *AND* (Minimum of subcondition values) and *OR* (Maximum of subcondition values).

2. Activation

Activation is the process which provides the end result of a rule. It determines the degree of membership of the conclusion of a rule on the basis of the degree of accomplishment of the condition which was determined in the previous aggregation step. In general, the *MIN* and *PROD* are used for the activation process. The activation process provides the result based on the outcome of the sub conditions. In fact, the activation process is an interpretation step for the components determined in the aggregation step.

3. Accumulation

Accumulation is the process used to obtain the combined result of all the linguistic rules after aggregation and activation have been applied. To complete the accumulation process, we have to use the *MAXIMUM* operation to find out the overall result (result from the activation step). Therefore, from the accumulation of the above rules, one can determine if the health status is normal or unmoral, i.e. to send alarm or not to send.

C. Defuzzification and testing

Defuzzification is the final step which maps fuzzy output variables to a crisp numerical value. The inference (i.e. three successive stages of aggregation, activation and accumulation) provides a degree of membership function as the result. This result has to be converted into a crisp numerical value.

A crisp numerical value is a precise value in a crisp set. The output value obtained from the membership function should provide the “best possible” result of the values contained in it. The *maximum height method* is used to find out the best possible solution in the defuzzification method. A test for this fuzzy model is carried on using real data obtained from (PhisoNet, 2017), where fuzzy variables data is incorporated to see the values for fuzzy output variables (Fig. 9).

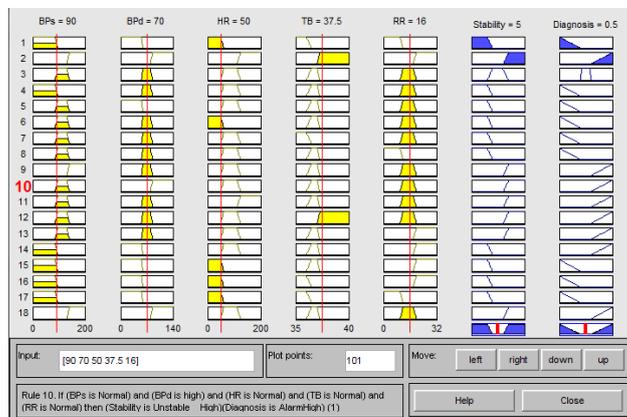


Fig. 9: A sample test for SPICU fuzzy model

Conclusion

A fuzzy model able to monitor and classify the condition of the vital signs of ill patients, sending information to an alerts system is presented. Monitoring, processing, validation and testing of the fuzzy model were carried out using database with real data. This model is presented in order to evaluate its effectiveness, taking into account the pre-adjustment of the relevance functions in the pursuit of reducing false alarms. The use of fuzzy logic in the medical area could be very useful as a tool to assist specialists in this area. Finally, from this study several possibilities for future work arise, such as: validation of the model in a real scenario and environment, confronting the real-time alarm generation and reception of messages, an increase of vital signs in the model, inclusion of specific alarms for each patient.

References

- Blood-Pressure-Chart-High-Low-Normal-Men-Women-AdultsChildren/<http://www.treatcure.com/blood/blood-pressure/> Accessed 1/8/2017
- Cecilia, H. and et al; January 2015, Fuzzy-NNARX based Tool for Monitoring and Patients Conditions using Selected Vital Signs Predicting. *IJCSNS*, VOL.15 No.1
- Dadashi, A., A. Rowhanimanesh and S. Choupankareh, 2015. A Neural Approach for Controlling Vital Signs in the Intensive Care Unit Patients. *Iranian Journal of Medical Informatics*, Vol 4.
- Dutta, S. 2013, Fuzzy Logic as a Decision Support Tool for Vital Signs Monitoring Msc Thesis, Page 47, researchdirect.uws.edu.au/islandora/object/uws%3A20939/.../view, Last accessed 1-8-2017
- Jauch, E.C., and et al., 2010, Guidelines for Cardiopulmonary Resuscitation and Emergency Cardiovascular Care. *Circulation. Journal of the American Heart Association*. Volume 122.
- Kim van Loon, 2017, Monitoring Vital Instability in Patients outside High Care Facilities, PhD thesis, <https://www.uu.nl/en/events/phd-defence-monitoring-vital-instability-in-patients-outside-high-care-facilities> Accessed 4-4-2017.
- Mamdani, EH: 1974, Application of fuzzy algorithms for control of simple dynamic plant, *Proceedings of IEEE.*, 121(12):1585-1588. <http://ieeexplore.ieee.org/abstract/document/5250910/>, accessed 5-5-2017
- National Library of Medicine, Resting pulse rate for age ranges, U.S., <https://medlineplus.gov/ency/article/002341.htm>, Accessed 16/7/2017.
- PhisoNet: Disponível em. [<http://www.physonet.org>], accessed 10/07/2017.

- Respiratory_Minute_Volume, https://en.wikipedia.org/wiki/Respiratory_minute_volume
- Sadrawiand, M., and et al., 2015. Computational Depth of Anesthesia via Multiple Vital Signs Based on Artificial Neural Networks, Hindawi Publishing, BioMed Research International.
- Umoh, U. and E. Nyoho, 2015, A Fuzzy Intelligent Framework for Healthcare Diagnosis and Monitoring of Pregnancy Risk Factor in Women. *Journal of Health, Medicine and Nursing*, Vol.18.