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Proposal for a fuzzy logic-based system to determine cardiovascular risk

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ABSTRACT

One of the key variables to determine the level of cardiovascular risk is the heart rate variability, which associates different metrics such as average of the RR intervals (average RR), standard deviation of the RR intervals (SDRR) and percentage of differences greater than 50 ms in RR intervals (pRR50). Given that these metrics make use of different measurement units, scales, and ranges, it is necessary to determine an output risk level in intelligible terms, taking as input the values of each one of them. Thus, this article proposes the development of a system based on fuzzy logic to determine the percentage or cardiovascular risk level. The fuzzy system is connected to an Arduino board with a heart rate sensor where the heart rate and heart rate variability values are obtained, so they are used to calculate the risk level metrics. Using the input values of each metric, as well as the 3 membership functions of the inputs, the output membership function, and a total of 18 inference rules defined from the inputs and outputs, the system obtains the output cardiovascular risk level. The fuzzy system was implemented using free hardware and software tools, making it available in medical campaigns for the early identification of heart conditions.

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1. INTRODUCTION

According to the World Health Organization (WHO) and the Pan American Health Organization (PAHO), heart conditions or cardiovascular diseases have historically been the main cause of mortality and/or morbidity worldwide, the most frequent being cerebrovascular diseases and cardiomyopathies [1], [2]. One of the key physiological variables for the prediction or early detection of heart conditions or cardiovascular risk is the heart rate variability (HRV) [3]–[6], which reflects the activity of the autonomous nervous system on the cardiac function, and it can be defined as the time variation that elapses between successive heart beats or between the RR intervals of the electrocardiogram [1], [7]–[9].

More precisely, a set of metrics have been defined in the time domain for the detection of cardiovascular risk. Among the ones that stand out are: average RR (the average of the RR intervals), standard deviation of the RR intervals (SDRR) and pRR50 (percentage of differences between consecutive RR intervals exceeding 50 milliseconds) [10], [11]. Considering that each one of these metrics have defined risk levels (low, moderate, high) that are expressed with different ranges and scales associated with the RR intervals, it is necessary to estimate a risk level from them in an intelligible range in numerical and linguistic terms. According to that, it is possible to take advantage of the models based on fuzzy logic to estimate the level of output risk from the three metrics mentioned. Fuzzy logic can be defined as a mathematical instrument that facilitates the process of reaching a specific conclusion from input information that can be considered undefined, inaccurate, or vague taking into account expert knowledge [12]–[18]. In this way, fuzzy logic allows the generation of intelligible results that relate numerical data with linguistic terms which are closer to natural language [19]–[21].

Different studies have been carried out regarding monitoring systems and physiological variables related to heart rate and heart rate variability. Thus, Delgado *et al.* [22] developed a free hardware-based system for heart rate monitoring in addition to the detection of tachycardia and bradycardia after capturing the heart rhythm in patients during a given time interval. Mota *et al.* [23] proposed a hardware-software system for capturing and monitoring the level of oximetry in patients, which by using sensors compatible with Arduino and the free hardware board ESP8266 capture the oximetry data and are sent to a server in order to allow remote monitoring through a web application. Pawar [24] proposed the development of a system based on free hardware for the capture and monitoring of the heart rhythm, which allows sending data obtained from the patient to the doctor via short message service (SMS), allowing this system to be used in rural medical campaigns. Valencia and Patiño [25] proposed a system based on free hardware for the monitoring and analysis of physiological variables (heart rate, skin conductivity) in students during the mechanical physics courses at the University of Quindío. Thomas *et al.* [26] proposed the development of a hardware-software system for monitoring heart rate and body temperature that captures data through free hardware sensors and sends them to an Arduino board, which transmit the data via Bluetooth to a mobile application. Petelczyc *et al.* [27], carried out a study on the observation errors associated with the metrics in both the frequency domain and the time domain of heart rate variability, using the Monte Carlo method, which showed that the data most sensitive to observation error are those corresponding to pRR50. Goumopoulos and Menti [10] conducted a study to determine the relationship between mental stress in a group of patients and the physiological variables captured by biosensors, as well as the information obtained by means of psychometric tests. With regard to physiological variables, the study monitors and analyzes galvanic skin conductivity and heart rate variability, calculating the metrics associated with the latter. Arvind *et al.* [28] developed a portable monitoring system for tracking heart rate variability and obtaining the metrics associated with this variable in the time and frequency domain, which showed results consistent with those obtained with commercial devices. Mott *et al.* [29] conducted a study on heart rate variability in horses, in order to identify the interbeat interval (IBI) in equines, given the specific particularities of the waveform in this context, for which commercial heart rate monitors such as: polar V800 and Actiheart 5 were used. The works described in this section present the capture, monitoring, and analysis of physiological variables such as heart rate variability, heart rate, skin conductivity, among others, using free hardware and commercial hardware. Despite the above, these studies did not make use of the risk metrics associated with heart rate variability to obtain cardiovascular risk levels using fuzzy logic, which would allow more precise and intelligible information to be obtained for patients and doctors, with a view to preventing deaths derived from cardiovascular diseases.

Based in the above, in this paper we propose as new contribution the development of a system based on fuzzy logic for the determination of cardiovascular risk that takes as input the values associated with 3 risk metrics (average RR, SDRR and pRR50) and as output a risk level percentage, which is obtained from the membership functions defined for the inputs and outputs, as well as a set of inference rules that relate the inputs to the output. The fuzzy system calculated cardiovascular risk metrics from data captured by an Arduino compatible heart rate sensor, and it was implemented using Java's jFuzzyLogic API. On the other hand, the membership functions and the 18 inference rules were specified in the fuzzy control language (FCL) language. The fuzzy system proposed aims to support its use in medical campaigns for the early detection of heart conditions in patients, by taking advantage of free hardware sensors and boards, as well as the advantages provided by fuzzy logic. The system is also intended to serve as a reference for the construction of systems based on fuzzy logic that take into consideration other metrics associated with heart rate variability for the determination of cardiovascular risk.

Consequently, section 2 presents the different methodological phases considered for the development of this research. Section 3 presents the results obtained, which includes the characterization of the cardiovascular risk metrics, the definition of the membership functions of the inputs and outputs of the system, the design of the inference rules, and the implementation of the fuzzy system. Finally, section 4 presents the conclusions and future work derived from this research.

2. RESEARCH METHOD

For the development of this research, an adaptation of the methodology considered in [30], [31] was carried out. It defined 4 methodological phases which are shown in Figure 1 i.e., characterization of metrics for measuring the level of cardiovascular risk, design of membership functions, definition of inference rules, and construction of the fuzzy system. According to this, phase 1 characterized 3 metrics in the time domain (average RR, SDRR, and pRR50) to obtain the level of cardiovascular risk from the heart rate variability, considering the ranges and levels associated with each one of them. The “average RR” metric corresponds to the sum of the RR intervals captured in a given period of time, divided by the number of intervals. The SDRR metric refers to the standard deviation of the RR intervals captured in a given period of time. The pRR50 metric is defined as the percentage of differences between consecutive RR intervals that exceed 50 milliseconds [1], [28]. From the characterization carried out in phase 1, the membership functions for the system’s inputs (3 risk level metrics) and output (output risk level percentage) were designed in phase 2. In phase 3, a total of 18 inference rules were defined in the FCL language, which allow relating the input variables of the system with the output variable. Finally, considering the membership functions and the defined inference rules, phase 4 implemented the fuzzy system by using the Java API jFuzzyLogic that calculates the risk metrics from the data obtained by a heart rate sensor (SEN023) and an Arduino DFRobot board.

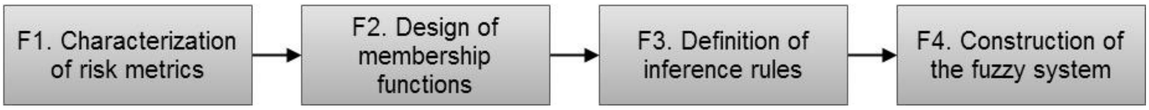

Figure 1. Considered methodology

3. RESULTS AND DISCUSSION

This section presents the results obtained from this research. In the first instance, the characterization of the risk metrics is presented, as well as the definition of the membership functions and the inference rules. Finally, the implementation of the fuzzy system is described.

3.1. Characterization of cardiovascular risk metrics

Regarding the implementation of the fuzzy system, Table 1 shows the 3 metrics considered as input variables of the system [11]. The “average RR” metric corresponds to the sum of the RR intervals captured in a given period of time, divided by the number of intervals. Similarly, the SDRR metric refers to the standard deviation of the RR intervals captured in a given period of time. On the other hand, the pRR50 metric is defined as the percentage of differences between consecutive RR intervals that exceed 50 milliseconds [1], [28]. Then, given that the fuzzy system uses metrics in terms of RR intervals and the sensor captures the data referring to the heart rate, (1) is used to obtain the RR intervals from the heart rate (HR) [32].

$$RR = \frac{60000}{HR} \tag{1}$$

Table 1. Cardiovascular risk level metrics

Metric	Risk Level
Average RR	High: RR<750 ms, Moderate: RR 750–900 ms, Low: RR>900
SDRR	High: SDRR <50 ms, Moderate: SDRR 50–100 ms, Low: SDRR>100 ms
pRR50	High: pRR50<3%, Low: pRR50>=3%

3.2. Membership functions design

Based on the ranges and levels considered in [11] and presented in Table 1, membership functions were specified in the FCL language, both for the system inputs (average RR, SDRR and pRR50) and for the output risk level, which is presented in the source code file in Figure 2. In accordance with the above, Figure 3 shows the 3 membership functions corresponding to the average RR, SDRR, and pRR50 metrics. Thus, concerning the average RR and SDRR metrics, the membership functions include three fuzzy sets: low, moderate, and high while for the pRR50 metric, two fuzzy sets were taken into account: low and high.

For providing precision to the membership functions defined in Figure 3, the functions designed for the input metrics to the fuzzy system are described below being obtained from the recommendations for the design of membership functions presented in [33]. Thus, considering that the “Average RR” metric has 3 fuzzy sets (low, moderate, and high), these sets are represented by (2)-(4).

$$\mu_{low\_average\_rr}(x) = \begin{cases} 1, & x < 740 \\ \frac{750-x}{10}, & 740 \le x \le 750 \\ 0, & x > 750 \end{cases} \tag{2}$$

$$\mu_{moderate\_average\_rr}(x) = \begin{cases} 0, & x < 740 \\ \frac{x-740}{80}, & 740 \le x < 820 \\ \frac{900-x}{80}, & 820 \le x \le 900 \\ 0, & x > 900 \end{cases} \tag{3}$$

$$\mu_{high\_average\_rr}(x) = \begin{cases} 0, & x < 890 \\ \frac{x-890}{10}, & 890 \le x \le 900 \\ 1, & x > 900 \end{cases} \tag{4}$$

```
FUZZIFY avg_rr
	TERM low:=(0, 1) (740, 1) (750, 0);
	TERM moderate:= (740, 0) (820, 1) (900,0);
	TERM high:= (890, 0) (900,1)(1000, 1);
END_FUZZIFY
FUZZIFY sdrr
	TERM low:=(0, 1) (40, 1) (50, 0);
	TERM moderate:= (40, 0) (70, 1) (100,0);
	TERM high:= (90, 0) (100, 1) (200, 1);
END_FUZZIFY
FUZZIFY prr50
	TERM high:=(0, 1) (2.5, 1) (3, 0);
	TERM low:= (2.5, 0) (3, 1)(100,1);
END_FUZZIFY
DEFUZZIFY risk_level
	TERM low := (0,1) (50,1) (55,0);
	TERM moderate := (50,0) (60,1) (70,0);
	TERM high := (65,0) (75,1) (85,0);
	TERM very_high := (80,0) (100,1);
	METHOD : COG;   // Use 'Center Of Gravity' defuzzification method
	DEFAULT := 0;   // Default value is 0 (if no rule activates defuzzifier)
END_DEFUZZIFY
```

Figure 2. Source code file in FCL language

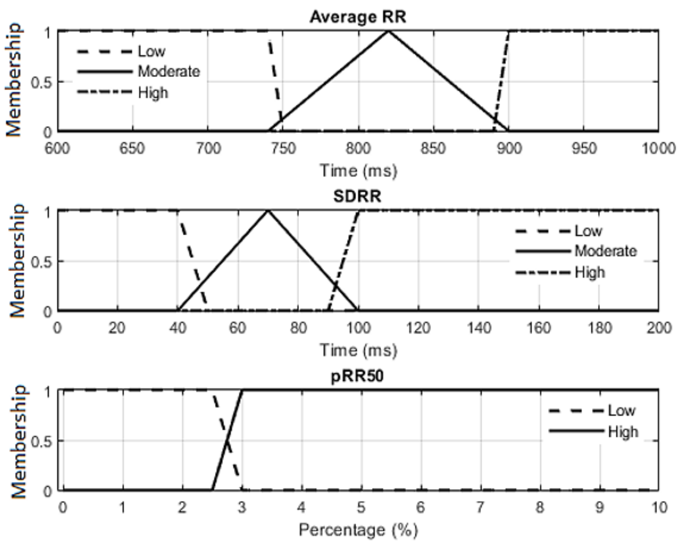

Figure 3. Membership functions for risk metrics

In the same way, considering that the "SDRR" metric is made up by 3 fuzzy sets (low, moderate, and high), these fuzzy sets are represented by (5)-(7), according to what is presented in [33].

$$\mu_{low\_sdrr}(x) = \begin{cases} 1, & x < 40 \\ \frac{50-x}{10}, & 40 \leq x \leq 50 \\ 0, & x > 50 \end{cases} \tag{5}$$

$$\mu_{moderate\_sdrr}(x) = \begin{cases} 0, & x < 40 \\ \frac{x-40}{30}, & 40 \leq x < 70 \\ \frac{100-x}{30}, & 70 \leq x \leq 100 \\ 0, & x > 100 \end{cases} \tag{6}$$

$$\mu_{high\_sdrr}(x) = \begin{cases} 0, & x < 90 \\ \frac{x-90}{10}, & 90 \leq x \leq 100 \\ 1, & x > 100 \end{cases} \tag{7}$$

Following this idea and taking into account that the “pRR50” metric is made up by 2 fuzzy sets (low and high), they are represented by (8) and (9) respectively, according to what is presented in [33].

$$\mu_{low\_prr50}(x) = \begin{cases} 1, & x < 2.5 \\ \frac{3-x}{0.5}, & 2.5 \leq x \leq 3 \\ 0, & x > 3 \end{cases} \tag{8}$$

$$\mu_{high\_prr50}(x) = \begin{cases} 0, & x < 2.5 \\ \frac{x-2.5}{0.5}, & 2.5 \leq x \leq 3 \\ 1, & x > 3 \end{cases} \tag{9}$$

On the other hand, Figure 4 shows the membership function that represents the cardiovascular risk percentage output where four fuzzy sets can be identified: low, moderate, high, and very high. Therefore, the fuzzy system not only obtains as an output a level of risk in percentage terms but also in linguistic terms.

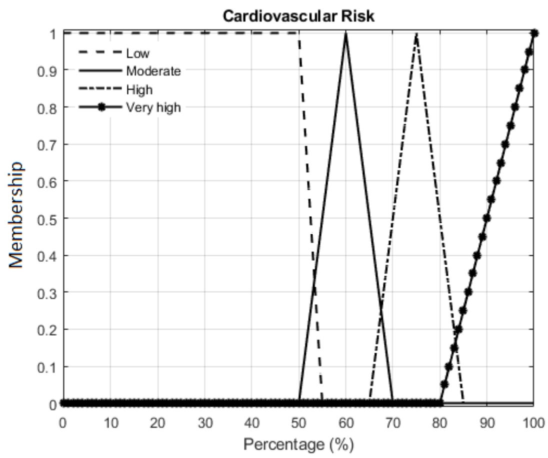

Figure 4. Membership functions for risk metrics

In order to specify the membership functions presented in Figure 4, the functions designed for the cardiovascular risk percentage output are described below obtained from the recommendations for the design of membership functions presented in [33]. Then, considering that the percentage or output risk level has 4 fuzzy sets (low, moderate, high, and very high), these sets are represented by (10)-(13).

$$\mu_{low\_risk}(x) = \begin{cases} 1, & x < 50 \\ \frac{55-x}{5}, & 50 \leq x \leq 55 \\ 0, & x > 55 \end{cases} \tag{10}$$

$$\mu_{moderate\_risk}(x) = \begin{cases} 0, & x < 50 \\ \frac{x-50}{10}, & 50 \leq x < 60 \\ \frac{70-x}{10}, & 60 \leq x \leq 70 \\ 0, & x > 70 \end{cases} \quad (11)$$

$$\mu_{high\_risk}(x) = \begin{cases} 0, & x < 65 \\ \frac{x-65}{10}, & 65 \leq x < 75 \\ \frac{85-x}{10}, & 75 \leq x \leq 85 \\ 0, & x > 85 \end{cases} \quad (12)$$

$$\mu_{very\_high\_risk}(x) = \begin{cases} 0, & x < 80 \\ \frac{x-80}{20}, & 80 \leq x \leq 100 \\ 1, & x > 100 \end{cases} \quad (13)$$

3.3. Inference rules

From the membership functions defined for both the input variables and the output variable of the system, a set of 18 inference rules were defined. They allow to relate the fuzzy sets of the inputs (low, moderate, and high) with the fuzzy sets of the output risk percentage (low, moderate, high, and very high). Thus, Table 2 presents the 18 defined inference rules specified in the FCL language.

Table 2. Inference rules

Rule	Inference rules
1	IF avg_rr IS low AND sdrr IS low AND prr50 IS low THEN risk_level IS low
2	IF avg_rr IS low AND sdrr IS low AND prr50 IS high THEN risk_level IS low
3	IF avg_rr IS low AND sdrr IS moderate AND prr50 IS low THEN risk_level IS low
4	IF avg_rr IS low AND sdrr IS moderate AND prr50 IS high THEN risk_level IS moderate
5	IF avg_rr IS low AND sdrr IS high AND prr50 IS low THEN risk_level IS low
6	IF avg_rr IS low AND sdrr IS high AND prr50 IS high THEN risk_level IS high
7	IF avg_rr IS moderate AND sdrr IS low AND prr50 IS low THEN risk_level IS low
8	IF avg_rr IS moderate AND sdrr IS low AND prr50 IS high THEN risk_level IS moderate
9	IF avg_rr IS moderate AND sdrr IS moderate AND prr50 IS low THEN risk_level IS moderate
10	IF avg_rr IS moderate AND sdrr IS moderate AND prr50 IS high THEN risk_level IS high
11	IF avg_rr IS moderate AND sdrr IS high AND prr50 IS low THEN risk_level IS moderate
12	IF avg_rr IS moderate AND sdrr IS high AND prr50 IS high THEN risk_level IS very_high
13	IF avg_rr IS high AND sdrr IS low AND prr50 IS low THEN risk_level IS low
14	IF avg_rr IS high AND sdrr IS low AND prr50 IS high THEN risk_level IS high
15	IF avg_rr IS high AND sdrr IS moderate AND prr50 IS low THEN risk_level IS moderate
16	IF avg_rr IS high AND sdrr IS moderate AND prr50 IS high THEN risk_level IS very_high
17	IF avg_rr IS high AND sdrr IS high AND prr50 IS low THEN risk_level IS high
18	IF avg_rr IS high AND sdrr IS high AND prr50 IS high THEN risk_level IS very_high

3.4. Fuzzy system built

Considering the membership functions designed and the inference rules defined, a fuzzy system whose functional structure is shown in Figure 5 was implemented. In the first place, a heart rate is captured during a determined period of time using the SEN0203 sensor; as it obtains the data, the sensor sends it to the Arduino DFRobot board. Then, the board sends the heart rate value to the fuzzy system through the serial port.

Once the heart rate value has been received within the fuzzy system, the value of the RR intervals is obtained through (1) in a way that the values are displayed on the screen as they are received. Once the capture period ends, the average RR, SDRR, and pRR50 metrics are calculated from the set of captured RR intervals. By using the membership functions defined for the entries, the degree of membership of the different metrics calculated is obtained. This together with the inference rules presented in Table 2, allow to obtain the output cardiovascular risk percentage. A description of the fuzzy system to verify the operation and usefulness of the system will consider the data captured at rest for 3 minutes for a 37-year-old real patient. The description of the system presented in this section was exemplified from real data from a patient, in order to demonstrate the usefulness of the proposal in terms of obtaining cardiovascular risk levels from the use of fuzzy logic, as well as to show the possibility of extrapolating the use of the system for the monitoring of cardiac conditions in patients within medical campaigns.

Based on the above, Figure 6 shows the main interface of the fuzzy system that was implemented using the jFuzzyLogic API and the FCL language. This interface has three tabs: “Capture”, “Metrics”, and “Fuzzy logic”. In the “Capture” tab, once the “Start” button is pressed, the heart rate data begins to be captured from the sensor and the Arduino board through the serial port. As the data is obtained, the information is presented on the screen and a graph is shown in real time implemented through the use of the JFreeChart Java library.

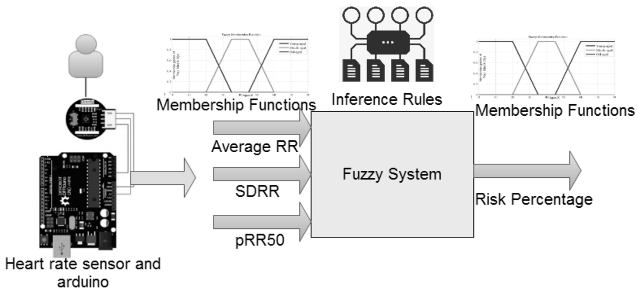

Figure 5. System functional structure

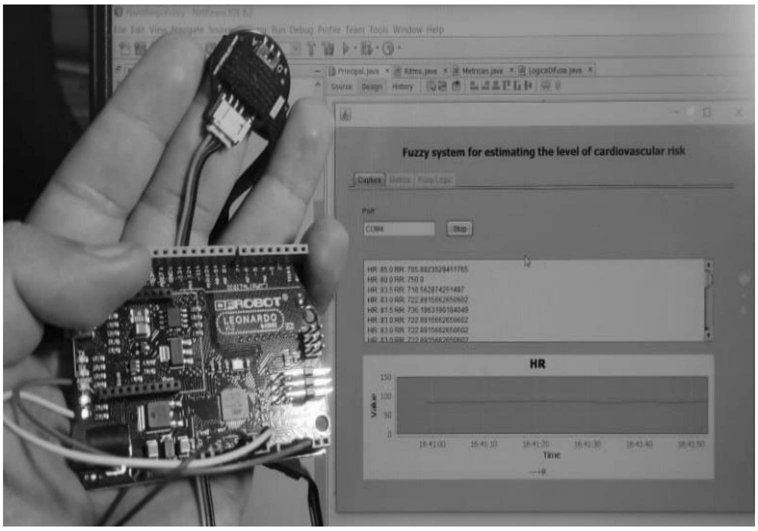

Figure 6. System main interface

On the “Metrics” tab, it is possible to perform the calculation of the 3 metrics presented in Table 1, as well as to obtain the number of captures and the maximum and minimum values of the heart rate and heart rate variability. Thus, Figure 7 illustrates the results obtained in the “Metrics” tab for the RR intervals captured from the 37-year-old real patient for 3 minutes.

It can be seen how during the 3 minutes, a total of 149 captures were made. The minimum value of the heart rate was 78 bps, and the maximum value was 88 bps while for the RR intervals, the minimum interval is 681.818 ms and maximum interval is 769.23 ms. Regarding the metrics in Table 1, the average RR value was 716, the SDRR value was 18.46 while the pRR50 value was 0%. The values obtained correspond to the input values of the fuzzy system which are considered in the “Fuzzy Logic” tab to obtain the level or output risk percentage.

When entering the “Fuzzy Logic” tab, the system is in charge of loading the values of the metrics obtained in the “Metrics” tab, hence the fuzzy system calculates the membership levels of each metric according to the functions presented in Figure 3. Taking into account the rules of inference, it determines the risk percentage or output level as shown in Figure 8. Thus, for the 149 RR intervals captured, 26.34% is obtained as an output, which is associated with the linguistic term “Low”. This can be seen more clearly in the Figure 8 graph that presents the fuzzy sets of the output risk level and an indicator that shows the location of the output percentage obtained. Likewise, in Figure 8, it is observed how the inference rule 2 is activated.

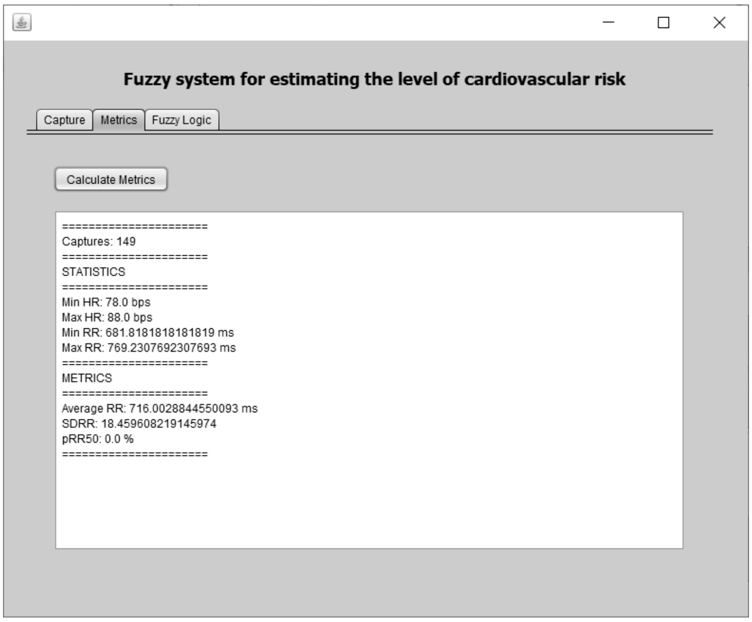

Figure 7. Fuzzy system “Metrics” tab

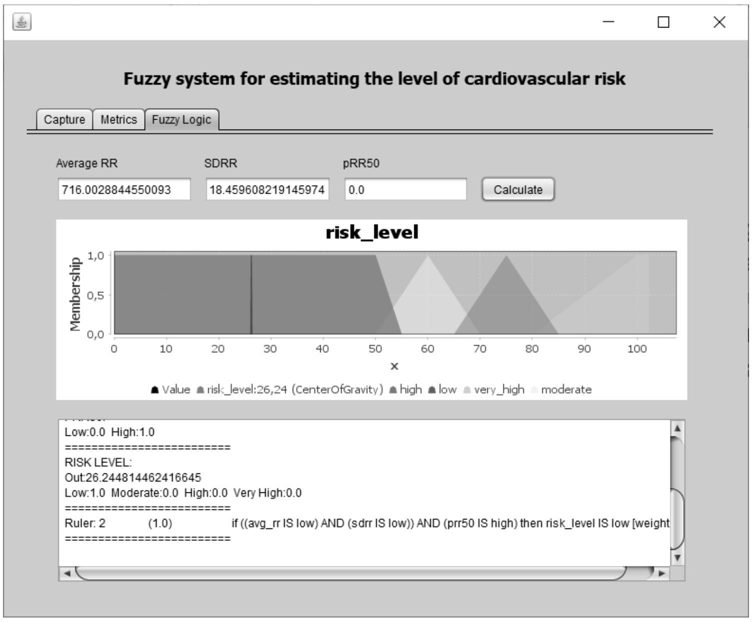

Figure 8. Fuzzy system “Fuzzy Logic” tab

4. CONCLUSION

Based on the existence of different risk metrics and their associated ranges, in this article a system based on fuzzy logic was proposed as a contribution to estimate the percentage or level of output cardiovascular risk, which takes as input the metrics of risk: average RR, SDRR, and pRR50. The fuzzy logic system performs the calculation of the metrics mentioned from the RR intervals captured by an Arduino compatible heart rate sensor. Both the membership functions and the system inference rules were specified in the FCL language. Thus, the proposal presented in this paper is not limited to the construction of a system for obtaining the metrics associated with heart rate variability but takes advantage of the benefits of fuzzy logic to obtain the levels of cardiovascular risk in a more precise and intelligible way for patients and medical personnel. The fuzzy logic system was implemented using a set of free hardware and software tools in a way that the SEN0203 sensor and the free hardware board were used to capture the heart rate while the free Java library jFuzzyLogic was used for the implementation of the fuzzy system. Therefore, based on the portability and ease of customization of the chosen tools, the fuzzy system is intended to be used in medical campaigns for the early identification of heart conditions.

The verification test carried out through the fuzzy system allowed to determine its usefulness and relevance in terms of capturing RR intervals, calculating risk metrics, and obtaining the cardiovascular risk at a mathematical, graphic, and linguistic level. Likewise, this system can be adapted by including additional risk metrics to the ones considered in addition to being able to integrate different types of inference rules not only of the Mamdani type but also Takagi-Sugeno for the construction of data training fuzzy rules. As future work derived from the present research in the first place is enriching the fuzzy system by including the storage functionality of the capture sessions in such a way that it is possible to keep a record on the evolution of the patients. Likewise, extrapolating the implemented system by considering other physiological variables such as blood pressure, as well as implementing supervised and unsupervised learning algorithms. Finally, we intend to make use of the advantages of the proposed system to evaluate the level of cardiovascular risk in patients with sedentary lifestyles.

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