Premature Ventricular Contraction Recognition using a Fuzzy Maximum Approaching Degree

Eder Pereira Neves [1,3*], Bruno Rodrigues Oliveira [2], Marco Aparecido Queiroz Duarte [3], Jozue Vieira Filho [4]

[1] *Department of Electrical Engineering, São Paulo State University (UNESP), Ilha Solteira, SP, Brazil.*
[2] *Pantanal Editora. Rua Abaete, 83, Sala B, Centro. 78.690-000, Nova Xavantina, MT, Brazil.*
[3] *Department of Mathematics, Mato Grosso do Sul State University (UEMS), Cassilândia, MS, Brazil.*
[4] *Telecommunication and Aeronautic Engineering, São Paulo State University (UNESP), São João da Boa Vista, SP, Brazil.*

**Corresponding author. E-mail: ederpereira@uems.br*

ABSTRACT. This work presents a new methodology for ventricular premature contraction arrhythmias recognition using a set of geometrical attributes recently proposed and a fuzzy maximum approaching degree. Pattern models based on triangular and trapezoidal membership functions are proposed and a committee comprising these functions is composed using some statistical data, beyond a mechanism for manual selection of attributes and automatic weighting for each attribute. The obtained results show the efficiency and validity of the proposed approach, with 99.07%, 98.36% and 99.79% of accuracy, sensibility and specificity, respectively, as good as the ones obtained by the state-of-art methods.

Keywords: Premature Ventricular Contraction; Geometrical Attributes; Fuzzy Maximum Approaching Degree.

DOI: https://doi.org/10.33837/msj.v6i1.1591

Received: February 1, 2023. Accepted: March 20, 2023.
Associate editor: Anderson Rodrigo da Silva

INTRODUCTION

The heart acts as a pump, receiving rich carbon dioxide blood from the circulatory system by the right atrium. This blood is sent to the lungs by the right ventricle. Then, it is oxygenated and ejected to the left atrium, and after to the left ventricle, which sends it again to the circulatory system through the aorta artery (Guyton, 2006).

The increased mortality in patients for treatment of premature ventricular contraction (PVC) is associated to the increased mortality in patients for treatment of acute myocardial infarction (AMI).

The ECG records the electrical activity of the heart. It is a stochastic signal formed by characteristic waves: P, Q, R, S and T, where P waves and QRS complex discriminate atrial and ventricular depolarization, and T wave reports ventricular repolarization (Latchamsetty; Bogun, 2015). A PVC occurrence changes, the ECG waveforms. Therefore, by analyzing such changes it is possible to detect their occurrence.

Due to the large amount of data to be analyzed and the variability of PVC patterns, the use of intelligent mathematical computational tools is extremely necessary to assist the expert in the diagnostic.

In this work, a new approach is presented for PVC recognition, combining the geometrical features porposed in (Oliveira; Abreu; Duarte; Vieira Filho, 2019) and the Fuzzy maximum approaching degree.

The remainder of the text is organized as follows: in the section 1, some fundamentals of Fuzzy logic are listed; methods for PVC recognition are described in section 2; the proposed approach is presented in section 3; results and discussions are described in section 4, and finally conclusions are presented in section 5.

Fuzzy Patterns Recognizing

Fuzzy logic is a system of reasoning and computation in which the objects of reasoning and computation are classes with limits not defined (Zadeh, 2015). In order to describe certain related phenomena the term“degree”has been used, representing partial qualities or truths or even standards of the best (Barros; Bassanezi, 2006).

Fuzzy sets, defined by Zadeh, associate an object membership grades to the set. In the classical or crisp case, when $f_x \in \{0,1\}$,the correspondent fuzzy set is $\mu_x \in [0,1]$. Membership functions characterize the system and can be generalized in a way that values attributed to elements in the universal set are within a specific range, indicating these elements relevance grade to the considered set. The most common membership functions are triangular and trapezoidal (Ross, 2017).

Pattern recognition is understood as a process of identifying structures, through comparisons to a previously known structure. The dataset for pattern recognition can be divided into two subsets: training and testing. Training subset is used to establish the parameters of the model used in the pattern recognition, while test subset serves to validate the obtained model.

Patterns are expressed as fuzzy sets $\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_m$. When a recognition system receives an attribute characterized by the crisp value x_0, using the maximum membership criterion, a pattern will be associated to x_0 if Equation (1) is satisfied (ROSS, 2017):

$$\mu_{\tilde{A}}(x_0) = max\{\mu_{\tilde{A}_1}(x_0), \mu_{\tilde{A}_2}(x_0), \ldots, \mu_{\tilde{A}_m}(x_0)\}, \quad (1)$$

i.e., x_0 means the greatest membership among all the m patterns membership.

In pattern recognition applications, the dimension of the attributes space is greater than one, therefore, each set of fuzzy patterns is defined as a collection of crisp values, such as $\tilde{A}_j = \{a_{j_1}, a_{j_2}, \ldots, a_{j_k}\}$ where k is the amount of attributes, $j = \{1, 2, \ldots, c\}$ and c is the number of classes in which the patterns are classified.In this approach it is common to introduce factors w_q,weighting the importance of the attribute $\tilde{a}_{jq}$ to the pattern, such that $\sum_{q=1}^{k} w_q = 1, \ \forall j$ (Ross, 2017).

Therefore, using a maximum-degree approach, given a pattern $\tilde{B} = \{b_1, b_2, \ldots, b_k\}$ and c classes, a maximum membership is given by

$$\mu_{\tilde{A}}(x) = \max_{1 \le j \le c} \left\{\sum_{q=1}^{k} w_q \mu_{\tilde{A}_j}(b_q)\right\}, \quad (2)$$

i.e., for each j class it is obtained the sum of $k$memberships, computed for a given attribute q, weighted by w_q. The greater from theses sums is related to the class that pattern $\tilde{B}$ resembles more. It is important to note that $\mu_{\tilde{A}}(x)$ is a crisp singleton.

State of the art

In this section some PVC recognition methods are described, aiming to provide an overview of the propositions employed to this problem solution.

In the work proposed by Oliveira et al. (2019) a new set of 12 attributes based on geometrical characteristics and the aid of machine learning methods were proposed in order to detect PVC heartbeats. Therefore, on each QRS complex, geometrical figures were constructed as specified in Figure 1, attributes extracted from each figure are shown in Table 1.

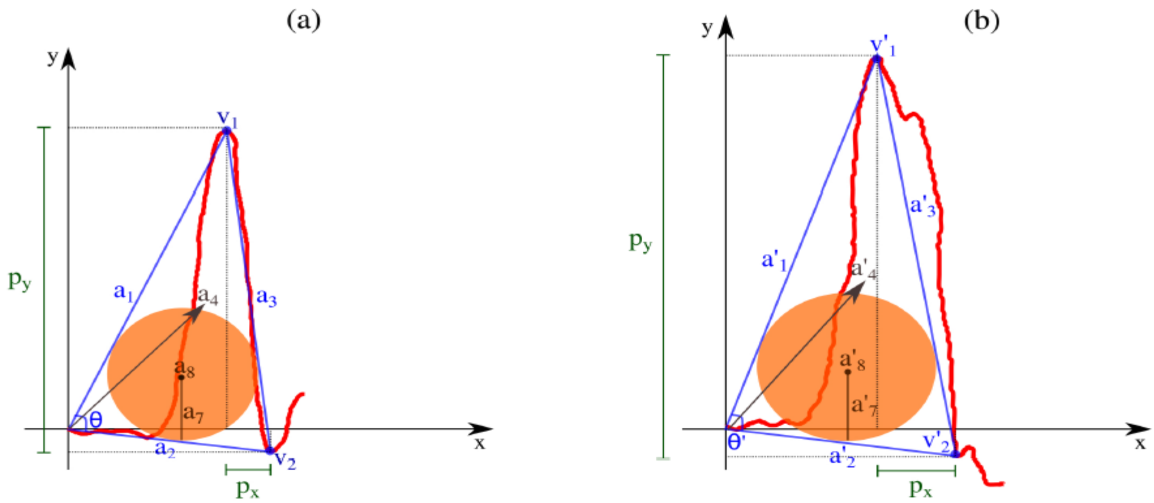

Figure 1: Examples of (a) normal and (b) PVC QRS complexes, with their respective geometrical figures, and the metrics obtained from them.

Table 1: Proposed attributes by Oliveira et al. (2019)

Formula	Description
$a_1 = \|v_1\|$	triangle side
$a_2 = \|v_2\|$	triangle side
$a_3 = \|v_1 - v_2\|$	triangle side
$a_4 = \|v_{1x} + v_{2x}, v_{1y} + v_{2y,}\|/3$	triangle of mass
$a_5 = \theta = arcos(v_1 * v_2/a_{2)}$	angle between a_1 and a_2
$a_6 = a_1\, a_2\, \sin(\theta)/2$	triangle area
$a_7 = 2a_6/p$	in-circle radius
$a_8 = \|(a_2 v_{1x} + a_3 v_{2x}, a_2 v_{1y} + a_3 v_{2y})\|/p$	in-center
$a_9 = 2\pi a_7$	in-center length
$a_{10} = \pi a_7^2$	in-circule area
$a_{11} = p_x = \|v_{1x} - v_{2x}\|$	distance between the projections in the axis x.
$a_{12} = p_y = \|v_{1y} - v_{2y}\|$	distance between the projections in the axis y.

Using a cross validation approach and the insertion of artificial PVC samples, aiming to balance the used database, Oliveira et al. (2019), obtained 99,00% of accuracy, 98,5% of sensibility, and 99,5% of specificity.

Gharieb et al. (2016) proposed attributes extraction via wavelet transform, which provides $\gamma_{j,k}$ coefficients, for $j = \{1,\ 2, \ldots,\ J\}$ scales, where $k = 0, \ldots, N_j - 1$ and N_j is the length of the vector of coefficients, which are the TKE (Teager-Kaiser Energy) operator inputs. TKE returns $e_{j,k} = \gamma_{j,k}^2 - \gamma_{j-1,k}\,\gamma_{j+1,k}$. The energy in each QRS is computed getting the maximum for each scale, i.e., $E_j = \max\{e_{j,k}\}$ and it is then normalized, obtaining an energy cumulative distribution: $cE_j = \sum_{i=1}^{j} E_i^2\ / \sum_{i=1}^{J} E_i^2$. Therefore, vector $[CE_1,\ CE_2, \ldots, CE_J]$ forms the space of attributes for different heartbeats. In this space, the centroids for each class are obtained using the Fuzzy c-Means (FCM) clustering method. In this way, in order to recognize a new pattern, authors implement a minimum distance measure between the centroid and the pattern.

Also using the wavelet transform, Shyu et al., 2004 proposed the computation of only two attributes: QRS complex area and duration, computed using wavelet coefficients in the scales 3 and 4, respectively. These attributes are provided as input for a four-layers fuzzy neural network: (1) membership; (2) rules; (3) hidden and (4) output. In the second layer, composed by six nodes, three distinct gaussian models were implemented as membership functions, one for normal class, one for PVC class, and one for the Zero class, where functions parameters were set analyzing the attributes average (m) and standard deviation (σ) using recordings 116 and 111 from MIT/BIH database (Goldberger, 2000) for each heartbeat pattern. However, for the zero membership function, parameters were combined as follows: $m = (m_1 + \sigma_1 + m_2 - \sigma_2)/2$ and $\sigma = (\sigma_1 + \sigma_2)/2$, where indexes 1 and 2 are respectively related to normal and PVC classes. Authors Shyu et al. (2004) still proposed a five-node hidden layer, which connects the rules layer to the output layer. The output layer contains two nodes, those nodes provide the prediction probability for each class.

In Yeh et al. (2010), a method called fuzzy c-means (FCM) is proposed to classify cases of heartbeat (ECG) signals. The proposed FCM consists of four main stages: (i) QRS extraction stage (Procedure-DOM) to detect the QRS waveform using the difference Operation method; (ii) qualitative characteristics stage (Procedure- ROM) o select qualitative resources using the band overlap method on ECG signals; (iii) Procedure-CCC is used to calculate the cluster center for each class; and (iv) procedure-HCD is used to determine the heartbeat case for the patient. ECG signals at MIT-BIH arrhythmia databases are adopted as reference data for the first two stages, and the last two stages are used to determine the heartbeat cases for the patient based on the outputs from the previous stages.

Proposed Approach

The proposed approach aims to classify heartbeats (QRS complexes) in Normal (N_b) or PVC (P_b) using fuzzy logic and the twelve geometrical attributes proposed by Oliveira et al. (2019), consisting in two phases, training and testing.

In the first stage, which is similar to the one employed in Yeh et al. (2010), statistics over training set are used to emulate the expert action in the knowledge basis construction. By means of the description of the values of minimum (M_i), maximum (M_a), average (M), average minus, ($m_p = m - \sigma$), and average plus ($m_n = m + \sigma$), the standard deviation (σ), for each of the attributes, membership functions are built for every attribute a_j, $j = 1, \ldots, 12$, using trapezoidal (TRA) and triangular (TRI) models, according to equations (3) and (4), respectively,

$$\mu_{a_{k,j}}^{(TRA)}(x) = max\left\{0, min\left\{1, \frac{x-m_i}{m_p-m_i}, \frac{m_a-x}{m_a-m_n}\right\}\right\} \tag{3}$$

and

$$\mu_{a_{k,j}}^{(TRI)}(x) = max\left\{0, min\left\{1, \frac{x-m_i}{m-m_i}, \frac{m_a-x}{m_a-m}\right\}\right\} \tag{4}$$

where$k \in \{N_b, P_b\}$ represents the heartbeat type (class). This stage is called training phase, since in it membership functions are obtained for every q attribute related to the every k class.

In the second stage, the test phase, two of the membership functions approaches obtained in stage 1 are implemented. The first one is based on the maximum degree approach, described in Section 2. In the second approach, a membership functions committee is proposed. The two approaches are presented in the following.

Approach 1: Given a pattern $\tilde{A}_k = \{a_{k,1}, a_{k,2}, \ldots, a_{k,12}\}$ related to the k class, its membership is given by Equation (5), using the maximum degree approach:

$$\mu^{(T)}_{(\tilde{A}_k)}(x) = \sum_{q=1}^{12} w_q \mu^{(T)}_{(\tilde{A}_k)}(a_{k,q}) \quad (5)$$

where $w_q$is the weight assigned to the membership related to the $q-th$criterion and $T \in \{TRA, TRI\}$ defines the membership function model. In order to identify k, one has to compute the higher maximum-degree, by means of Equation (6):

$$c = \underset{k \in \{N_b, P_b\}}{arg\,max} \{\mu^{(T)}_{(\tilde{A}_k)}\} \quad (6)$$

i.e., at the end, $c \in \{N_b, P_b\}$.

Approach 2: It is noted in Equation (6) that T. can be kept fixed for a comparison only related to class k, or it can be got in the set $\{TRA, TRI\}$., resulting in a membership functions committee, since both models are used, and the one which returns the maximum between the membership functions is chosen to predict the pattern class, i.e.,

$$\mu^{(T)}_{(\tilde{A}_k)}(x) = max \left\{\mu^{(TRA)}_{(\tilde{A}_k)}(x), \quad \mu^{(TRI)}_{(\tilde{A}_k)}\right\} \quad (7)$$

which is later used in Equation (6) in order to predict the k class (Ross, 2017).

It is noteworthy that the maximum degree based approach is dependent on the weights w_J assigned to the membership functions for each attribute, according to Equation (5). Therefore, w_J can be used to select the attributes that will participate in the prediction making $w_J \neq 0$ or by mitigating the relevance of certain attributes to the total pertinence, taking $w_J \approx 0$.

On this last condition, since the maximum-degree approach also depends on the individual values of the relative pertinence to each class, then when $\mu^{(T)}_{(\tilde{A}_k)}(a_{k,q}) =, \mu^{(T)}_{(\tilde{A}_k)}(a_{\delta,q})$ for $k \neq \delta$ and $\delta \in \{N_b, P_b\}$, it implies that the membership functions overlap, i.e., their definition values m_i, m_a, m, m_n and m_p according to equations (3) and (4) are the same. So, the class prediction for an $\tilde{A}$ pattern is ambiguous, since the membership will be the same for both classes. This finding suggests that if the areas of the membership functions and their definition values are close to or equal, then the respective $w_q$weight must be inferior to the ones belonging to the membership functions that do not overlap or have less overlap. In other words, w_q weight can be weighted by a factor obtained from the intersection between the membership functions. Thus, initially considering $w_q = 1, \forall q$, after taking the intersection between the membership functions for each class, this vector is updated by calculating

$$w_q \leftarrow \frac{w_q}{\mu^{(T)}_{a_{k,q}}(x)\, \mu^{(T)}_{a_{\delta,q}}(x)}, q = 1, \ldots, 12, \delta \neq k \quad (8)$$

and then it is normalized as

$$w_q \leftarrow \frac{w_q}{\sum_{q=1}^{12} |w_q|} \quad (9)$$

Therefore, in the first stage, before executing approaches 1 and 2, weights w_q can be modified, so that those attributes whose membership functions result in greater ambiguity (greater intersection) are attenuated.

RESULTS AND DISCUSSION

In order to test the proposed method, a first step consists in analyzing the statistics of the ECG recordings used in the cross validation experiments implemented in Oliveira et al. (2019), These data are composed by 44 recordings from MIT/BIH (Goldberger, Amaral, Glass, Hausdor, 2000), namely: 101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230, 100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234, with 36,468 Normal and PVC heartbeats, these latter corresponds to the real amount plus 29,526 PVC heartbeats artificially generated taking randomly the mean of two PVC patterns, in order to balance the database (Oliveira, Abreu, Duarte, Vieira Filho, 2019).

Table 2 provides the obtained intervals from statistical analysis from the ECG recordings. In this training stage, for each class, 25,527 vectors of patterns are used, totaling 612,000 analyzed attributes, corresponding to 70 % of the database.

Table 2: Statistical attributes for the dataset.

Attribute	Normal (N_b)				PVC (P_b)			
	m_i	m_p	m_n	m_a	m_i	m_p	m_n	m_a
a_1	43.00	42.99	43.03	44.33	43.00	43.03	43.19	44.21
a_2	44.00	86.10	114.36	128.11	84.03	92.73	113.42	128.13
a_3	1.45	43.12	71.37	85.37	41.25	49.99	70.61	85.84
a_4	29.00	43.03	52.45	57.06	42.33	45.23	52.13	57.04
a_5	0.00	0.01	0.04	0.25	0.02	0.07	0.11	0.25
a_6	0.03	25.88	124.98	953.39	27.89	166.51	407.78	1163.50
a_7	0.40	0.47	0.65	1.89	0.40	0.49	0.61	0.69
a_8	0.72	10.92	13.33	14.58	10.59	11.52	13.26	14.69
a_9	2.53	2.96	4.11	11.89	2.54	3.05	3.86	4.32
a_{10}	0.51	0.69	1.35	11.24	0.51	0.77	1.20	1.48
a_{11}	0.26	0.76	2.36	11.79	0.83	3.99	6.32	11.96
a_{12}	1.00	43.09	71.35	85.00	41.00	49.67	70.38	85.00

Based on the values from Table 2, membership functions are built for each a_q attribute, considering trapezoidal (1) and triangular (2) models. It is emphasized that in (YEH, WANGB, CHIOU, 2010) only triangular functions are used. The membership functions for the 12 attributes, from (a) to (l), are shown in Figures 2 and 3 for trapezoidal and triangular models, respectively, where red and black lines represent membership functions for N_b and N_b classes, respectively.

Considering the 30% not used data in training stage, which are 10,928 patterns for each class, totaling 21,856 analyzed patterns, the obtained results with the proposed approach are discribed in Table 3, where all attributes were considered with the same weight. Performance measures are accuracy $A_{cc} = (TP + TN)/(TP + TN + FP + FN)$, sensibility $S_e = TP/(TP + FN)$ and specificity $S_p = TN/(TN + FP)$computed from the values of true positives and negatives, TP and TN, false positives and negatives, FP and FN, respectively.

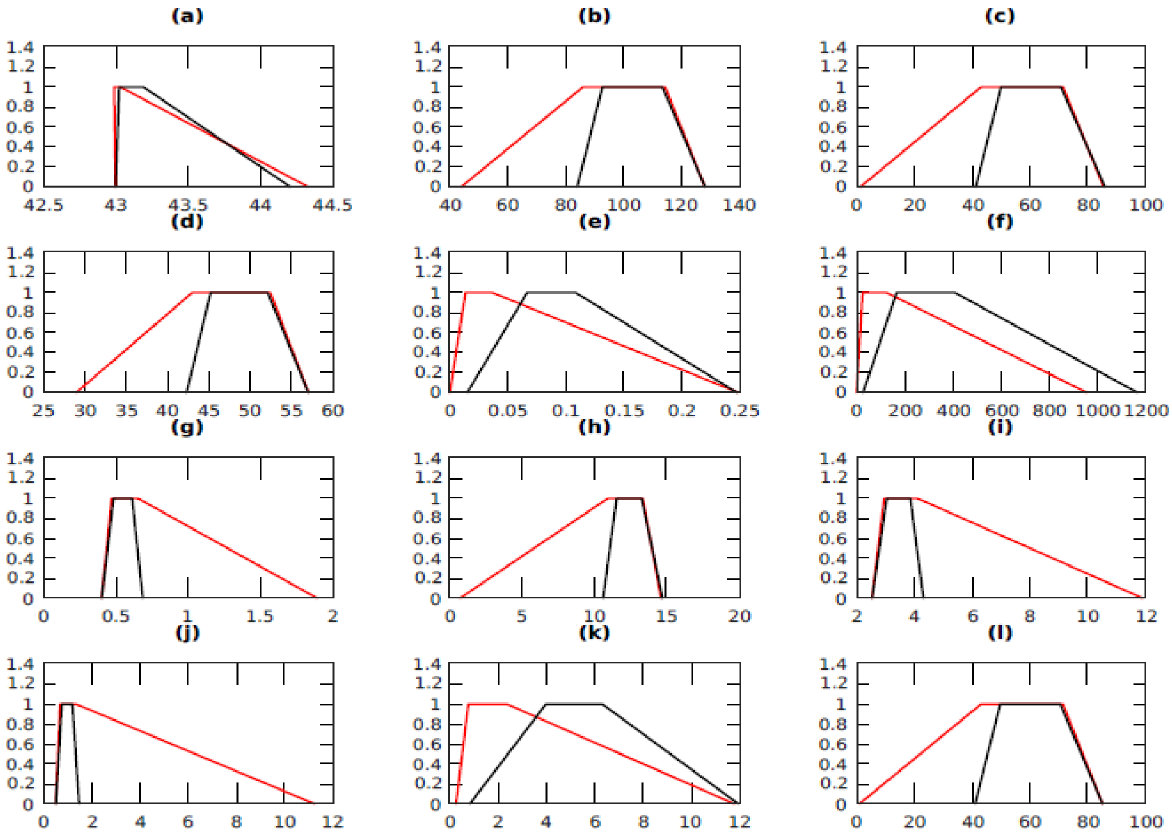

Figure 2: Trapezoidal membership functions for attributes from a_1 to a_{12}, (a)-(l). Red and black lines represent Normal and PVC classes, respectively. The attributes membership are in the y axis and the values they assume are in the x axis.

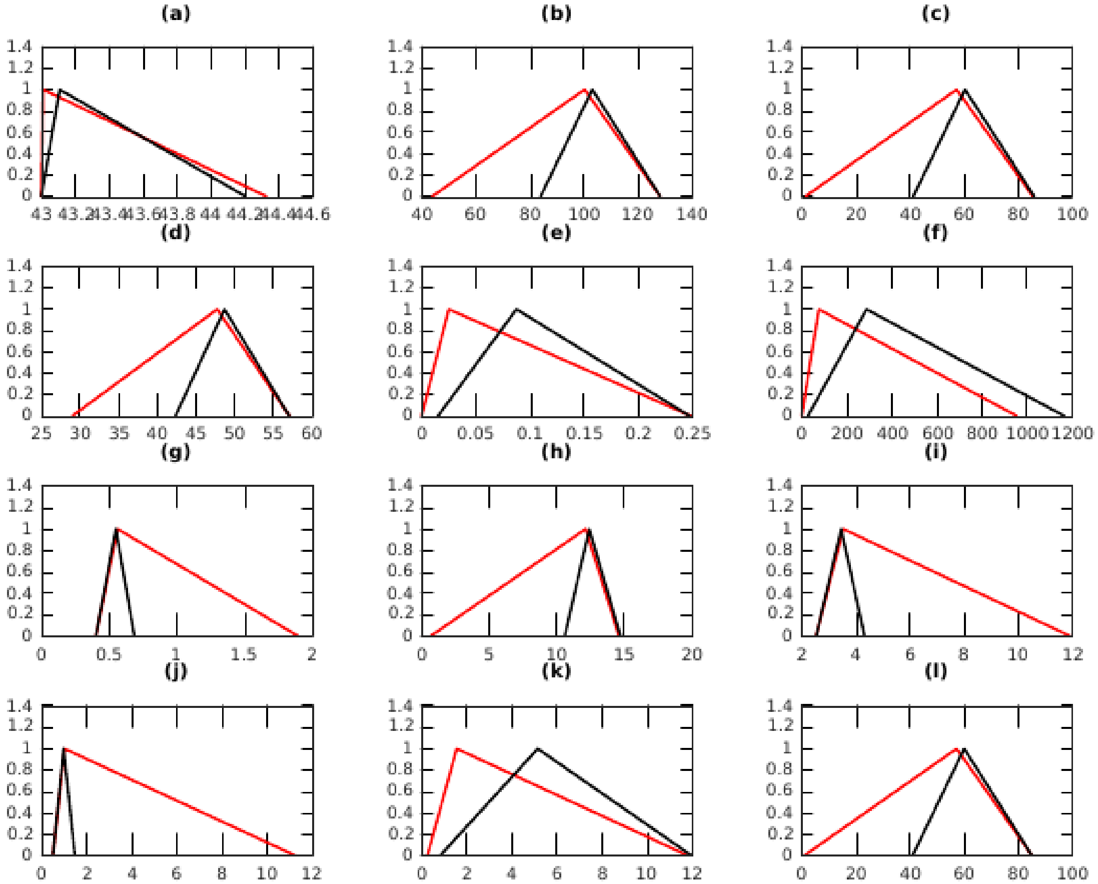

Figure 3: Triangular membership functions for attributes from $\boldsymbol{a_1}$ to $\boldsymbol{a_{12}}$, (a)-(l). Red and black lines represent Normal and PVC classes, respectively. The attributes membership are in the $\boldsymbol{y}$ axis and the values they assume are in the $\boldsymbol{x}$ axis.

Table 3: Results considering three membership function models.

Model	TP	TN	FP	FN	A_{cc}	S_e	S_p
Trapezoidal	16,424	18,202	6	1,791	**95.86%**	91.74%	99.99%
Triangular	9,666	18,212	3	8,549	76.95%	53.90%	**100.00%**
Committe	11,205	18,212	3	7,010	81.38%	62.75%	**100.00%**

Table 4: Results considering the Attribute, exclusion, only with the trapezoidal model.

Attribute	A_{cc}	S_e	S_p
a_1	95.64%	91.30%	99.98%
a_2	96.10%	92.21%	99.99%
a_3	96.06%	92.12%	99.99%
a_4	96.10%	92.21%	99.99%
a_5	95.03%	90.08%	99.98%
a_6	94.45%	88.89%	100.00%
a_7	96.45%	92.93%	99.98%
a_8	96.05%	92.10%	99.99%
a_9	96.31%	92.63%	99.98%
a_{10}	96.44%	92.89%	99.98%
a_{11}	94.32%	88.66%	99.98%
a_{12}	96.10%	92.21%	99.99%

Table 5: Obtained weight values considering the intersection between the pattern membership functions for each attribute.

Attribute $\mathbf{a_q}$	Triangular	Trapezoidal
a_1	7.7×10^{-2}	9.8×10^{-2}
a_2	1.9×10^{-3}	1.4×10^{-3}
a_3	1.9×10^{-3}	1.4×10^{-3}
a_4	5.8×10^{-3}	4.3×10^{-3}
a_5	4.5×10^{-1}	5.4×10^{-1}
a_6	1.0×10^{-4}	1.0×10^{-4}
a_7	3.0×10^{-1}	2.1×10^{-1}
a_8	2.0×10^{-2}	1.6×10^{-2}
a_9	4.4×10^{-2}	3.5×10^{-2}
a_{10}	8.0×10^{-2}	6.4×10^{-2}
a_{11}	9.9×10^{-3}	1.0×10^{-2}
a_{12}	1.9×10^{-3}	1.4×10^{-3}

Table 6: Results considering the modified weights according to Table 5.

Model	TP	TN	FP	FN	A_{cc}	S_e	S_p
Trapezoidal	17,172	18,205	10	1,043	99.07%	98.36%	99.79%
Triangular	10,896	18,214	1	7,319	83.70%	67.42%	99.98%
Committe	14,813	18,211	4	3,404	94.64%	89.33%	99.95%

In order to verify each attribute importance in the pattern recognition, it was set $w_q = 0$ in Equation (5) for the $q-th$ attribute, and the classification was performed disregarding its contribution. Table 4 shows the obtained results only with the trapezoidal model, since it generates better results, where the "attribute" column assigns the excluded attribute.

It was also considered the changing of weights by calculating the intersection between the pattern membership functions in relation to the 12 implemented attributes, according to Equation (8). The obtained modified weights are described in Table 5 for each attribute q and for each defined membership function model.

Using w_q values from Table 5 new performance results are obtained, as shown in Table 6.

In general, all mentioned approaches use some transformation over the ECG signal, in order to obtain the attributes, set, except for that proposed by Oliveira et al. (2019), impacting on the computational cost.

Results in Table 3 show that the trapezoidal model had a better performance, mostly in PVC detection, i.e., greater sensibility and more true positives. However, it was only 0.01 % superior in relation to Normal heartbeats classification. It is also noteworthy that the use of both models improves only the prediction in the Normal class, since the triangular model degrades PVC class patterns predictions.

When attributes selection is considered, results presented in Table 4, related to trapezoidal model, show that a_7 attribute exclusion provided accuracy and sensibility increasing in 0.59 % and 1.19 %, respectively, although specificity has worsened in 0.01 %. On the other hand, a_{11} exclusion caused 1.54 %, 3.08 % and 0.01 % increasing in accuracy, sensibility and specificity, respectively. By analyzing results from Table 5, it is noted that a_7 attribute has the second greater weight, while a_{11}has the seventh. Therefore, together these results indicate that a_7 exclusion improved the performance. However, it does not imply that this attribute has less informative value than the others. Because when $w_7 = 0$, the disregarded weight is proportionally distributed to the other attributes, in this case $w_q = 0.09\ \forall_q \neq 7$, these values are greater than the ones assigned to the attributes. Thus, more weight is assigned to attributes that would have smaller weights if it was considered the intersection between membership functions (last column in Table 5), resulting in an increase in performance. The same reasoning applies to a_{11}.

In Table 6, it is noted that performance increases of 3.21 % in accuracy and 6.62 % in sensitivity and decreases 0.2 % in specificity, for trapezoidal model, when compared to results considering equal weights. These results indicate that mitigating the attributes membership functions that generate greater ambiguity leads to less false negatives, but then increases false positives, to a lesser extent. This finding evidences that the proposed approach allows the expert to change the prediction system, so that it returns less the more false-detections. Generally, systems that produce fewer false positives are preferred, since in positive diagnosis presence, auxiliary exams may be required for confirmation.

In Table 7 the obtained results with the proposed method, using the trapezoidal model, since it presented better results, are compared with the ones from state-of-the-art methods.

Table 7: Comparing results among different approaches.

Approach	A_{cc}	S_e	S_p
Proposed method, Trapezoidal model	99.07%	98.36%	99.79%
Yeh et al. (2010)	93.57%	-	94.86%
Shyu et al. (2004)	97.04%	96.67%	99.02%
Gharieb et al. (2016)	100.00%	-	-

Although the approach presented by Yeh et al. (2010) demonstrated good results using 30 ECG records, our proposal with 44 records surpassed it in measures of accuracy and specificity.

In the results presented by Shyu et al. (2004) and Gharieb et al. (2016) PVC arrhythmia was also considered. Shyu et al. (2004) was worse than the proposed method in all measures and Gharieb et al (2016) was better than the proposed method in 0.93% of accuracy. However, recognition was performed over 7 and 6 recordings, respectively, and 80 heartbeats were analyzed in the second work. In addition, both approaches used the wavelet transform, fuzzy neural networks, and fuzzy clustering.

Generally speaking, in relation to the recognition system, the proposed approach is simpler than the other methods, since most of its operations are sums and products.

It can be emphasized that one advantage of the proposed method is the possibility of selection/attenuation of attributes at recognition time and its simple implementation. Therefore, an expert may verify how each attribute influences in the PVC detection, and this influence is related to morphological issues, physiological or even due to some medicine ingestion.

CONCLUSIONS

Results presented and discussed in this paper show that the fuzzy maximum-grade approaching based on geometrical characteristics extracted from QRS complexes is a suitable tool to enhance PVC-like arrhythmias diagnosis, having performed superior to the predecessor methods when a large dataset is considered.

Besides good performance, other advantage in the proposed approach is the possibility to select the attributes that will compose the prediction model, such mechanism can be used by the specialist in order to verify the contribution of a specific attribute to the diagnosis. However, the proposed approach has a drawback related to the database imbalance, compromising performance in preliminary experiments. Therefore, in future works it is intended to expand the set of attributes, obtaining more membership functions in order to better model PVC pattern variabilities, in addition to apply the proposed approach in other databases, especially those unbalanced.

CONFLICT OF INTEREST DECLARATION

The authors declare no potential conflict of interest in connection with the research, authorship, and/or publication of this article.

ACKNOWLEDGEMENTS

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance code 001.

REFERENCES

Barros, L. C., & Bassanezi, R. C. (2006). Topics of fuzzy logic and biomathematics. *Campinas: IMECC-UNICAMP*.

Garcia, T. B., & Garcia, D. J. (2019). *Arrhythmia Recognition: The Art of Interpretation: The Art of Interpretation*. Jones & Bartlett Learning.

Gharieb, R. R., Massoud, M., Nady, S., & Moness, M. (2016, December). Fuzzy c-means in features space of teager-kaiser energy of continuous wavelet coefficients for detection of PVC beats in ECG. In*2016 8th Cairo International Biomedical Engineering Conference (CIBEC)*(pp. 72-75). IEEE.

Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circulation*, *101*(23), e215-e220.

Guyton, A. C., & Hall, J. E. (2006). Treaty of medical physiology. Elsevier.

Latchamsetty, R., & Bogun, F. (2015). Premature ventricular complexes and premature ventricular complex induced cardiomyopathy. *Current Problems in Cardiology*, *40*(9), 379-422.

Oliveira, B. R., de Abreu, C. C. E., Duarte, M. A. Q., & Vieira Filho, J. (2019). Geometrical features for premature ventricular contraction recognition with analytic hierarchy process based machine learning algorithms selection. *Computer methods and programs in biomedicine*, *169*, 59-69.

Ross, T. J. (2017). *Fuzzy logic with engineering applications*. John Wiley & Sons.

Santos, J. D., Meira, K. C., Camacho, A. R., Salvador, P. T. C. D. O., Guimarães, R. M., Pierin, Â. M. G., & Freire, F. H. M. D. A. (2018). Mortality due to acute myocardial infarction in Brazil and its geographical regions: analyzing the effect of age-period-cohort. *Ciência & Saúde Coletiva*, *23*, 1621-1634.

Shyu, L. Y., Wu, Y. H., & Hu, W. (2004). Using wavelet transform and fuzzy neural network for VPC detection from the Holter ECG.*IEEE Transactions on Biomedical Engineering*,*51*(7), 1269-1273.

Yeh, Y. C. (2012). An Analysis of ECG for Determining Heartbeat Case by Using the Principal Component Analysis and Fuzzy Logic. *International Journal of Fuzzy Systems*, *14* (2).

Zadeh, L. A. (2015). Fuzzy logic–a personal perspective, Fussy Sets and Systems, *281*, 4-20.

To cite this paper:

Neves, E. P., Oliveira, R. B., Duarte, M.A.Q. &, Vieira Filho, J. (2023). Premature Ventricular Contraction Recognition using a Fuzzy Maximum Approaching Degree. *Multi-Science Journal*, *6*(1): 7-14. DOI: https://doi.org/10.33837/msj.v6i1.1591