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An arrhythmia classification system based on the RR-interval signal

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Arrhythmia classification; RR-interval signal; Knowledge-based system; Deterministic automaton

Summary

Objective: This paper proposes a knowledge-based method for arrhythmic beat classification and arrhythmic episode detection and classification using only the RR-interval signal extracted from ECG recordings.
Methodology: A three RR-interval sliding window is used in arrhythmic beat classification algorithm. Classification is performed for four categories of beats: normal, premature ventricular contractions, ventricular flutter/fibrillation and 2° heart block. The beat classification is used as input of a knowledge-based deterministic automaton to achieve arrhythmic episode detection and classification. Six rhythm types are classified: ventricular bigeminy, ventricular trigeminy, ventricular couplet, ventricular tachycardia, ventricular flutter/fibrillation and 2° heart block.
Results: The method is evaluated by using the MIT-BIH arrhythmia database. The achieved scores indicate high performance: 98% accuracy for arrhythmic beat classification and 94% accuracy for arrhythmic episode detection and classification.
Conclusion: The proposed method is advantageous because it uses only the RR-interval signal for arrhythmia beat and episode classification and the results compare well with more complex methods.

1. Introduction

Arrhythmia can be defined as either an irregular single heartbeat (arrhythmic beat), or as an irregular group of heartbeats (arrhythmic episode). Arrhythmias can affect the heart rate causing irregular rhythms, such as slow or fast heartbeat [1]. Arrhythmias can take place in a healthy heart and be of minimal consequence (e.g. respiratory sinus arrhythmia which is a natural periodic variation in heart rate, corresponding to respiratory activity), but they may also indicate a serious problem that may lead to stroke or sudden cardiac death [2,3]. Therefore, automatic arrhythmia detection and classification is critical in clinical cardiology, especially when performed in real time. This is achieved through the analysis of the electrocardiogram (ECG) and its extracted features.

Several researchers have addressed the problem of automatic detection and classification of cardiac rhythms [4–23]. Some techniques are based on the detection of a single arrhythmia type and

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its discrimination from normal sinus rhythm, or the discrimination between two different types of arrhythmia [4—11]. Techniques that belong to this category include time-domain analysis [4], sequential hypothesis testing algorithm [5], threshold-crossing intervals [6], artificial neural networks [7,8], time-frequency analysis [9], fuzzy adaptive resonance theory mapping [10] and the sequential detection algorithm [11]. Another class of proposed methods for arrhythmia detection and classification is based on the detection of different heart rhythms and their classification in two or three arrhythmia types and the normal sinus rhythm [12—18]. Techniques used for this purpose include multiway sequential hypothesis testing [12], wavelet analysis [13], artificial neural networks [14], complexity measure [15], multifractal analysis [16], wavelet analysis combined with radial basis function neural networks [17] and non-linear dynamical modelling [18]. It is noticeable that all methods address the detection of only a few types of arrhythmia (atrial tachycardia, ventricular tachycardia, atrial fibrillation and ventricular fibrillation).

Another field of interest is the ECG beat-by-beat classification, where each beat is classified into several different rhythm types [19—23]. Methods of this kind classify more arrhythmic beat types. However, they focus on single beat classification and not arrhythmic episode detection. The techniques for beat classification are based on artificial neural networks [19], fuzzy neural networks [20], ''mixture of experts approach'' [21], hermite functions combined with self-organizing maps [22] and time-frequency analysis combined with knowledge-based systems [23].

Most of the studies, either for single arrhythmia type detection, detection of different heart rhythms or beat-by-beat classification, are based on the analysis of the ECG signal. In these methods ECG features are extracted and used for the detection and/or classification of arrhythmias. However, this is not always feasible due to: (a) the presence of noise making feature extraction difficult and in some cases impossible (e.g. P wave), and (b) the process being time consuming and ineffective for real time analysis. An alternative would be to use only the RR-interval signal. In this case, it is expected that certain types of arrhythmias can be detected and classified.

This work proposes a method for the classification of the cardiac rhythms, based only on the RR-interval signal. The method consists of four steps: (a) preprocessing of the ECG recording, (b) QRS detection and computation of the RR-interval signal, (c) arrhythmic beat classification and (d) arrhythmic episode detection and classification. In the preprocessing step the ECG was filtered for baseline wandering correction (step a). Then, QRS detection is performed and the RR-interval signal is constructed (step b). In the arrhythmic beat classification step beat-by-beat classification is applied using rules that utilize the duration of the examined cardiac cycle and the duration of the previous and next cycles, in a three RR-interval window (step c). Four different categories of cardiac rhythms are recognized (normal sinus beat, premature ventricular contraction, ventricular flutter/fibrillation, 2° heart block). The results of the beat classification step are used to detect and classify arrhythmic episodes (step d). The algorithm for the arrhythmic episode detection and classification is based on a deterministic automaton, utilising expert's knowledge. Six cardiac rhythms are detected and classified (ventricular bigeminy, ventricular trigeminy, ventricular couplet, ventricular tachycardia, ventricular flutter/fibrillation, 2° heart block).

2. Material and methods

The proposed knowledge-based system consists of four steps: preprocessing, QRS detection and RR-interval signal computation, arrhythmic beat classification and arrhythmic episode detection and classification. Fig. 1 shows the procedure followed.

2.1. Preprocessing

ECG signals can be contaminated with several types of noise, such as power line interference (A/C), electromyographic noise (EMG) and baseline wandering (BW), which can affect the QRS detection algorithm. The baseline wandering is modelled with low order polynomials [24], which are then subtracted from the recorded signal.

2.2. QRS detection and RR-interval signal computation

The only feature extracted from the ECG is the R wave. Initially, a point in the QRS complex is detected (QRS point), using the algorithm proposed by Hamilton and Tompkins [25,26]. Then, the main wave of the QRS complex (R wave) is identified in the window [QRS − 280 ms, QRS + 120 ms] by locating the point where the signal has its maximum absolute value. The RR-interval signal is constructed by measuring the time interval between successive R waves.

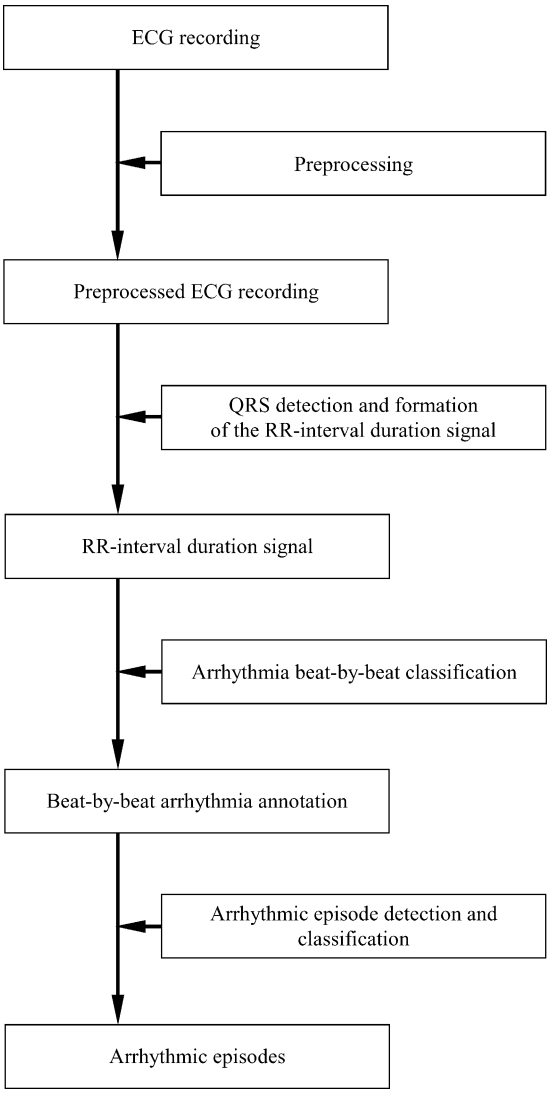


Figure 1 Schematic of the procedure followed by the presented method.

2.3. Arrhythmic beat classification

Arrhythmia beat-by-beat classification is performed on the RR-interval signal using a set of rules. The rules are provided by medical experts and are based on clinical procedures for detecting arrhythmic events from the RR-intervals. The rules are used for the classification of the middle RR-interval of a 3 RR-interval sliding window. The classification concerns the second beat of the middle RR-interval. The beats are classified in four categories: (1) normal sinus beats (N) and three arrhythmic ones: (2) premature ventricular contractions (PVC), (3) ventricular flutter/fibrillation (VF) and (4) 2° heart block (BII). The beat classification categories and their corresponding annotations from the MIT-BIH arrhythmia database for each category are given in Table 1. It is assumed that a beat not belonging to one of the above arrhythmic categories is classified as normal.

The algorithm starts with window i consisting of the $RR1_i$, $RR2_i$ and $RR3_i$ intervals. The middle RR-interval ($RR2_i$) is considered a priori normal and is classified in category 1. The three rules used in the present approach are described in detail below:

Rule 1: Ventricular flutter/fibrillation (classifies the RR-intervals from ventricular flutter/fibrillation episodes—category 3). The rule is based on the classification of the total VF episode and not the classification of a single beat. Therefore, it is triggered if $RR2_i$ is much smaller than $RR1_i$ ($RR1_i > 1.8*RR2_i$) and the duration of $RR2_i$ is less than 0.6 s. In this case, $RR2_i$ is considered as the start of a VF episode and the windows (i.e. windows $i+1$, $i+2$, ..., $i+n$) are examined for two conditions:
Condition 1: The duration of all intervals in a window following i is less than 0.7 s ($RR1_k < 0.7$ and $RR2_k < 0.7$ and $RR3_k < 0.7$). This condition ensures that all RR-intervals in the VF episode have high frequency.
Condition 2: The total window duration is less than 1.7 s ($RR1_k + RR2_k + RR3_k < 1.7$). This condition ensures that if one of the RR-intervals does not have duration less than 0.7 s, but the total window duration is small, then it is considered as a continuing VF episode and not as two separate episodes.If one of these conditions is true then the middle RR-interval of the window is classified in category 3. When a window is reached, where none of the two conditions are satisfied, the VF episode has ended. If the number of sequential RR-intervals (n) classified in category 3 is less than 4, the algorithm returns to window i and continues with the next rule. This is because a threshold of four consecutive classified RR-intervals has been used to define a VF episode.

Rule 2: Premature ventricular contractions (classifies the PVCs—category 2). If one of the following conditions is true then the $RR2_i$ interval is classified as PVC.
Condition 1: If $RR1_i > 1.15*RR2_i$ and $RR3_i > 1.15*RR2_i$, then isolated PVCs are classified.
Condition 2: If $|RR1_i - RR2_i|$ is less than 0.3 s and both $RR1_i$ and $RR2_i$ intervals are less than 0.8 s and 1.2 times the average length of the intervals $RR1_i$ and $RR2_i$ is less

Table 1 Beat annotation in the MIT-BIH arrhythmia database

MIT-BIH annotation symbol	Type of arrhythmia	Classification
N	Normal beat	Normal (N) (category 1)
P	Paced beat	
f	Fusion of paced and normal beat	
P	Non-conducted P-wave (blocked APB)	
L	Left bundle branch block beat	
R	Right bundle branch block beat	
Q	Unclassifiable beat (beat annotations)	
V	Premature ventricular contraction (beat annotation)	Premature ventricular contraction (PVC) (category 2)
[	Start of ventricular flutter/fibrillation	Ventricular flutter/fibrillation (VF) (category 3)
!	Ventricular flutter wave	
]	End of ventricular flutter/fibrillation (beat annotations)	
(BII	2° heart block (rhythm annotation)	2° heart block (BII) (category 4)

than $RR3_i$ then PVC couplets are classified. This is because the first two intervals of the window *i* must be short and of approximately the same length and the last interval of the window *i* must be longer than the other two. Condition 2 is satisfied when $RR3_i > RR2_i \approx RR1_i$.

Condition 3: If $|RR2_i - RR3_i|$ is less than 0.3 s and both $RR2_i$ and $RR3_i$ intervals are less than 0.8 s and the 1.2*average length of the intervals $RR2_i$ and $RR3_i$ is less than $RR1_i$, then PVC couplets are classified. This is because the last two intervals of the window *i* must be short and of approximately the same length and the first interval of the window *i* must be longer than the other two. Condition 3 is satisfied when $RR1_i > RR2_i \approx RR3_i$.

Rule 3: 2° heart block (classifies the RR-intervals from 2° heart block episodes—category 4). If both conditions 1 and 2 are true then the $RR2_i$ interval is classified as BII.

Condition 1: The duration of the $RR2_i$ interval is more than 2.2 s and less than 3.0 s ($2.2 < RR2_i < 3.0$).

Condition 2: $|RR1_i - RR2_i|$ is less than 0.2 s or $|RR2_i - RR3_i|$ is less than 0.2 s. Condition 2 insures that an RR-interval, which satisfies condition 1, is not isolated and is almost equal to the previous or the next RR-interval ($RR2_i \approx RR1_i$ or $RR2_i \approx RR3_i$).

The algorithm continues with the next window. The rules are applied sequentially and if a beat is classified to a category by one rule then this classification cannot be changed by a following rule. The beat classification procedure is summarized in Fig. 2, while a diagram of the algorithm is shown in Fig. 3.

2.4. Arrhythmic episode detection and classification

Arrhythmic episode detection and classification is performed using the deterministic automaton shown in Fig. 4. The results of the step c (beat classification) are used as input of the automaton. Six types of arrhythmic episodes can be detected and classified: (i) ventricular bigeminy, (ii) ventricular trigeminy, (iii) ventricular couplets, (iv) ventricular tachycardia, (v) ventricular flutter/fibrillation and (vi) 2° heart block. The rhythm classification categories and the corresponding rhythm annotations from the MIT-BIH arrhythmia database are given in Table 2. It is assumed again that the rhythm is normal unless an episode belonging to one of the above arrhythmia types is detected

Table 2 Rhythm annotation in the MIT-BIH arrhythmia database

MIT-BIH annotation symbol	Type of arrhythmia
(N	Normal sinus rhythm
(B	Ventricular bigeminy
(T	Ventricular trigeminy
	Ventricular couplets
(VT	Ventricular tachycardia
(VFL	Ventricular flutter/fibrillation
(BII	2° heart block

1. Initialization

$RR2_i$ from window i is classified as normal (category 1)

2. Rule 1 – Ventricular flutter/fibrillation beat classification

a. If $RR2_i < 0.6$ sec and $1.8*RR2_i < RR1_i$ then

i. $RR2_i$ is classified in category 3.

ii. The $RR2_k$ of all windows k = i+1, i+2, … i+n with ($RR1_k < 0.7$ and $RR2_k < 0.7$ and $RR3_k < 0.7$) or ($RR1_k + RR2_k + RR3_k < 1.7$) are classified in category 3.

b. If the number of intervals that are sequentially classified in category 3 is less than 4 then they all are classified in category 1 and the algorithm returns to window i.

3. Rule 2 – Premature ventricular contractions

If $((1.15*RR2_i < RR1_i)$ and $(1.15*RR2_i < RR3_i))$ or

$((|RR1_i - RR2_i|<0.3)$ and $((RR1_i<0.8)$ and $(RR2_i<0.8))$ and

$(RR3_i>1.2*\text{mean}(RR1_i, RR2_i))$ or

$((|RR2_i - RR3_i|<0.3)$ and $((RR2_i<0.8)$ and $(RR3_i<0.8))$ and

$(RR1_i>1.2*\text{mean}(RR2_i, RR3_i))$

then $RR2_i$ is classified in category 2.

4. Rule 3 – 2° heart block beats

If $(2.2 < RR2_i < 3.0)$ and

$(|RR1_i - RR2_i| < 0.2$ or $|RR2_i - RR3_i| < 0.2)$ then

then $RR2_i$ is classified in category 4

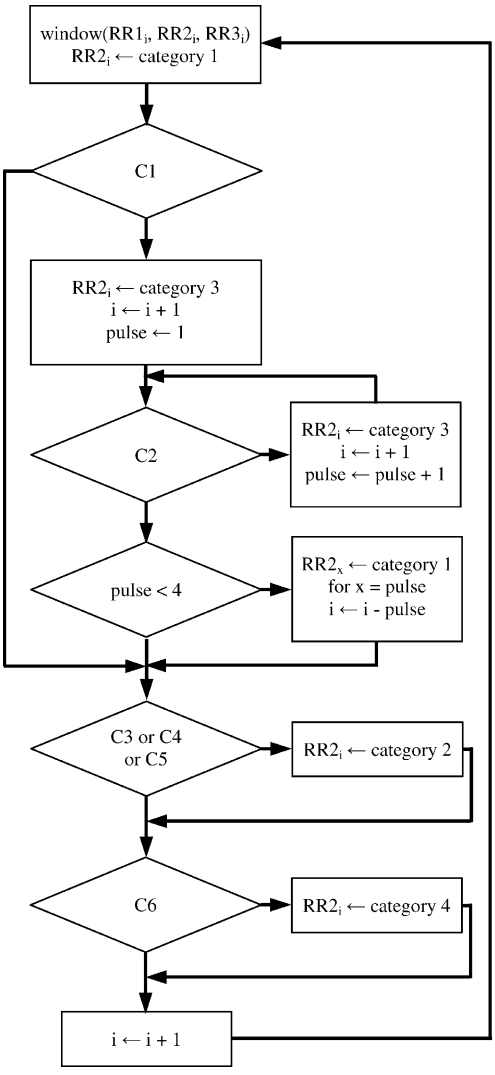
5. Update Window

i = i + 1

Figure 2 Beat classification algorithm.

and classified. All episodes start with a specified type of classified beat (PVC for ventricular bigeminy, trigeminy, couplets and tachycardia, VF for ventricular fibrillation and BII for 2° heart block) and end with any type of classified beat (e.g. a ventricular flutter/fibrillation episode is considered as a sequence of beats: VF-VF-...-VF-XX, where XX is any type of beat other than VF). Therefore, in stage 1 of the automaton, the detection starts when one of those beat types occurs. A PVC classified beat indicates a possible ventricular bigeminy, trigeminy, couplets or tachycardia (stage 2), a VF classified beat indicates a possible ventricular fibrillation episode (stage 7) and a BII classified beat indicates a possible 2° heart block episode (stage 8). If any other type of classified beat occurs then the algorithm remains at its current stage (stage 1).

When a PVC classified beat appears the automaton moves to stage 2 for possible ventricular bigeminy, trigeminy, couplets or tachycardia episode detection. Stages 3—6 deal with the discrimination between these episode types. A PVC-N-PVC-N-...-N-PVC sequence is considered as ventricular bigeminy and a PVC-N-N-PVC-N-N-...-PVC-N-N-PVC sequence as ventricular trigeminy. Ventricular couplets are determined as two consecutive PVC classified beats followed by a non-PVC classified beat, while ventricular tachycardia is deter-



C1: $(RR2_i < 0.6)$ and $(1.8*RR2_i < RR1_i)$

C2: $((RR1_k < 0.7)$ and $(RR2_k < 0.7)$ and $(RR3_k < 0.7))$

or $(RR1_k + RR2_k + RR3_k < 1.7)$

C3: $((1.15*RR2_i < RR1_i)$ and $(1.15*RR2_i < RR3_i))$

C4: $((|RR1_i - RR2_i| < 0.3)$ and

$((RR1_i < 0.8)$ or $(RR2_i < 0.8))$ and

$(RR3_i > 1.2*\text{mean}(RR1_i, RR2_i))$

C5: $((|RR2_i - RR3_i| < 0.3)$ and

$((RR2_i < 0.8)$ or $(RR3_i < 0.8))$ and

$(RR1_i > 1.2*\text{mean}(RR2_i, RR3_i))$

C6: $(2.2 < RR2_i < 3.0)$ and

$(|RR1_i - RR2_i| < 0.2$ or $|RR2_i - RR3_i| < 0.2)$

Figure 3 Diagram of the beat classification algorithm.

mined as three or more consecutive PVC classified beats. Due to the similarity at the beginning of the ventricular bigeminy and trigeminy episodes (PVC-N beats) flags are used for insuring that only one episode is detected. When the automaton reaches stage 6, a ventricular tachycardia episode is detected since three consecutive PVC beats have already been identified. The automaton remains at stage 6 for as long as consecutive PVC beats are recognized. When another type of beat occurs the automaton proceeds to the appropriate stage (stage 7 for VF beat, stage 8 for BII beat and stage 1 otherwise).

In the case of a VF classified beat the automaton moves to a new stage (stage 7) and remains there for as long as VF classified beats are recognized. When a different classified beat occurs, the algorithm completes the ventricular fibrillation episode followed by a transition to the appropriate stage (stage 2 for a PVC beat, stage 8 for a BII beat and stage 1 otherwise). The same happens when a BII classified beat occurs; the automaton moves to stage 8 and stays there for as long as BII classified beats are recognized. When a different beat type is found, the episode is completed and the automaton proceeds to the appropriate stage (stage 2 for PVC beat, stage 7 for VF beat and stage 1 otherwise). A detailed description of the automaton is given below:

Stage 1. Initial stage of the automaton. If a PVC, VF or BII classified beat occurs then the automaton proceeds to the appropriate stage (stages 2, 7 and 8); otherwise it remains in stage 1.

Stage 2. Possible ventricular bigeminy, trigeminy, couplet or tachycardia. If the next beat is N then the automaton proceeds to stage 3. If the next beat is a PVC and a bigeminy or trigeminy episode has already started,

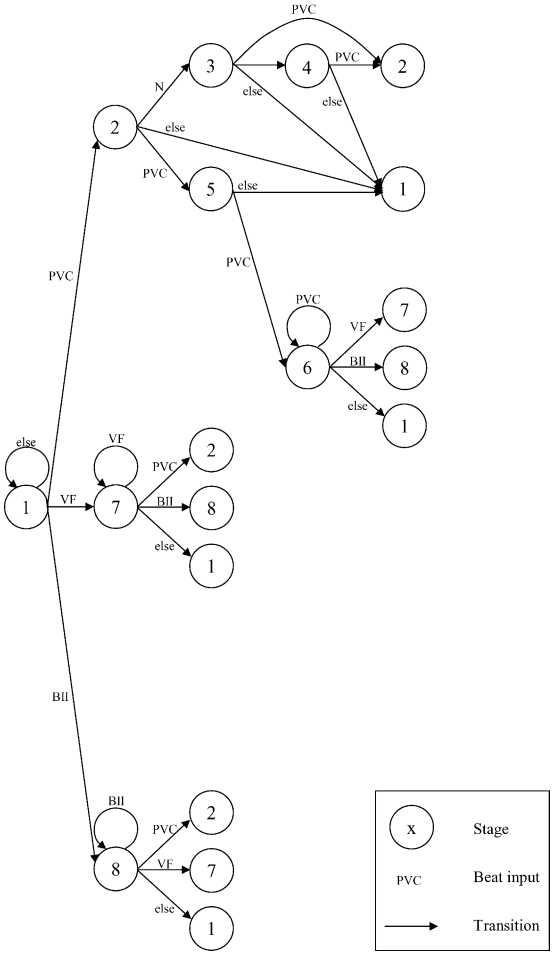


Figure 4 Deterministic automaton used for arrhythmic episode detection and classification.

the beat is considered as the end of the episode and the automaton proceeds to stage 5. If the next beat is neither N nor a PVC and a bigeminy or trigeminy episode has already started, the beat is considered as the end of the episode and the automaton returns to stage 1.

Stage 3. Possible ventricular bigeminy. If the next beat is a PVC and a trigeminy episode has already started, the beat is considered as the end of the episode and the automaton returns to stage 2. If the next beat is N and a bigeminy episode has already started, the beat is considered as the end of the episode and the automaton returns to stage 1, otherwise it proceeds to stage 4 (this is the only transition in the automaton that requires not only the beat type but also a flag value). If the next beat is neither N nor a PVC and a bigeminy or a trigeminy episode has already started, the beat is considered as the end of the episode and the automaton returns to stage 1.

Stage 4. Possible ventricular trigeminy. If the next beat is a PVC then the automaton returns to stage 2; otherwise, if a trigeminy episode has already started, the beat is considered as the end of the episode and the automaton returns to stage 1.

Stage 5. Ventricular couplet or tachycardia. The beat sequence is PVC-PVC so if the next beat is a PVC then the automaton proceeds to stage 6 for ventricular tachycardia (three consecutive PVC beats), otherwise it recognizes a ventricular couplet and returns to stage 1.

Stage 6. Ventricular tachycardia. Three consecutive PVC classified beats have been recognized, so a ventricular tachycardia episode is detected. However, the number of beats in the episode must be determined. Therefore, as long as PVC beats are recognized the automaton remains at stage 8. The first non-PVC classified beat will determine the end of the episode and the stage to which the automaton will proceed (stage 7 if classified as a VF, stage 8 if classified as a BII and stage 1 if classified otherwise).

Stage 7. Ventricular flutter/fibrillation. A VF classified beat occurred and is considered as the start of a ventricular flutter/fibrillation episode. The number of beats in the episode must be determined and as long as VF beats follow the automaton remains at stage 7. The first non-VF classified beat will determine the end of the episode and the stage to which the automaton will proceed (stage 2 if classified as a PVC, stage 8 if classified as a BII and stage 1 if classified otherwise).

Stage 8. 2° heart block. A BII classified beat occurred and is considered as the start of a heart block episode. The number of beats in the episode must be determined, therefore as long as BII beats are recognized the automaton remains at stage 8. The first non-BII classified beat will determine the end of the episode and the stage to which the automaton will proceed (stage 2 if classified as a PVC, stage 7 if classified as a VF and stage 1 if classified otherwise).

An arrhythmic episode is identified only when a minimum number of beats has been reached.

For ventricular bigeminy this number is 5 beats (PVC-N-PVC-N-PVC), for ventricular trigeminy 7 beats (PVC-N-N-PVC-N-N-PVC), for ventricular tachycardia 3 beats (PVC-PVC-PVC), for ventricular flutter/fibrillation 3 beats and for 2° heart block 2 beats. If more than one rhythm type occurs the one that started first prevails (e.g. in the PVC-PVC-N-PVC-N-PVC sequence a ventricular couplet is detected and not a ventricular bigeminy episode or both a couplet and a bigeminy). If a ventricular couplet takes place while another rhythm occurs (atrial flutter, atrial fibrillation) it is ignored.

3. Results

The MIT-BIH arrhythmia database was used for the evaluation of the presented method. Both beat annotation and rhythm annotation were used as follows:

1. *If*: the beat does not belong to an atrial fibrillation episode (AFIB), an atrial flutter episode (AFL) or a 2° heart block episode (BII) *then*: it is annotated using the MIT-BIH arrhythmia database beat annotation.
2. *Else*: it is annotated as an AF if it belongs to an atrial flutter or fibrillation episode and as a BII if it belongs to a 2° heart block episode (BII).

This was based on the instructions of an expert cardiologist, in order to focus on both the arrhythmic beats and the arrhythmic episodes.

Two datasets are used for arrhythmic beat classification (Table 3). The first dataset (D1) was created using all beats from all records of the MIT-BIH arrhythmia database [27,28], excluding: (a) the beats that are cut off due to the use of a window in the method (i.e. 2 beats at the start and 2 beats at the end of each record due to the window length) and (b) the beats that do not belong to the types of arrhythmia that can be classified by the method (i.e. all beats annotated as A, a, J, S, F, e, j and E and all beats included in atrial flutter or atrial fibrillation episodes are excluded). The second dataset (D2) was created using all beats from all records of MIT-BIH arrhythmia database excluding 2 beats at the start and 2 beats at the end of each record, which were cut off for the same reasons as in D1.

Table 3 Evaluation datasets for the beat classification step

Category	Number of beats in dataset D1	Number of beats in dataset D2
Normal (N) (category 1)	86262	102793
Premature ventricular contraction (PVC) (category 2)	6183	6183
Ventricular flutter/ fibrillation (VF) (category 3)	484	484
2° heart block (BII) (category 4)	420	420
Total	93349	109880

D1 is a controlled dataset as it contains only the types of beats and cardiac rhythms that can be classified by the presented method. Thus, D1 is used to validate the method in a controlled environment. The D2 dataset is an expanded version of D1 and represents a more realistic environment since it contains beats and cardiac rhythms that cannot be classified by the method.

The efficiency measures used are: sensitivity, specificity, positive predictive value and accuracy. The obtained results are given in Table 4 for dataset D1 and in Table 5 for dataset D2. For each dataset results are also presented separately for the 100 series records and 200 series records of the MIT-BIH arrhythmia database [27] included in D1 and D2 respectively. The respective results for dataset D1 for sensitivity, specificity and positive predictive value are 98.98, 88.99 and 99.09% for N classified beats; 87.27, 99.04 and 86.54% for PVC classified beats; 98.76, 99.98 and 97.15% for VF classified beats and 99.05, 99.95 and 89.85% for BII classified beats. The accuracy for dataset D1 is 98.20%. Sensitivity and positive predictive value obtained for the 100 series and the 200 series records of the D1 dataset for N classified beats are almost identical, but they differ in PVC classified beats: in the 100 series records 94.94% sensitivity and 96.15% positive predictive value is obtained, while in the 200 series records those are much smaller (85.14% sensitivity and 83.95% positive predictive value). Specificity for the 100 series and the 200 series records of the D1 dataset for PVC classified beats is almost identical, but it differs in N classified beats (94.94% for 100 series and 87.60% for 200 series). In dataset D2 the accuracy is 94.26%. A similar decrease in the obtained sensitivity, specificity and positive predictive value between the 100 and 200 series records of the D2 dataset is observed.

In the 100 series records of dataset D1 only 51 normal beats are misclassified as PVC (0.11%) and 68 PVCs are misclassified as normal beats (5.06%), while there are no misclassifications of normal or PVC beats to any other category. In the 200 series records of dataset D1 misclassification rates are higher, especially for PVCs: 784 normal beats are misclassified as PVC (1.94%) and 47 as BII beats

Table 4 Results for beat classification algorithm using dataset D1

	Data base annotation				Positive predictive value (%)
	N	PVC	VF	BII	
100 series (D1 dataset)					
N	45969	68	0	0	99.85
PVC	51	1275	0	0	96.15
VF	0	0	0	0	
BII	0	0	0	0	
Sensitivity (%)	99.89	94.94			99.75 (accuracy)
Specificity (%)	94.94	99.89			
200 series (D1 dataset)					
N	39410	706	3	3	98.23
PVC	784	4121	3	1	83.95
VF	1	13	478	0	97.15
BII	47	0	0	416	89.85
Sensitivity (%)	97.93	85.14	98.76	99.05	96.61 (accuracy)
Specificity (%)	87.60	98.08	99.97	99.90	
D1 dataset (total)					
N	85379	706	3	3	99.09
PVC	835	4121	3	1	86.54
VF	1	13	478	0	97.15
BII	47	0	0	416	89.85
Sensitivity (%)	98.98	87.27	98.76	99.05	98.20 (accuracy)
Specificity (%)	88.99	99.04	99.98	99.95	

Table 5 Results for beat classification algorithm using dataset D2

	Data base annotation				Positive predictive value (%)
	N	PVC	VF	BII	
100 series (D2 dataset)					
N	46050	68	0	0	99.85
PVC	208	1275	0	0	85.97
VF	0	0	0	0	
BII	0	0	0	0	
Sensitivity (%)	99.55	94.94			99.42 (accuracy)
Specificity (%)	94.94	99.55			
200 Series (D2 dataset)					
N	51228	706	3	3	98.23
PVC	5209	4121	3	1	83.95
VF	49	13	478	0	97.15
BII	49	0	0	416	89.85
Sensitivity (%)	90.61	85.14	98.76	99.05	90.31 (accuracy)
Specificity (%)	87.60	90.92	99.90	99.92	
D2 dataset (total)					
N	97278	774	3	3	99.09
PVC	5417	5396	3	1	86.54
VF	49	13	478	0	97.15
BII	49	0	0	416	89.85
Sensitivity (%)	98.98	87.27	98.76	99.05	94.26 (accuracy)
Specificity (%)	88.99	94.77	99.94	99.96	

Table 6 Results for arrhythmia episode detection and classification

	MIT-BIH arrhythmia database annotation			D1 dataset			D2 dataset		
	100 series	200 series	Total	100 series	200 series	Total	100 series	200 series	Total
Ventricular couplets									
Reported	98	715	813	98	652	750	98	715	813
Detected	98	715	813	98	633	731	95	694	789
Sensitivity (%)	100	100	100	100	97.09	97.47	95.00	97.06	96.91
Specificity (%)	100	99.76	99.80	100	62.57	67.63	96.88	46.98	50.03
Positive predictive value (%)	100	99.86	99.88	100	74.82	77.44	96.94	47.05	50.16
Ventricular bigeminy									
Reported	55	166	221	55	166	221	55	166	221
Detected	55	166	221	55	146	201	55	147	202
Sensitivity (%)	100	100	100	100	87.95	90.95	100	88.55	91.40
Specificity (%)	96.30	93.22	93.60	96.21	96.11	96.12	94.33	88.43	88.81
Positive predictive value (%)	91.67	71.86	75.95	91.67	78.07	81.38	87.30	38.58	45.50
Ventricular trigeminy									
Reported	20	63	83	20	63	83	20	63	83
Detected	20	63	83	20	41	61	20	39	59
Sensitivity (%)	100	100	100	100	65.08	73.49	100	61.90	71.08
Specificity (%)	95.29	96.87	96.67	95.21	99.83	99.25	95.45	98.45	98.22
Positive predictive value (%)	71.43	65.63	66.94	71.43	95.35	85.92	71.43	54.17	59.00
Ventricular tachycardia									
Reported	1	70	71	1	70	71	1	70	71
Detected	1	70	71	1	57	58	1	45	46
Sensitivity (%)	100	100	100	100	81.43	81.69	100	60.81	71.08
Specificity (%)	98.41	100	99.76	100	99.91	99.93	99.49	95.08	95.45
Positive predictive value (%)	25.00	100	95.95	1	98.28	98.31	50.00	30.20	30.46
Ventricular flutter/fibrillation									
Reported	0	6	6	0	6	6	0	6	6
Detected	0	6	6	0	6	6	0	6	6
Sensitivity (%)		100	100		100	97.47		100	100
Specificity (%)		100	100		99.92	99.93		99.73	99.75
Positive predictive value (%)		100	100		85.71	85.71		50.00	50.00
2° heart block									
Reported	0	5	5	0	5	5	0	5	5
Detected	0	5	5	0	5	5	0	5	5
Sensitivity (%)		100	100		100	100	100	97.06	96.91
Specificity (%)		100	100		99.92	99.93		99.95	99.96
Positive predictive value (%)		100	100		83.33	83.33		83.33	83.33

(0.12%), while 706 PVCs are misclassified as normal beats (14.58%) and 13 as VF beats (0.26%). In the 100 series records of dataset D2 misclassification between normal and PVC categories is low: 208 normal beats are misclassified as PVC (0.45%) and 68 PVCs are misclassified as normal beats (5.05%). Again, there is no misclassification of normal or PVC beats to another category. In the 200 series records of dataset D2, 5209 normal beats are misclassified as PVC (9.21%), 49 as VF beats (0.09%) and 49 as BII beats (0.09%), while 706 PVCs are misclassified as normal beats (14.58%) and 13 as VF beats (0.27%).

For the arrhythmic episode detection and classification two separate evaluations were performed. Firstly, the method was evaluated using the MIT-BIH arrhythmia database beat and rhythm annotation

(as explained in the first paragraph of Section 3) instead of step c (beat classification) of the method. Secondly, the method was evaluated using the beat classification obtained from step c. The results are presented in Table 6. In the first case all episodes in both 100 and 200 series are detected (100% sensitivity for all arrhythmic episodes). Specificity was also high for all episodes (98.20% for ventricular couplet, 93.60% for ventricular bigeminy, 96.67% for ventricular trigeminy, 99.76% for ventricular tachycardia and 100% for ventricular flutter/fibrillation and 2° heart block). However, there was 1 falsely detected ventricular couplet (99.88% positive predictive value), 70 falsely detected ventricular bigeminy episodes (75.95% positive predictive value), 41 ventricular trigeminy episodes (66.94% positive predictive value) and 3 ventricular tachycardia episodes (95.95% positive predictive value). In the second case, the respective results for sensitivity, specificity and positive predictive value for dataset D1 are: 97.47, 67.63 and 77.44% for ventricular couplets; 90.95, 96.12 and 81.38% for ventricular bigeminy; 73.49, 99.25 and 85.92% for ventricular trigeminy; 81.69, 99.93 and 98.31% for ventricular tachycardia; 100, 99.93 and 85.71% for ventricular flutter/fibrillation and 100, 99.93 and 83.33% for 2° heart block. The respective results for sensitivity, specificity and positive predictive value for dataset D2 are 97.05, 50.03 and 50.16% for ventricular couplets; 91.40, 88,41 and 45.50% for ventricular bigeminy; 71.08, 98.22 and 59% for ventricular trigeminy; 61.33, 95.45 and 30.46% for ventricular tachycardia; 100, 99,75 and 50% ventricular flutter/fibrillation and 100, 99.96 and 83.33% for 2° heart block. However, 213 ventricular couplets, 46 ventricular bigeminy episodes, 10 ventricular trigeminy episodes and 1 episode of ventricular tachycardia, ventricular flutter/fibrillation and 2° heart block were falsely detected in dataset D1 and 784 ventricular couplets, 202 ventricular bigeminy episodes, 33 ventricular trigeminy episodes, 105 ventricular tachycardia episodes, 6 ventricular flutter/fibrillation episodes and 1 2° heart block episode were falsely detected in dataset D2.

4. Discussion

A knowledge-based approach to classify arrhythmic beats and to detect and classify arrhythmic episodes using the RR-interval signal, which can be easily extracted from ECG recordings, is proposed. The obtained results indicate that the method performs well (95% accuracy for arrhythmic beat classification and 94% accuracy for arrhythmic episode detection and classification). The method is limited to detecting types of arrhythmic episodes that are related to the information carried by the RR-interval signal. Thus, arrhythmias such as atrial flutter and atrial fibrillation cannot be detected. Three types of arrhythmic beats and six types of arrhythmic episodes have been classified (not including normal). All other types of beats or episodes are classified as normal. This category can be used to detect and classify other types of arrhythmic beats or episodes using the ECG recording and its features. Expert cardiologists have proposed the range of the values of the parameters used in this work. However, the specific values used have been obtained through parametric analysis.

The method is advantageous to what has been presented in the literature because: (a) it uses only the RR-interval signal, which can be extracted with high accuracy even for noisy or complicated ECG recordings (e.g. the 200 series of the MIT-BIH arrhythmia database), while the extraction of all other ECG features or any other type of ECG analysis is seriously affected by noise. Therefore, methods depending on ECG features, besides the R wave, or ECG analysis are expected to have a significant reduction in their performance when the signal is affected by noise [19—22]; (b) it is based on medical knowledge, which is usually ignored in similar systems [19,20,22]; (c) it performs in real time (processing of a 30 min ECG signal takes about 15 min on a Pentium IV, 2.0 GHz, 256 MB RAM); (d) the method is based only on the analysis of the RR-interval signal using a knowledge-based scheme. Therefore, processing time is reduced since only one feature is required compared to other methods that use more features or other types of ECG analysis [19—22]; (e) the arrhythmic episode step both detects and classifies the episodes in contrast to existing methods which classify predetermined arrhythmic ECG segments; (f) it provides classification for a relatively large number of types of arrhythmic episodes (five); (g) it is fully automated, in contrast to other methods [21,22].

The datasets used in the step c (beat classification) are relatively large (93,349 beats in D1 and 109,880 beats in D2). The obtained accuracy is 98.20% for D1 and 94.26% for D2. This is due to the nature of the D1 and D2 datasets. Dataset D1 contains beats belonging to categories that can be classified by the method (i.e. related to the information that the RR-interval signal carries). Dataset D2 contains all beats from D1 and beats belonging to categories that cannot be classified by the method (i.e. beats belonging to atrial flutter and atrial fibrillation episodes). It is expected that these ''extra'' beats will be classified as N because the

presented method does not provide with a rule to classify them into a category. However, this is not always true as several of these ''extra'' beats are misclassified into other categories, leading to lower accuracy when dataset D2 is used.

Sensitivity, specificity and positive predictive value for the three types of arrhythmic beats are also high (Tables 4 and 5). It is noted that the percentage of normal beats in the datasets is high, but this is close to reality as ECG recordings have high percentages of normal beats. A decrease in the performance of the method is observed from the 100 series records to 200 series records (99.75–96.61% in D1 and 99.42–90.31% in D2). This is due to the higher complexity of the recordings of the 200 series (presence of noise, types of arrhythmias which cannot be detected by the method, alterations in the observed arrhythmic episodes). However, the accuracy in both datasets remains high (98.20% in D1 and 94.26% in D2). Also, the misclassification rate is low in almost all examined cases.

The algorithm performs very well in step d (episode detection and classification) when the MIT-BIH arrhythmia database annotation is used as input. The sensitivity is 100% for all classes of arrhythmic episodes, but some episodes are falsely detected. This is due to: (a) some ventricular bigeminy and trigeminy episodes in the database containing two consecutive PVCs, which are perceived by the method as two episodes instead of one; (b) in three cases in the database PVC sequences are annotated as an idioventricular rhythm but classified by the algorithm as ventricular tachycardia episodes; (c) the database is not annotated for ventricular couplets—only their number per record is mentioned.

High accuracy is also achieved when the beat classification results obtained in step c (beat classification) are used as input of step d. However, the

Table 7 Summary of previous works

Authors	Method	Signal	Dataset	Accuracy (%)
Osowski and Linh [20]	Feature extraction: cumulants of the second, third and fourth order Classification: fuzzy hybrid neural network	ECG	7185 beats from MIT-BIH; 4035 training–3150 testing [N: 2250, A: 658, L: 1200, V: 1500, R: 1000, I: 472, E: 105]	96.06
Dokur and Olmez [19]	Feature extraction: discrete wavelet transform Classification: intersecting spheres network	ECG	3000 beats from MIT-BIH; N, L, R, P, p, a, E, V, F, f: 300 from each category; 1500 training–1500 testing	95.7
Hu et al. [21]	Feature extraction: PCA in 29 points from QRS, instantaneous and average RR-interval, QRS complex width Classification: mixture of experts (SOM, LVQ)	ECG	25 min from each record in MIT-BIH 200 series excluding records 212, 217, 220, 222 and 232 [N: 43897, v: 5363]	95.52
Langerholm et al. [22]	Feature extraction: hermite functions, RR-interval Clustering: self-organizing maps	ECG	109963 beats from MIT-BIH, [N: 75053, L: 8074, R: 7259, A: 2544, a: 150, J: 83, S: 2, V: 7129, F: 803, b: 472, e: 16, j: 229, E: 106, P: 7028, f: 982, Q: 33]	98.49
Tsipouras et al. [23]	Feature extraction: RR-interval Classification: knowledge-based system	RR-interval signal	30000 beats from MIT-BIH [N, P, f, P, Q, L, R: 25188, V, F: 2950, A, a, J, S: 1213, e, j, n, E: 265, [,!,]: 384]	95.85
This work	Feature extraction: RR-interval	RR-interval signal	93349 beats from MIT-BIH [N, P, f, P, L, R, Q: 86262, V: 6183, [,!,]: 484, BII: 420]	98.20
	Classification: knowledge-based system		109880 beats from MIT-BIH [N, P, f, P, L, R, Q: 102793, V: 6183, [,!,]: 484, BII: 420]	94.26

number of falsely detected and non-detected episodes increases due to beat misclassifications in the step c (beat classification). Furthermore, long ventricular bigeminy and trigeminy episodes were detected as two or more consecutive episodes, due to misclassifications of PVC beats. Non-detected ventricular tachycardia episodes caused one or more false ventricular couplet detection.

A summary of the results obtained for arrhythmic beat classification by other methods is shown in Table 7. The works by Dokur and Olmez [19], Osowski and Linh [20], Hu et al. [21] and Lagerholm et al. [22] are based on the analysis of the ECG signal, which is much more time-consuming than the proposed method, while the approach proposed in [23] and in the present work is based on the analysis of the RR-interval signal alone. All methods indicate high performance, 95—98% (the accuracy for [21] was calculated from the results presented in Table VI of [21] while the accuracy for [22] was calculated based on the results presented in Table VI of [22]). Osowski et al. classify seven beat categories; Dokur et al. classify ten beat categories while Lagerholm et al. classify sixteen beat categories. Hu et al. classify four beat categories, but they present results for only two of them (as shown in Table 7). The first was annotated as V and included the premature ventricular contractions and the ventricular escape beats; the second was annotated as N and included all other beat categories. The methods proposed in [19] and [20] are evaluated using very small datasets. In [21] initial labelling of the beats was required and there was no automatic QRS detection—the points of the database annotation were used. The method was evaluated using the last 25 min of the records in the 200 series, apart from records 212, 217, 220, 222 and 232. In [22] all MIT-BIH arrhythmia database records were used for evaluation but the primary objective was to perform clustering with an expert performing the final beat classification. In the present work four beat categories are automatically classified, without any human interference, in contrast to [21] and [22]. The approach uses only the RR-interval signal and not the entire ECG. All the MIT-BIH arrhythmia database records are used in the evaluation. There is no training stage, as in other approaches [19—21] because the classification is based on medical knowledge and no initial labelling of the beats is required, as in [21]. In addition, the method performs detection and classification of episodes and cannot be directly compared with other works since they use already detected episodes for classification into different arrhythmic types.

An obvious extension of the present work is the incorporation of fuzzy logic. Step c (beat classification) of the method is implemented as a set of knowledge-based rules, therefore, could be modified to include fuzzy logic. In addition, the rules used in the proposed method or other rules, can be extracted using data mining techniques. Such results will be presented in a future communication.

5. Conclusions

An efficient method for arrhythmia beat classification and arrhythmic episode detection and classification has been developed. The method is based on the RR-interval signal extracted from ECG recordings. A set of rules is used for beat classification in four beat categories and a deterministic automaton is used for the arrhythmic episode detection and classification into six categories. Both, the rules and the deterministic automaton are based on medical knowledge and observations upon RR-intervals of arrhythmic episodes. The evaluation of the method was performed using the MIT-BIH arrhythmia database with a high accuracy in both beat and episode classification.

Provided that there is no atrioventricular block, the use of the RR-interval signal cannot be used for distinguishing supraventricular from ventricular arrhythmias. Even though the focus is on the ventricular arrhythmias (due to the fact that the RR-interval monitors the ventricular activity), an alternative approach would be to recognize cardiac rhythms (premature beat, bigeminy, trigeminy, tachycardia, flutter/fibrillation) but not differentiate between atrial (or supraventricular) and ventricular origin of the arrhythmia and then use ECG features (such as the P wave) to achieve this differentiation. The combination of the method with knowledge-based procedures or other existing methods using the ECG signal and its features could be used to achieve classification of other types of arrhythmic beats and episodes. To our knowledge there is no other attempt in the literature to use rule-based systems for classification of beats or episodes using only the RR-interval signal. Furthermore, the use of knowledge-based systems in the automatic arrhythmia detection and classification is very limited. Since the method performs in real time and is not affected by noise and alterations in arrhythmic episodes, it can be proven very useful in clinical practice.

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