KNOWLEDGE-BASED SYSTEMS FOR ARRHYTHMIA DETECTION AND CLASSIFICATION

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In this paper two knowledge-based methods for arrhythmia detection and classification using ECG recordings are described, which utilize different information of the ECG signal. The first uses features of the ECG signal (R wave, QRS duration, P wave, RR interval, PR interval, PP interval, QRS similarity and P wave similarity), which are fed into a decision-tree like knowledge-based system. The system can classify all types of arrhythmias. The second is based on the utilization of the RR-duration signal only. Initially, rules based on medical knowledge are used for arrhythmic beat classification and the results are fed into a deterministic automato for arrhythmic episode detection and classification. The system can be used for the classification of limited types of arrhythmia due to the fact that only limited information is carried by the RR-duration signal.

1. Introduction

Arrhythmia is an irregular or abnormal single heartbeat or a group of heartbeats. Arrhythmias can affect the heart rhythm and rate causing irregular rhythms, slow or fast heartbeat [1]. Respiratory sinus arrhythmia (RSA) is a natural periodic variation in heart rate, corresponding to respiratory activity. Arrhythmias can take place in a healthy heart and be of minimal consequence, but they may also indicate a serious problem and lead to stroke or sudden cardiac death [2,3]. Therefore, automatic arrhythmia detection and classification are critical in clinical cardiology, especially if it can be performed in real time. The electrocardiogram (ECG) and its features are used for arrhythmia detection and classification.

Automated methods can help the expert to make a decision and save time. Most of those methods are based on the extraction of specific features of the ECG signal and classification of arrhythmias. The arrhythmia detection methods include sequential hypothesis test [4], time – frequency analysis [5], wavelet analysis [6,7], multifractal analysis [8] and methods based on neural networks [9,10,11]. Some attempts have been made for the classification of arrhythmias [12,13,14].

It is the aim of this work to illustrate the use of knowledge – based systems in arrhythmia detection and classification from ECGs. Two systems are presented. The first uses the ECG signal and its features along with a decision tree like rule-based algorithm. The second is based on the RR duration signal and utilizes a beat-by-beat classification followed by an episode classification schema.

2. Materials and methods

2.1. *ECG signal analysis*

The first method consists of two stages: preprocessing and classification. In the first stage features of the ECG signal such as QRS complex, P wave, RR interval and PP interval are extracted. In addition, the similarity of consecutive QRS complexes and P waves is examined. The extraction of QRS complex is achieved using an algorithm proposed by Tompkins [15] and the P wave using the method described in [16]. The first algorithm has been validated and its performance is quite high. The second is difficult to be validated since no annotated database for P wave exists. The similarity of QRS complexes depends on the amplitude, duration and shape of the waveform. Initially, amplitude and duration are examined and if a waveform satisfies those criteria, its shape is classified to one of the six classes shown in Fig.1. A similarity measure (correlation coefficient) is used for P wave

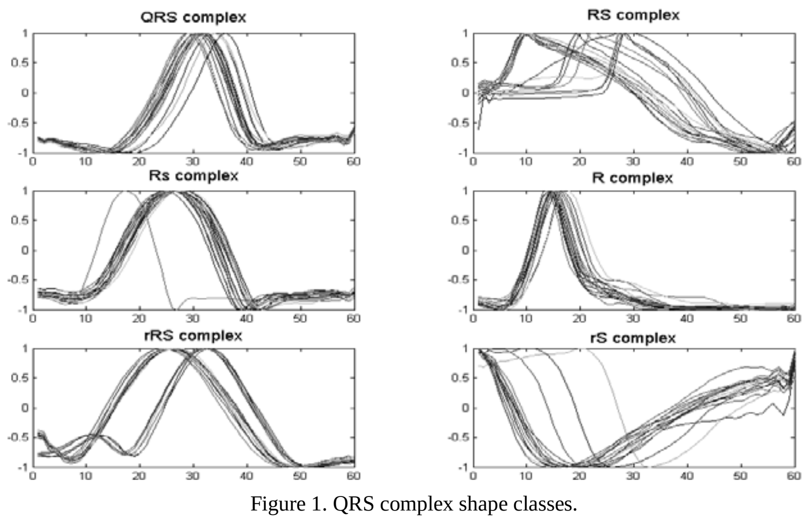

Figure 1. QRS complex shape classes.

similarity.

The above features are used in the second stage, the classification stage. Our classifier is a decision tree like algorithm, which is based in rules, provided by medical experts. The tree consists of four major modules. Each module leads to the classification of some types of arrhythmia. The tree is

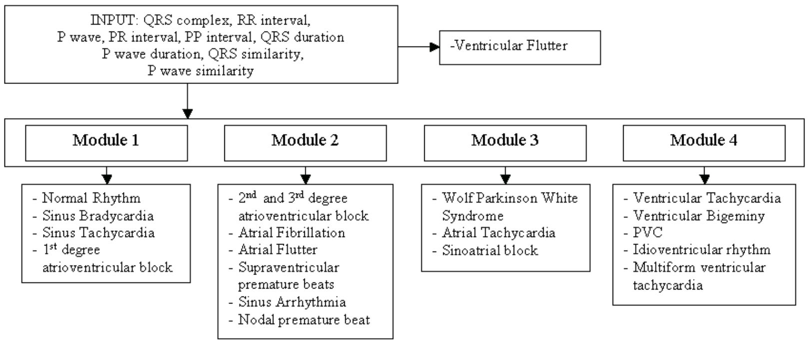

Figure 2: Decision tree like arrhythmia classifier.

shown in Fig. 2.

In Fig. 3 part of the module 3 is presented which leads to classification of arrhythmic episodes of PVC (Premature Ventricular Contraction), couples of PVC and Ventricular Tachycardia.

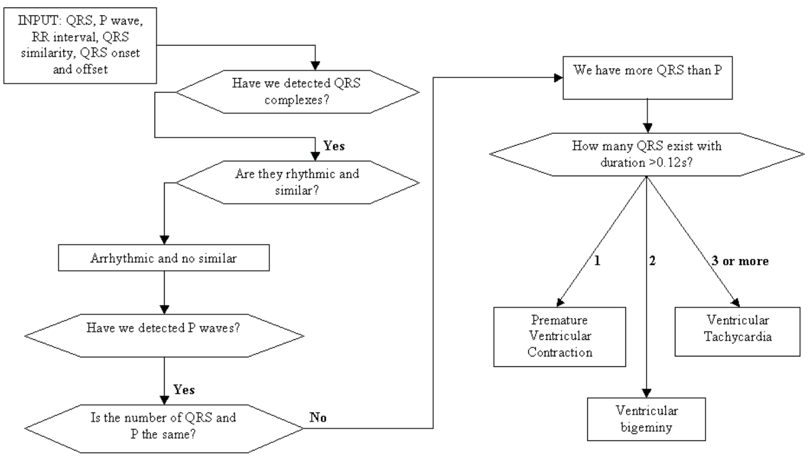

Figure 3: Module 3 details.

2.2. *RR duration signal analysis*

RR duration signal analysis consists of three stages: preprocessing, arrhythmic beat classification and arrhythmic episode detection and classification. Initially, QRS detection is performed on the ECG signal [15] and the RR-interval signal is constructed by measuring the time intervals between successive R waves.

The extracted RR interval signal is used for arrhythmia beat classification. A set of rules, provided by medical experts, are used for the classification. The classification is performed in a 3 RR interval sliding window, classifying the middle RR interval. The RR intervals are classified in four categories: (1) normal sinus beats (N), (2) premature ventricular contractions (PVC), (3) ventricular flutter/fibrillation (VF) and (4) 2^o heart block (BII). We assume that a beat not belonging to one of the above arrhythmic categories is classified as normal (category 1). The algorithm starts with window i consisting of the $RR1_i$, $RR2_i$ and $RR3_i$ intervals. The three rules used in our approach are given in Fig. 4.

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1.    Initialization
   RR2_i from window i is classified as normal (category 1)
2.    Rule 1 – Flutter/fibrillation classification beats
   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 continuously 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*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*mean(RR2_i, RR3_i))
   then RR2_i is classified in category 2.
4.    Rule 3 – 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 RR2_i is classified in category 4
5.    Update window
   a.    i = i + 1
   b.    Go to step 1
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Figure 4: Beat classification algorithm

A deterministic automato, shown in Fig. 5, is used for arrhythmic episode detection and classification. The results from the beat classification stage are fed into the automato, which detects and classifies six types of arrhythmic episodes: (i) ventricular bigeminy, (ii) ventricular trigeminy, (iii) ventricular couplets, (iv) ventricular tachycardia, (v) ventricular flutter/fibrillation and (vi) 2^o heart block.

For each episode a minimum length must be reached. The length for ventricular bigeminy 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, for ventricular flutter/fibrillation 3 beats and for 2^o heart block 2 beats. If more than one rhythm type occurs the one that started first prevails.

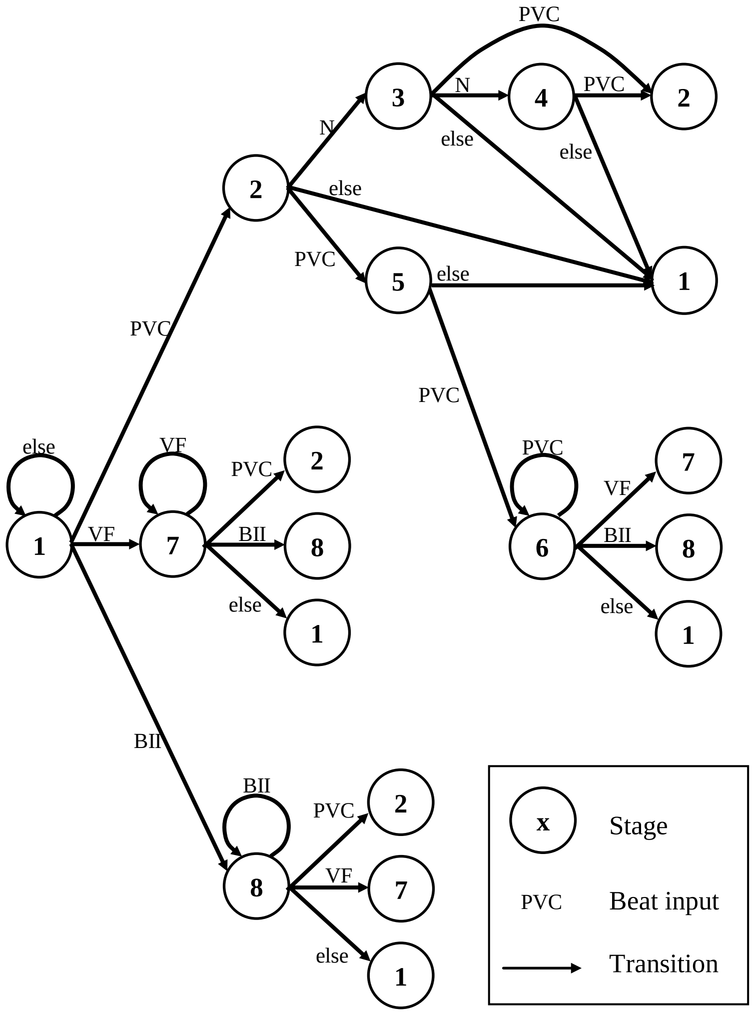

Figure 5: Deterministic automato used for arrhythmic episode detection and classification.

3. Results

The following measures are used for the evaluation of the proposed methods:

$$\text{Sensitivity} = \frac{\#\text{ of beats correctly classified in category}}{\text{total }\#\text{ of beats in category}}, \tag{1}$$

$$\text{P.Predictivity} = \frac{\#\text{ of beats correctly classified in category}}{\text{total }\#\text{ of beats classified in category}}, \tag{2}$$

$$\text{Total Performance} = \frac{\sum_{\text{categories}} \text{correctly classified beats}}{\text{total beats}}. \tag{3}$$

We evaluated the first method in the classification of PVC, PVC couples and Ventricular Tachycardia (VT) from the remainder arrhythmias. The 100 series of the MIT-BIH arrhythmia database [17] was used for evaluation of the method. The obtained sensitivity and the positive predictivity for PVC is 96,89% and 99,53%, respectively, for VT 100% and 1,39%, respectively, and for PVC couples 95,08% and 53,79%, respectively.

The dataset used for the evaluation of the second method was created using all beats from all records of the MIT-BIH arrhythmia database [17] excluding: 2 beats at the start and 2 beats at the end of each record, all beats annotated as A, a, J, S, F, e, j and E and all beats included in atrial flutter or atrial fibrillation episodes because they do not belong to the types of arrhythmia which can be classified by our method. The results for sensitivity and positive predictivity are 98.98% and 99.09%, respectively, for N classified beats, 87.27% and 86.54%, respectively, for PVC classified beats, 98.76% and 97.15%, respectively, for VF classified beats and 99.05% and 89.85%, respectively, for BII classified beats. The total performance is 98.20%.

The arrhythmic episode detection and classification approach was evaluated using the beat classification obtained in the second stage. Sensitivity and positive predictivity are 97.47% and 77.44%, respectively, for ventricular couplets, 90.95% and 81.38%, respectively, for ventricular bigeminy, 73.49% and 85.92%, respectively, for ventricular trigeminy, 81.69% and 98.31%, respectively, for ventricular tachycardia, 100% and 85.71%, respectively, for ventricular flutter/fibrillation and 100% and 83.33%, respectively, for 2^o heart block.

4. Discussion

The use of knowledge-based methods in the detection and classification of arrhythmic episodes in ECG recordings has been demonstrated. The methods are based on rules, which are provided by medical experts. The proposed methods indicate high efficiency and compare well with other existing methods.

The first method utilizes all the available information in the ECG signal. However, preprocessing is required to extract several features, which might be a difficult task in the presence of noise. This can be avoided using the second proposed method, which requires only QRS detection. In the second method only the RR interval signal is used therefore only selected types of arrhythmia can be detected and classified.

However, the methods can be combined and work effectively in the detection and classification of all types of arrhythmia. The major advantage of the proposed knowledge-based methods is that they work in real-time and can be easily implemented in hardware to be provided for the clinician as an add-on for existing ECG equipment. We believe that the parameters of the methods need some tuning and the performance can be even higher.

5. Conclusions

We have developed two knowledge-based methods for arrhythmia detection. The first method utilizes the ECG signal and features extracted from it while the second method is based on the RR interval signal. The first method can detect all types of arrhythmia but some of the ECG features that are used are difficult to be extracted (e.g. P wave). The second method is very efficient, but it is limited to specific types of arrhythmias, due to the fact that the RR interval monitors the ventricular activity. A hybrid approach, combining both methods, could be used to achieve better results for classification of all types of arrhythmia.

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