Premature Ventricular Contraction Arrhythmia Detection Using Wavelet Coefficients

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Abstract: *Premature ventricular contraction (PVC) detection is an important task in critical care medicine. However, making this task automatic is not that simple. In this paper, we are describing a method for PVC arrhythmia detection. This method is based on the use of wavelet detail coefficients to discriminate between normal beats and abnormal beats (PVCs). The proposed method was tested against selected records of the MIT-BIH Arrhythmia Database (MITDB). Results are very satisfactory and show that it is possible to detect PVC arrhythmia using wavelet detail coefficients applied to QRS complexes.*

I.   Introduction

Arrhythmia detection is an important task in critical care medicine. Actually, the accurate and early detection of the different types of arrhythmia can prevent of dangerous heart problems. Premature ventricular contraction (PVC) is one of these arrhythmias. Many researches focused on the problem of automatic detection of PVC arrhythmia [1, 2, 3] and this research area is still active today due the difficulty to find a generalization of arrhythmia detec- tors. Indeed, PVC morphology changes from a subject to another and from a situation (at rest, say) to another situation (sport activity, say). In literature, complex meth- ods combining learning algorithms, clustering techniques, adaptive thresholds, morphology detection among others are reported. In this paper, a very simple method for PVC detection is described. This method is based on the use of a single threshold applied to the magnitudes of wavelet de- tail coefficients measured over ECG signals. The method is tested against records (106, 116, 119, 205 and 221) of the MIT-BIH Arrhythmia database (MITDB) [4]. These records were chosen because they contain normal QRS beats (N) and PVC beats. Records 116 and 205 contain other kinds of arrhythmia which were not considered in this work. The results were satisfactory and prove the reliability of the proposed method. A generalization of the proposed method can hardly be done using the single threshold scheme but can be done combining the present work to other detectors reported in literature. This paper is organized as follows. In section 2, the method is explained in details. Results and discussions are made in section 3 and section 4 concludes this paper.

II.   Method

2.1. MIT-BIH Arrhythmia Database (MITDB)

MIT-BIH arrhythmia database (MITDB) [4] is a widely used ECG database available freely in physionet website [5]. It contains 48 records of 30 min length each with
360 Hz sampling frequency. The ECG records present a
variety of waveforms, artifacts, complex ventricular, junc- tional and supraventricular arrhythmias and conduction ab- normalities. Each record is accompanied by an annotation file in which each ECG beat has been identified by expert cardiologists. These labels are used to evaluate the perfor- mance of our detector. In this work we have chosen to use only five records (106, 116, 119, 205, 221) which contain normal (N) and PVC beats. Records 116 and 205 contain other kinds of arrhythmia which were not considered in this work.

2.2. Discrete Wavelet Transform

Discrete wavelet transform (DWT) decomposes a signal at different scales. The signal is passed through series of mirror filters (high pass and low pass filters). At each level, the high pass filter produces detail information d_n while the low pass filter produces coarse approximations A_n . In DWT decomposition

over level j, all obtained de- tails are kept whereas only the coarse approximation ob- tained in level j is kept, i.e., for level j decomposition of a signal we will obtain j+1 coefficients (3 detail coefficients
+ 1 coarse approximation) representing the decomposed signal. Several wavelet families exist and the choice of the appropriate wavelet is important. In this paper we are using HAAR wavelet (see subsection 2.3 for choice ex- planation).

2.3. ECG Signal Decomposition

In our previous work, we developed a QRS detector based on wavelet coefficients [6]. The detail coefficients ob- tained over level 5, used in [6] and shown in Table 1, show a great potential for QRS detection and also a great poten- tial of discrimination between normal (N) and abnormal beats. This is the property we are using in this article to discriminate between normal beats (N) and PVC beats.
Then, the same wavelet and same detail coefficients
used in [6] are used in this paper. Table 1 shows corre-

Table 1. Correspondence between detail coefficients and range frequencies

Detail	frequency range d_1	90Hz...180Hz d_2	45Hz...90Hz d_3	22,5Hz...45Hz d_4
11,25Hz...22,5Hz d_5	5,62Hz...11,25Hz			

spondence between the details and range of frequencies. An example of ECG segment decomposed over level 5 using HAAR wavelet is shown in Figure 1. It is clear that there is a difference in detail coefficients magnitudes in the case of normal beats and PVC beats. Only detail co- efficient d_5 shows comparable magnitudes for normal and PVC beats. Then, detail coefficients d_1, d_2, d_3 and d_4 can be used to descriminate between normal and PVC beats.

2.4. Selection of appropriate detail coefficients

Most of the energy of ECG signal is concentrated within the QRS complex [7]. Then, it is supposed that d_3, d_4 and d_5, which represent lowest frequencies (QRS complex en- ergy is withing low frequencies range) would be the most appropriate detail coefficients to be used to discriminate between normal and PVC beats. However, Figure 1 shows that d_5 can not be used to discriminate between normal and PVC beats as we can see the example of peaks cor- responding to normal and PVC beats depicted in Figure 1 (d_5) where the magnitudes of both peaks corresponding to normal and PVC beats are similar. In contrary, according to Figure 1, d_1 and d_2 show a potential of discrimination. Evidently, more investigation is needed to decide which detail coefficients to use. Figures 2 and 3 show plots com- bining the different detail coefficients. In Figure 2, the magnitudes of d_3 corresponding to QRS beats are plotted versus magnitudes of d_4 corresponding to the same QRS beats. It is clear that the two clusters (Normal and PVC) are somehow separated in the plan. Especially, clusters are better separated along d_4 axis. Similarly, a plot (Fig- ure 3) of the magnitudes of d_1 corresponding to QRS beats are plotted versus magnitudes of d_2 corresponding to the same QRS beats. It appears from Figure 3 that the two clusters (Normal and PVC) are merged and their separa- tion using d_1 and d_2 is not possible. Then, we decided to use detail coefficients d_3 and d_4 to discriminate between normal and PVC beats. It appears also that the magnitudes of d_3 and d_4 corresponding to normal beats are higher than those corresponding to PVC beats. Then, the product of d_3 and d_4 is processed and used to discriminate between normal and PVC beats. The following algorithm summa- rizes the procedure used for PVC beats detection using Haar wavelet coefficients:

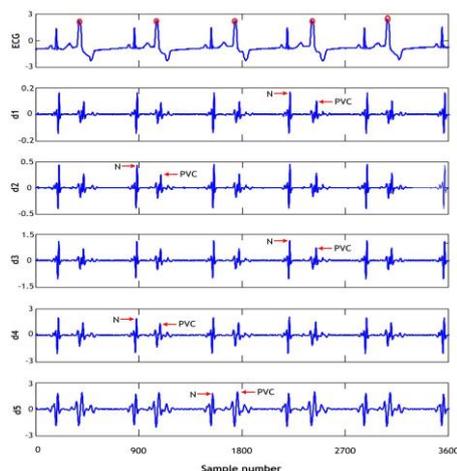1 Apply Haar wavelet transform to ECG signal x(i),

Fig. 1. Decomposition of ECG signal using Haar wavelet over level 5 for record 119 of the MITDB (segment in the range 22.2-45 s). ECG signal is depicted in mV whereas details are depicted in arbitrary units. PVC beats are marked by red circles. Example of peaks in d_1, d_2, d_3, d_4 corresponding to normal and PVC beats are shown by red arrows.

3 PVC beats detection: Compare h(i) associated to QRS complex number i with a threshold λ ($0 < \lambda < 1$), if h(i) $< \lambda \Rightarrow$ QRS number i is a PVC

beat else normal beat.

Figure 4 shows an example of the product h applied to record 119 of the MITDB. In order to show the plot in 2-D dimensions the magnitudes of d_3 corresponding to QRS beats are plotted versus values of h corresponding to the same QRS beats. When screening Figure 4, we find that the two clusters (normal and PVC beats) are completely separated using the axis h which means that for threshold λ value in the range $0.47 < \lambda < 0.74$ all QRS beats are correctly classified. This is not the case for all records, Figure 5 shows an example of the magnitudes of d_3 cor- responding to QRS beats plotted versus values of h corre- sponding to the same QRS beats in the case of record 106 which is not a completely separable case. Even though, the two clusters (normal and PVC beats) in the case of record 106 are not completely separable but the Figure 5 shows that the use of h enhanced the separability in com- parison to Figure 3 where the two clusters are merged. Then, the choice of the value of λ will influence the ob-

2 Compute the product h $= | \Pi^4_{j=3}$
are normalized),
$d_j | (d_3, d_4$ and h
tained results. According to the obtained figures the value
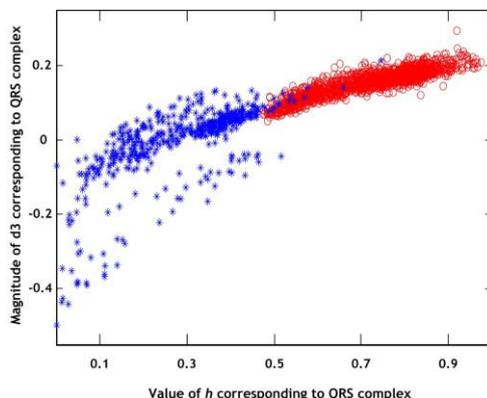$\lambda = 0.45$ appears to be a good choice.

Fig. 2. Magnitudes of d_3 corresponding to QRS com- plexes vs. Magnitudes of d_4 corresponding to the same QRS complexes for the record 106 of the MITDB. d_3 and d_4 are depicted in arbitrary units. Normal beats are repre- sented by red circles whereas PVC beats are represented by blue asterisks.

III.   Results And Discussion

In order to evaluate the method developed in this paper we introduce three statistical measures. The sensitivity S_e, specificity S_P and total classification accuracy A_{cc} de- fined respectively as:

$$S_e = \frac{TP}{TP + FN} \quad (1)$$

$$S_P = \frac{TN}{TN + FP} \quad (2)$$

$$A_{cc} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

where TP are the correctly classified PVC beats (True Positive), FP are misclassified normal beats (False Positive) which means normal beat classified as PVC beat,
FN are the misclassified PVC beats (False Negative) which means PVC beats classified as normal beats and TN are the correctly classified normal beats (True Negative). The sensitivity is used for evaluating the ability of the algo- rithm to detect PVC beats and the specificity is used for evaluating the ability of the algorithm to detect normal beats. The total classification accuracy (A_{cc}) is used for evaluating the accuracy of the algorithm. These statistical measures are expressed in percentages.

Obtained results are summarized in Table 2. The proposed method performs well since total accuracy is 98.48% which is a good result. Actually, in this paper we showed that us- ing a single fixed threshold, one can obtain high classifica- tion accuracy of normal and PVC beats. This means that the chosen value h to characterize ECG beats and make the discrimination between two classes: normal and PVC
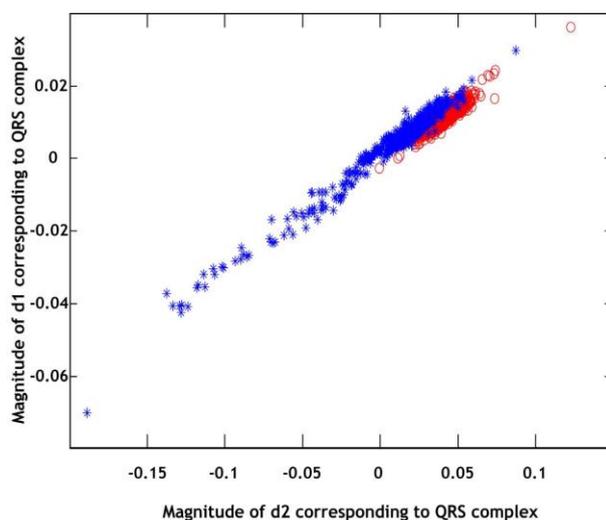

Fig. 3.   Magnitudes of d_1 corresponding to QRS com- plexes vs. Magnitudes of d_2 corresponding to the same QRS complexes for the record 106 of the MITDB. d_1 and d_2 are depicted in arbitrary units. Normal beats are repre- sented by red circles whereas PVC beats are represented by blue asterisks.

beats is a good discrimination feature. This confirm our assumptions about the use of detail coefficients d_3 and d_4 which are in the frequency range of QRS beats. Based on the obtained results, we enumerate the most important findings and comments:

1. The proposed DWT based-method provides good results. Then, it appears that wavelet transform is well suited for ECG signal processing.

2. Generalization of the proposed method using a sin- gle fixed threshold to discriminate between the two classes: normal and PVC beats is not possible since the high inter-patient variations. However, the use of the value h as a feature combined to other fea- tures for training/validation scheme, will enhance significantly obtained results.

3. Detail coefficient d_4 is the best coefficient detail for characterizing and discriminating normal and PVC beats.

4. DWT detail coefficients can also be used to detect other kinds of arrhythmias.

IV.   Conclusion

In this paper, a method to discriminate between normal and PVC beats was proposed. The method based on the use of DWT detail coefficients, uses a single fixed thresh- old to separate normal beats from the PVC beats. This threshold was obtained by combining two DWT detail co- efficients. Results are satisfactory and show that it is pos- sible to make good classification of normal and PVC beats using DWT detail coefficients. In order to generalize the

Table 2. Obtained results

Records	Normal beats	PVC beats	TN	TP	FN	FP	S_e	S_P	A_{cc}
106	1507	520	1507	486	34	0	93.46	100	98.32
116	2302	109	2244	107	2	58	98.17	97.48	97.51
119	1543	444	1543	441	3	0	99.32	100	99.85
205	2571	71	2570	69	2	1	97.18	99.96	99.89
221	2031	396	1958	394	2	73	99.5	96.41	96.91
Total	9954	1540	9822	1497	43	132	97.21	98.67	98.48

proposed methods we need to calculate other features us- ing different methods such as methods based on ECG mor- phology. Then, combine these features to the feature de- veloped in this work and use them in a training/validation scheme using an optimal classifier such as support vector machine.

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