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PVC discrimination using the QRS power spectrum and self-organizing maps

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ABSTRACT

This paper deals with the discrimination of premature ventricular contraction (PVC) arrhythmia using the fractal behavior of the power spectrum density of the QRS complexes. The linear interpolation of the QRS complex power spectrum density in Bode diagram in two different frequency intervals gives two straight lines with two different slopes. The scatter plot of one slope versus the other shows that there exists two distinct regions which represent the normal beats and the PVC beats. Therefore the PVC beats are classified using a self-organizing map fed by the two slopes of the QRS complex power spectrum. The MIT/BIH arrhythmia database is then used to evaluate the usefulness of the proposed method in the discrimination of the premature ventricular contraction (PVC) arrhythmia. The results have indicated that the method has achieved 82.71% of sensitivity and 88.06% of specificity over 46 records from the MIT-BIH arrhythmia database.

1. Introduction

Cardiovascular diseases are still a major cause of mortality around the world. A report published by the World Health Organization states that an estimated of 17 million people die from cardiovascular diseases each year [1]. Arrhythmias represent one of the serious heart diseases and ventricular arrhythmias are the most life threatening. Premature ventricular contraction (PVC) is an arrhythmia caused by the existence of ectopic centers in the ventricles that changes the path propagation of the activation front and leads to generation of QRS complexes with wide and bizarre waveforms. The PVC waveforms can also be uniform or multiform for the same patient besides they represent a lot of variations from patient to another. Many studies have shown that PVCs, when associated with other heart diseases such myocardial infarction, can be linked to increased mortality [2,3], consequently their immediate detection and treatment is essential for patients with heart diseases. Hence an automatic detection and a quick and reliable identification and classification of these conditions constitute a challenge for a cardiovascular diagnostic system and a considerable importance in critical care.

In the last decades, significant amount of research work for automatic detection and classification of PVC beats have been done. Some methods are simples they have been developed for the discrimination between normal and PVC beats only and some are more complex methods, they have developed to classify several arrhythmias into different classes or clusters at the same time. Because of our proposed approach is validated in the MIT-BIH database [4] only some of the recent methods using this database have been considered for description and comparison.

Wieben et al. [5] have developed a classifier based on filter bank features and decision trees. The algorithm has achieved a sensitivity of 85.3% and a positive predictivity of 85.2%. Using only 14 records of the MIT-BIH database, the classifier based on neural networks presented by Al-Nashash [6] has achieved a sensitivity of 98.1% and a positive predictiv-

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ity of 94.7%. Combining Hermite functions and self-organizing maps neural networks, Lagerholm et al. [7] have built a classifier for QRS complexes clustering with a very low degree of misclassification (about 1.5% beats misclassified). A QRS complex classification method using Mahalanobis distance as a classification criterion for four QRS complex time domain features has been developed by Moreas et al. [8]. The classifier has been tested on 44 records of the MIT-BIH database and the results were 90.74% of sensitivity and 96.55% of positive predictivity. A neural network classifier fed by 26 parameters from two ECG leads has also proposed by Christov and Bortolan [9]. Using the whole MIT-BIH database, they have achieved 99.7% of correct detection of normal beats and 98.5% of premature ventricular beats. A fuzzy neural network-based classifier using several features extracted from a quadratic spline wavelet presented by Shyu et al. [10] has achieved a classification rate of 99.7%. The arrhythmia beat classification method based on the RR-interval signal extracted from ECG recordings proposed by Tsipouras et al. [11] has achieved 98% of accuracy. A neural network-based PVC classifier using wavelet transform and timing interval features was proposed by Inan et al. [3]. They have achieved an accuracy of 95.16% for 93,281 beats from 40 records and an accuracy of 96.82% for 22 files outside the training set in clustering several beats. De Chazal et al. [12] have used ECG morphology and heartbeat interval features to classify the beats. The achieved results were 98.8% of specificity and 77.7% of sensitivity. Tsipouras et al. [13] and Exarchos et al. [14] have used fuzzy expert systems to classify arrhythmic beat and ischemic beat. They have achieved an accuracy of 96.43% and 96.00%, respectively, using 109,880 beats. Chen [15] has proposed a detector of PVC beats based on a nonlinear trimmed moving average filter. He has reported a sensitivity of 97.8% and a specificity of 99.7% for 34 records. Asl et al. [16] have used a support vector machine-based PVC arrhythmia classification method using 15 features of the heart rate variability signal. Using 109,000 beats, they have achieved an accuracy of 98.96%. Yu and Chen [17] have proposed a classifier based on wavelet transform and probabilistic neural network to discriminate 6 ECG beat types. Feeding the classifier by 11 features, they have achieved an accuracy of 99.65% for 23 records. The classifier proposed by Krasteva and Jekova [18] is based on QRS template matching for recognition of ventricular ectopic beats using a lot of and complex features including cross-correlation, morphological, frequency, and temporal characteristics of the QRS complex. The authors have reported a sensitivity of 98.4% and specificity of 98.86% over 48 records of the MIT/BIH arrhythmia database and 77 records of the MIT-SVDB.

Several problems were met in the PVC detection and classification in the research work sited above and some of these problems are summarized as follows:

- ECG commonly presents high inter- and intra-patient variability, both in morphology and timing. Therefore, achieving a simpler classifier with high accuracy over a large number of patients is a very difficult problem to address.
- The features selected from ECG signal are very susceptible to variations of ECG morphology, to its temporal characteristics and to external artifacts.
- Features extraction processes are faced with the issue of identifying the most relevant parameters which will aid in the overall diagnostic process from the hundreds that are available.
- The detection process must be fast for real time implementation.

The main objective of this paper is to introduce two new heuristic QRS features which serve to distinguish between normal beats and ventricular ectopic beats. These features called slopes are computed by linear interpolation of the QRS complex power spectrum density in the log–log Bode diagram in two different frequency intervals. Because the PVC's waveforms are wider than the normal ones, we have chosen a very narrow window (150 ms) to extract the QRS complexes from the ECG signal in order to create a difference between the power spectrum of the QRS complex of normal beats and the PVC beats. The self-organizing map (SOM) used for the clustering of the QRS complexes is fed by a vector of two inputs only. Despite of the very small subset of feature and the simple rules that we have used, the proposed method have been compared with the more complex methods cited above.

2. Materials

2.1. Pre-processing

The main objective of the pre-processing is to reduce several kinds of artefacts in the ECG signal, like power line interference, respiration, and muscle tremors. We have used the band pass filter designed in [9] made up from three filters as follows:

a. Notch filter for power line interference suppression, implemented by moving averaging of samples in one period of the power line interference (60 Hz). The filter's frequency response has a first zero at the interference frequency (60 Hz).
b. Low-pass filter for electromyographic noise elimination with a first zero at about 35 Hz implemented by moving averaging of samples in 30 ms time intervals.
c. High-pass recursive filter for drift suppression.

The high-pass recursive filter is given by:

$$Y_n = C_1(X_n - X_{n-1}) + C_2 Y_{n-1} \quad (1)$$

where $C_1=1/(1+\tan(F_c\pi T))$ and $C_2=(1-\tan(F_c\pi T))/(1+\tan(F_c\pi T))$, where T is the sampling period and $F_c = 1$ Hz is the chosen cut-off frequency. The equivalent high-pass filter cut-off frequency of 1 Hz is close than the accepted bandwidth (0.67–30 Hz) for 'monitor' type ECG (IEC 62D/60601-2-27 1994) [19].

2.2. Power spectrum of the QRS complex

Sometimes the frequency content of the waveform provides more useful information than the time domain representation. Many biological signals like the ECG demonstrate diagnostically useful properties when viewed in the fre-

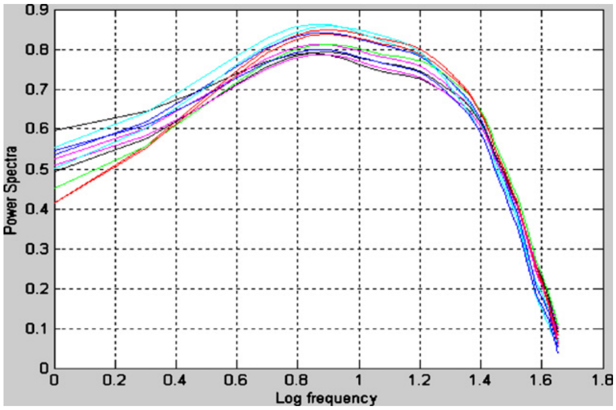


Fig. 1 – Power spectrum of normal QRS.

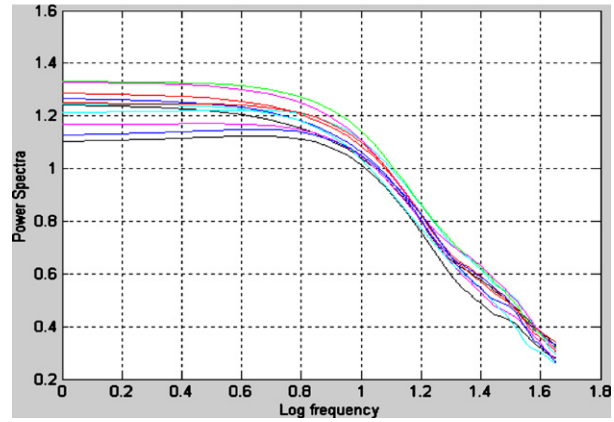


Fig. 2 – Power spectrum of PVC QRS.

quency domain. The power spectrum of normal ventricular depolarization (the QRS complexes) has been demonstrated by Goldberger et al. [20] to show an inverse power law. This inverse power law spectrum is a potential quantitative approach for characterizing the erratic fluctuation of the heart that can be used to develop a quantitative way to distinguish the normal and the abnormal beats. Consequently, if the depolarization of the ventricles is from ectopic origin, like in the case of the PVC, the power spectrum will be affected since the impulse of the depolarization does not follow the normal path (the His and Purkinje network). Otherwise when the activation pulse originates in the atrium and travels through the normal conduction path, the QRS complex has a sharp and narrow deflection, and the spectrum contains high-frequency components. When the activation pulse originates in the ventricle and does not travel through the normal conduction path, the QRS complex becomes wide, and the high-frequency components of the spectrum are attenuated [20]. It has also been shown that the general form of this frequency distribution of the QRS complex appears to be independent of both the spatial position of the recording electrodes and the precise shape of the waveform [21].

To exploit its power law property as a potential quantitative approach for characterizing cardiac abnormalities, the power spectrum of the QRS complex has been obtained and plotted. Figs. 1 and 2 contain respectively the log–log plots of the power spectrum versus the frequency of the QRS complex of normal beats and the QRS complex of PVC beats. The QRS complexes used in this context were extracted from the band-pass filtered data based on the MIT-BIH arrhythmia database annotations. From Figs. 1 and 2 a significant discrepancy can be clearly seen between the slopes of the lines that best fit these two log–log plot spectra in the same frequency interval. Therefore these features can be used to discriminate PVC from normal beats.

3. Methods

In this section a new method of normal and PVC beats classification in the ECG signal is presented. The classifier based on the self-organizing maps (SOM) neural networks uses new features extracted from the morphology of the power spectrum of the QRS complexes performed by a linear regression in the log–log plan.

3.1. Extraction of the QRS complexes

The QRS complexes were extracted from the band-pass filtered MIT/BIH arrhythmia database annotations. Each extracted segment contains a complete QRS segment of 150 ms (69.4 ms before the *R* wave and 83.3 ms after the *R* wave) as shown in Fig. 3. A Blackman window, given in Eq. (2), was applied to each segment to reduce discontinuities

$$w(n) = 0.42 - 0.5\cos\left(\frac{2\pi n}{N-1}\right) + 0.08\cos\left(\frac{2\pi n}{N-1}\right),$$
$$\text{for}\quad 0 < n < N-1 \qquad (2)$$

The narrow window has the disadvantage of information loss of PVC beats, but would cover the QRS complex of normal beats; the short window has the advantage to extract the QRS complex of normal beats in the best conditions without other waves as *P* and *T* waves. Therefore, we do not care about information loss of PVC beats but we focus on good QRS complex of normal beats. The power spectrum of QRS complex of nor-

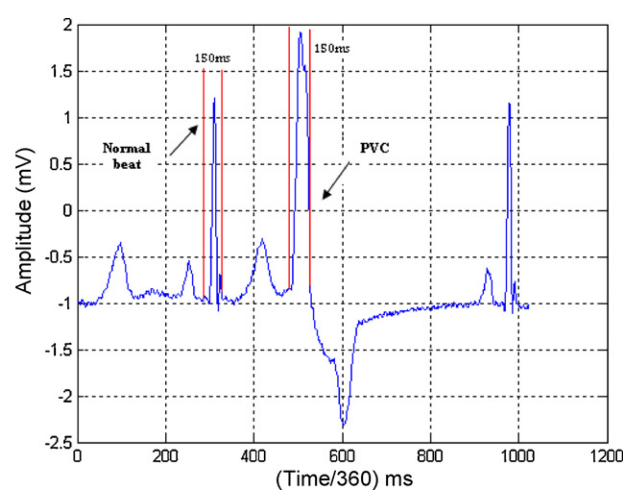


Fig. 3 – Extraction of the QRS complexes.

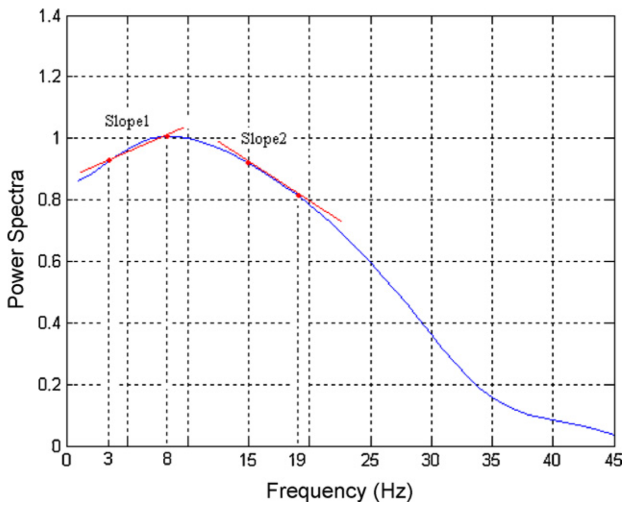


Fig. 4 – Approximation of power spectrum of QRS complex.

mal beats and the power spectrum PVC segment truncated by insufficiency window have different behavior in Bode plot.

3.2. *Power spectrum and slopes computation*

First, the power spectrum of each QRS complex is calculated using FFT algorithm. Second, the logarithms of the power spectrum and the frequency are calculated to get the power law property. Next, the two slopes of the lines that best fit the log–log spectra in the two frequency intervals [3 Hz, 8 Hz] and [15 Hz, 19 Hz], as shown in Fig. 4, are computed using the linear regression technique. The two slopes obtained can then be used as features to discriminate PVC from normal beats by plotting a slope versus another. The two frequency intervals has been chosen based on the results obtained in [22] where the authors have found out from the histogram of the power spectra of the QRS complexes that there were major discrepancies between normal beats and PVC beats in 4 Hz, 8 Hz, 16 Hz and 20 Hz frequencies.

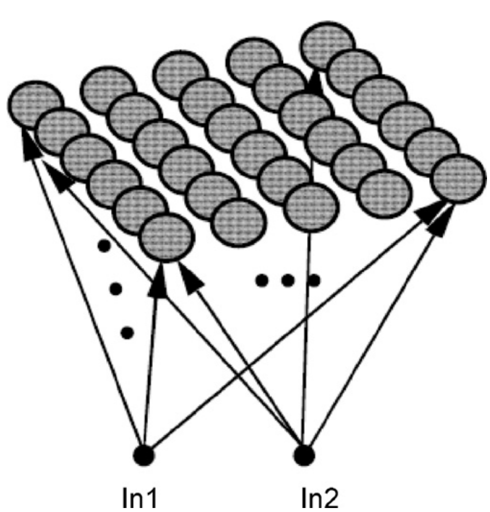


Fig. 5 – Two-dimensional self-organizing maps network structure.

Table 1 – Beat annotation in the MIT-BIH arrhythmia database.

MIT-BIH annotation	Type of arrhythmia	Category
N	Normal beat	Class N
A	Atrial premature beats	Class N
L	Left bundle branch beat	Class N
R	Right bundle branch beat	Class N
P	Paced beat	Class N
a	Aberrated atrial premature beat	Class N
J	Nodal (junctional) premature beat	Class N
S	Supraventricular premature beat (atrial or nodal)	Class N
e	Atrial escape beat	Class N
j	Nodal (junctional) escape beat	Class N
V	Premature ventricular contraction	Class V

3.3. *Self-organizing maps*

Like in many other areas, neural networks have made a significant mark in the domain of biomedical engineering. The capability of learning from data without any a priori knowledge makes the neural networks quite suitable for classification. The self-organizing maps are one of the neural networks used in the applications of classification in the ECG signals.

Self-organizing map is an unsupervised self-learning algorithm that discovers the natural association found in the data. SOM combines an input layer with a competitive layer where the units compete with one another for the opportunity to respond to the input data. The winner unit represents the category for the input pattern. Similarities among the data are mapped into closeness of relationship on the competitive layer [23].

The SOM here defines a mapping from the input data space R^2 onto a two-dimensional array of units. Each unit in the array is associated with a parametric reference vector weight of dimension two. The lattice type of the array is defined as rectangular as shown in Fig. 5.

Each input vector is compared with the reference vector weight w_j of each unit. The best match, with the smallest Euclidean distance $d_j = ||x - w_j||$, is defined as 'response', and the input is mapped onto this location. Initially, all reference vector weights are assigned to small random values and they are updated as

$$\Delta w_{ji} = \begin{cases} \eta(x_i - w_{ij}); & \text{for unit } j \\ 0; & \text{otherwise} \end{cases} \tag{3}$$

where η is the learning rate parameter.

4. Results and discussion

A total of 46 ECG records are studied from the MIT-BIH arrhythmia database. The beats are classified in two categories: normal beats category (class N) and premature ventricular contractions PVC category. The beat classification categories and their corresponding annotations from the MIT-BIH arrhythmia database for each category are given in Table 1.

In this work we have only used the modified limb lead II (MLII), therefore records 102 and 104 are excluded.

4.1. Scatter plot of slopes

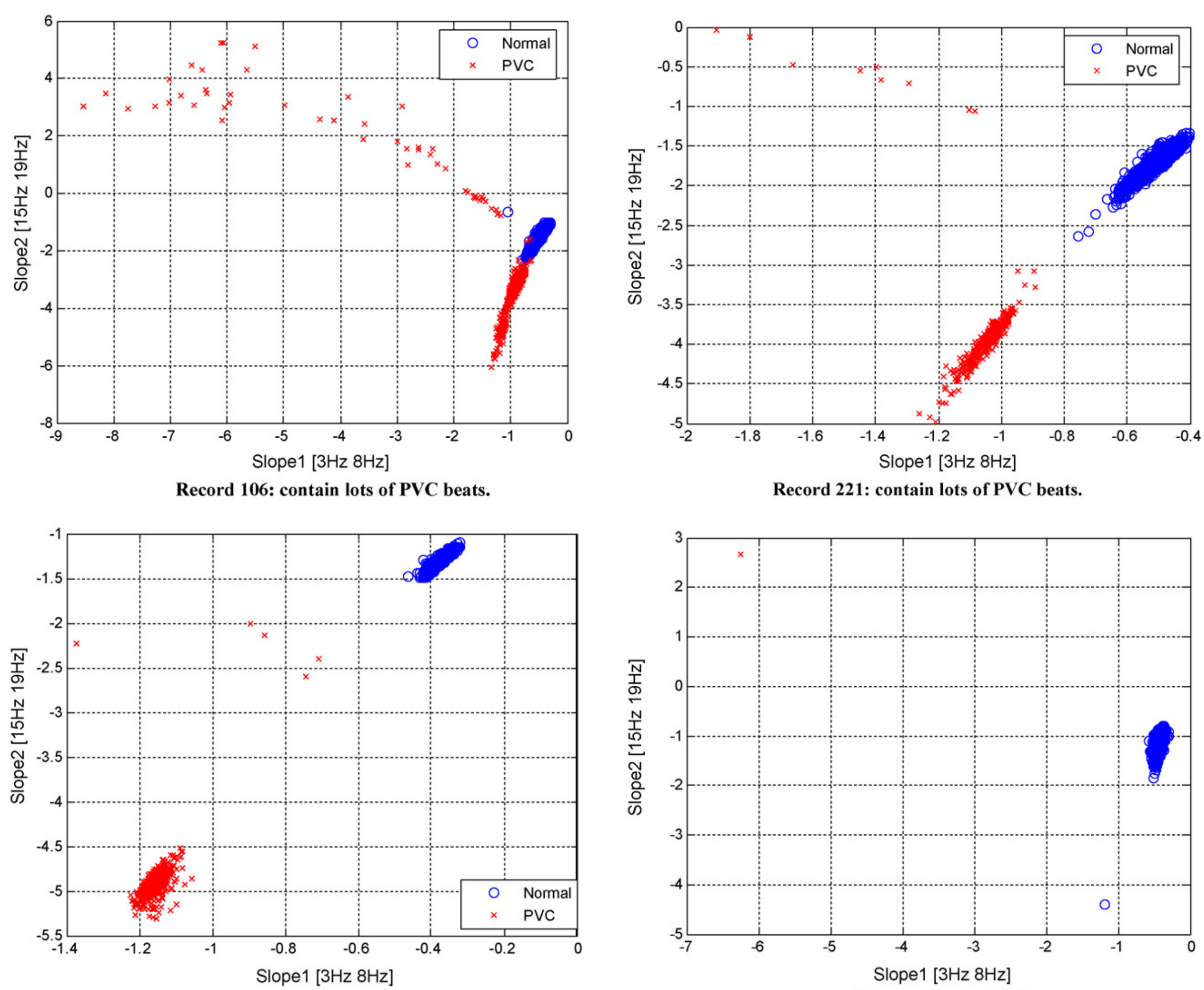
Each beat is featured only with the couple of slopes, Slope1 and Slope2, obtained from the lines that best fit the log–log spectra of the QRS complex of the two frequency intervals [3 Hz, 8 Hz] and [15 Hz, 19 Hz] respectively. The scatter plots of Slope2 versus Slope1 of six records among the 46 chosen records are given in Fig. 6. The blue circles (◯) indicate normal ECG beats, and the red crosses (×) are abnormal (PVC) beats.

The visualization of the scatter plots of Fig. 6 of Slope2 versus Slope1 shows that there is a very good class separation between normal and PVC beats. The normal beats are on top and the PVC beats are on bottom.

4.2. Slopes mapping

Because we found that the two features extracted from the QRS power spectrum represent normal and PVC beat conditions with acceptable discrimination capability then beat clustering based on neural networks using this set of descriptive measurements (Slope1 and Slope2) can be realized for the classifications of the two conditions. Then, instead of using a lot of morphological features in time scale, the slopes computations reduce the dimensionality of the problem, reduce the processing time and simplify the classifier's architecture. Several methods of clustering can be used to separate the two classes represented by the couple Slope1 and Slope2. In this work, we have chosen self-organizing map because of its simplicity and its easy implementation using functions available on Matlab software (all computations and simulations were performed in Matlab7). Besides, self-organizing maps clustering algorithm conserves some of the neighborhood (topology) which facilitates the interpretation by cardiologist since similar clusters are presented as neighbors in the map.

In our case, we have a classical mapping problem from a two-dimensional input space to a two-dimensional output space where the inputs are the slopes and the outputs are the positions in the output space. Therefore, by increasing the



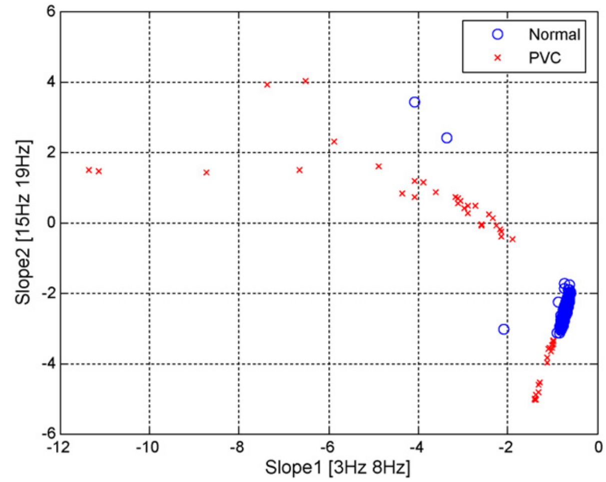
Record 106: contain lots of PVC beats.

Record 221: contain lots of PVC beats.

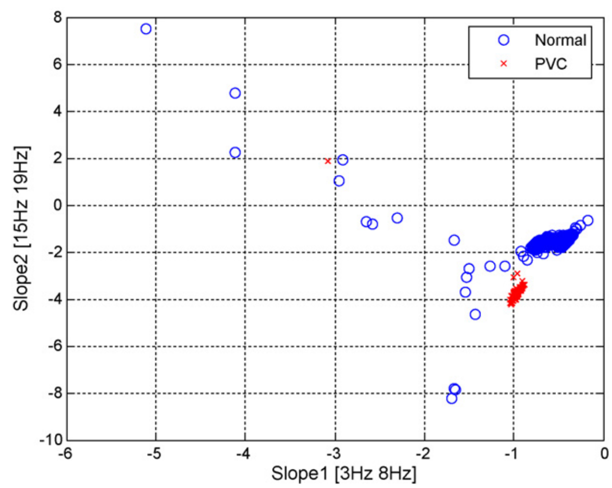
Record 119: contain lots of PVC beats.

Record 100: contain one PVC beat.

Fig. 6 – The scatter plots of Slope2 versus Slope1 of six records.



Record 124: contain lots of PVC beats.



Record 116: contain lots of PVC beats.

Fig. 6 – (*Continued*).

size of the output map one will have more cluster centers and, thus, allow for better separation between beats with different shapes. On the other hand a very large output map will be more difficult to use for the physician. We have found that a SOM structure with 5×5 nodes was enough to ensure good separation of the two classes, the normal beats class and the PVC beats class.

The scatter plots of Fig. 6 show almost the same distribution of the slopes for all the records and this feature allows us to choose a single record in the training stage. In addition, the number of training data must be very small in comparison to the total beats to be clustered. Therefore, the map was initialised randomly and it was trained with 100 slopes of normal beats and 100 slopes of PVC beats from the record 106. The choice of record 106 was made because, in the scatter plots of Fig. 6, it shows a very neat class separation. Therefore the normal beat class represents the entire output SOM nodes that response to normal slopes in the training stage, the same thing for PVC class beat. A beat is defined as misclassified if it ends up in a cluster where the dominant beat is a different one.

4.3. *Evaluation*

The performances of this method are measured in terms of expressions used in the literature and are given as

$$\text{Accuracy } \% = \frac{\text{Number of total tested beats} - \text{FN} - \text{FP}}{\text{Number of total tested beats}} \times 100 \qquad (4)$$

$$\text{Specificty } \% = \frac{\text{Number of normal tested beats} - \text{FP}}{\text{Number of normal tested beats}} \times 100 \qquad (5)$$

$$\text{Sensitivity } \% = \frac{\text{Number of PVC tested beats} - \text{FN}}{\text{Number of PVC tested beats}} \times 100 \qquad (6)$$

where FP stands for the words false positive and it represents the normal beats clustered as PVC beats and FN stands for the words false negative and it represents the number of PVC beats clustered as normal beats. We have tested all the 46 records

Table 2 – Results of slopes mapping.

Record	Number of normal beats	Number of PVC beats	Total tested beats	F.N	F.P	Accuracy (%)	Specificity (%)	Sensitivity (%)
100	2,272	1	2,273	0	1	99.956	99.956	100.00
101	1,865	0	1,865	0	1	99.946	99.946	–
103	2,084	0	2,084	0	1	99.952	99.952	–
105	2,531	41	2,572	38	68	95.879	97.313	7.32
112	2,539	0	2,539	0	1	99.961	99.961	–
113	1,795	0	1,795	0	3	99.833	99.833	–
114	1,836	43	1,879	0	4	99.787	99.782	100.00
115	1,953	0	1,953	0	1	99.949	99.949	–
116	2,303	109	2,412	2	16	99.254	99.305	98.17
119	1,543	444	1,987	5	0	99.748	100.000	98.87
121	1,862	1	1,863	0	38	97.960	97.959	100.00
122	2,476	0	2,476	0	1	99.960	99.960	–
123	1,515	3	1,518	1	0	99.934	100.000	66.67
124	1,572	47	1,619	0	3	99.815	99.809	100.00
200	1,775	826	2,601	63	1	97.539	99.944	92.37
201	1,765	198	1,963	144	85	88.334	95.184	27.27
202	2,117	19	2,136	9	7	99.251	99.669	52.63
205	2,585	71	2,656	17	1	99.322	99.961	76.06
208	1,963	992	2,955	1	145	95.059	92.613	99.90
209	3,003	1	3,004	0	3	99.900	99.900	100.00
210	2,456	194	2,650	23	11	98.72	99.55	88.14
212	2,748	0	2,748	0	1	99.96	99.96	–
213	3,031	220	3,251	14	83	97.02	97.26	93.64
214	2,005	256	2,261	94	17	95.09	99.15	63.28
215	3,199	164	3,363	81	3	97.50	99.91	50.61
219	2,090	64	2,154	13	0	99.40	100.00	79.69
220	2,047	0	2,047	0	1	99.95	99.95	–
221	2,031	396	2,427	8	0	99.67	100.00	97.98
222	2,483	0	2,483	0	14	99.44	99.44	–
223	2,132	473	2,605	270	7	89.37	99.67	42.92
228	1,691	362	2,053	23	4	98.68	99.76	93.65
230	2,255	1	2,256	0	0	100.00	100.00	100.00
231	1,569	0	1,569	0	1	99.94	99.94	–
232	1,780	0	1,780	0	1	99.94	99.94	–
233	2,248	830	3,078	223	9	92.46	99.60	73.13
234	2,750	3	3,572	0	0	100.00	100.00	100.00
107	2,078	59	2,137	9	2,033	4.45	2.17	84.75
108	1,747	16	1,763	7	1,709	2.67	2.18	56.25
109	2,494	38	2,532	7	2,485	1.58	0.36	81.58
111	2,123	1	2,124	0	404	80.98	80.97	100.00
117	1,535	0	1,535	0	395	74.27	74.27	–
118	2,262	16	2,278	11	560	74.93	75.24	31.25
203	2,536	444	2,980	63	981	64.97	61.32	85.81
207	1,755	105	1,860	9	1,668	9.84	4.96	91.43
217	2,046	162	2,208	6	1,638	25.54	19.94	96.30
Total	96,445	6600	10,3864	1141	12,405	86.96	88.06	82.71

of the MIT/BIH database and the results of the classification obtained are reported in Table 2.

The AAMI standards recommend the exclusion of records with paced beats. Then, when paced beats are excluded, we have achieved a total accuracy of 94.02% as shown in Table 3. This confirms the effectiveness of the proposed method despite its simplicity and the small data processing needed and the large variation in beat waveform and the large number of tested beats (95,127 beat).

We have remarked that when we have used large windows to extract QRS complex (for example, 220 ms before *R* wave and 83 ms after *R* wave) there is an overlapping of the normal and PVC beats in the scatter plots and the total accuracy does not exceed 50%. We can explain that by the frequency content of added segment like PQ segment and ST segment, those segments will change significantly the value of the two slopes.

We believe also that the value of slopes for normal QRS complex result from the inverse power law of QRS complex, but the value of the slopes in the case of PVC beats results from the lost of information due to the narrow window used in extraction.

4.4. *Comparison with other methods*

A summary of the results obtained for arrhythmic beat classification by the proposed method and other methods is shown in Table 4. Because of our proposed approach is validated in

Table 3 – Results of mapping according to AAMI standards.

	Total beats	Normal Beats	PVC beats	Accuracy (%)	Specificity (%)	Sensitivity (%)
All records (without 102, 104, 106)	103,864	96,445	6600	86.96	88.06	82.71
All records without (102, 104, 106) and (107, 109, 217)	95,127	88,072	6236	94.02	95.18	82.2

Table 4 – Summary of the results obtained the proposed and other methods.

Authors	Specificity (%)	Sensitivity (%)	Method type	Database
Proposed method	95.18	82.20	Power Spectrum of QRS and SOM	MIT-BIH
Krasteva and Jekova [18]	98.86	98.40	QRS template matching and linear classifier	MIT-BIH
Inan et al. [3]	85.20	–	wavelet-transformed with timing information	MIT-BIH
Wieben et al. [5]	–	85.30	Filter bank features and decision tree classifier	MIT-BIH
Moreas et al. [8]	99.76	90.74	Real-time QRS delineation and application of Mahalanobis distance classifier	MIT-BIH
De Chazal et al. [12]	98.80	77.70	Estimation of morphology and RR interval features with linear discrimination classifier	MIT-BIH
Christov and Bortolan [9]	99.70	98.50	Estimation of morphology features with neural net works classifier	MIT-BIH
Chen [15]	99.70	97.80	A nonlinear trimmed moving average filter	MIT-BIH

the MIT-BIH database, our PVC classification results were compared to the results reported in Refs. [15,18] because they have the best results we have seen in the literature. In [15] the reported specificity is 99.7%, this is very good result for the 34 records used, but we still do not know the performance of the method for the remaining 14 records. The work which uses all the 48 MIT-BIH records is presented in [18]. This method gives also a very good result but it uses a lot of and complex features including cross-correlation, morphological, frequency, and temporal characteristics of the QRS complex which means more calculation complexities. The need of expert to decide normal or abnormal beat in initialization step is their second weakness.

In our work we use a little data in training stage (100 slopes of normal beats and 100 slopes of PVC beats) only from a single record (106), which represent a significant progress in the generalization of PVC discrimination, the second advantage is that we cluster only two features, and we use 46 records from the MIT/BIH for the evaluation.

5. Conclusion

A discrimination method to distinguish between normal and PVC beats in ECG signals based on the combination of the fractal behavior of the power spectrum of the QRS complex and the self-organizing map neural network (SOM) is presented. The features used for the classification task were the slopes of the linear interpolation of the QRS complex power spectrum density in the log–log Bode diagram in two different frequency intervals. Although only two features were used to characterize each beat, the classification methodology is reliable with an accuracy of 94.02%. We believe that the combination of our method with other techniques will give significant improvement.

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