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Ranking of pattern recognition parameters for premature ventricular contractions classification by neural networks

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Abstract

Detection and classification of ventricular complexes from a limited number of ECG leads is of considerable importance in critical care or operating room patient monitoring. Beat-to-beat detection allows the heart rhythm evolution to be followed and various types of arrhythmia to be recognized. A quantitative analysis is proposed of pattern recognition parameters for classification of normal QRS complexes and premature ventricular contractions (PVC). Twenty-six parameters have been defined: the width of the QRS complex, three vectorcardiogram parameters and 11 from two ECG leads. These parameters include: amplitudes of positive and negative peaks, area of positive and negative waves, various time-interval durations, amplitude and angle of the QRS vector, etc. They are measured for all QRS complexes annotated as 'normals' and 'PVCs' from the 48 ECG recordings of the MIT-BIH arrhythmia database. Neural networks (NN) are shown to be a useful instrument for the analysis of large quantities of parameters. Separate ranking of any parameter and homogeneous group ranking (amplitude, area, interval, slope and vector) were performed. From the two ECG leads, the first three ranked parameter groups for clustering of PVCs are amplitude, slope and interval, while for N clustering they are vector, amplitude and area. Considering the entire parameter set, we obtained N = 99.7% correct detection of normal QRS complexes and PVC = 98.5% of premature ventricular complexes. The study also shows that simultaneous analysis of two ECG channels yields better accuracy compared to using a single channel: the improvement is 0.1% in the classification of N beats and 4.5% for PVC beats.

Keywords: neural networks, premature ventricular contraction classification, QRS recognition

1. Introduction

ECG signal analysis is the most common way to study and diagnose cardiac dysfunctions. The normal signal is characterized by recurrent or periodic waveforms with each beat. Beat-to-beat detection and classification of the QRS complexes allows the heart rhythm evolution to be followed and arrhythmias such as premature ventricular contractions (PVC) to be detected.

Detection and classification of ventricular beat changes is of considerable importance in real-time critical care or operating room patient monitoring. It is also important for older patients, in particular those with underlying heart disease. The clinical significance is dependent on PVC frequency, complexity and homodynamic response. In these applications it is important to develop signal-processing techniques that allow real-time feature extraction for the classification of the QRS complexes and other ventricular beat patterns.

Adaptive signal processing has been used for on-line estimation of non-stationary signals that present a recurrent behaviour (Widrow and Stearns 1985, Ferrara and Widrow 1981, Thakor and Yi-Sheng 1991, Laguna *et al* 1992).

Trahanias and Skordalakis (1989) have detected PVC changes or QRS pattern alterations by heuristic descriptors characterizing the QRS waveforms. They have proposed a 'bottom-up' approach to the detection problem by first recognizing the non-decomposable primitive patterns (peak patterns and segment patterns) and then the ECG patterns (QRS complexes).

The QRS and PVC detection algorithm of Millet *et al* (1997) includes a set of measured parameters: maximal positive and negative peaks, area as the sum of absolute values, integral as the sum of values, number of signal samples of 70% higher amplitude compared to the highest peak, and distance between the highest peak and the averaged position (centroid) of the smaller peaks. They have obtained statistical indices for sensibility (Se) and specificity (Sp) of 94.6% and 98%, respectively, from exploration of seven MIT-BIH records (105, 109, 124, 201, 213, 214 and 215). A version of the main algorithm improved Sp to 97.3%. The authors did not describe the criteria for choosing these seven records.

Laguna *et al* (1996) presented an adaptive Hermite model for on-line beat-to-beat estimation of QRS features. They have considered the width of the complex as the most relevant for ectopics detection. Their estimation system was based on a multiple-input adaptive linear combiner, using as inputs the succession of the QRS complexes and the Hermite functions, with a procedure that adaptively estimates the width-related parameter.

Lagerholm *et al* (2000) used Hermite functions and self-organizing maps for ECG complex clustering. Each QRS complex was decomposed into Hermite basis functions, with the resulting coefficient and width parameter used to represent the complex. Unsupervized self-organizing neural networks (NN) were used to cluster the data. The authors reported the resulting clustering with 1.5% degree of misclassification for the MIT-BIH arrhythmia database.

Moraes *et al* (2002) extracted four QRS complex features presenting the best results: width, total sum of the areas under the positive and negative curves, total sum of the absolute values of sample variation and total peak-to-peak amplitude. They have stated that these features follow a normal distribution, allowing the use of the Mahalanobis distance as a classification criterion. After an initial learning period, the algorithm extracts the four features from every new QRS complex and calculates the Mahalanobis distance between its feature set and the centroids of all existing classes to determine the class in which the new QRS belongs. Forty-four records have been used from the MIT-BIH database for testing and the results were 90.74% sensitivity and 96.55% positive predictivity.

Ham and Han (1996) used fuzzy adaptive resonance theory mapping for classification of cardiac arrhythmias. Based on MIT-BIH database annotations, cardiac beats for normal and abnormal PVC complexes have been extracted, scaled and Hamming windowed, after band-pass filtering, to yield a sequence of 100 samples for each QRS segment. From each of these sequences, two linear predictive coding coefficients were generated using Burg's maximum entropy method. The two coefficients, along with the mean-square value of the QRS complex segment, were used as features for each condition to train and test a fuzzy neural network for classification of normal and PVC conditions. The authors reported 97% sensitivity and 99% specificity from only six MIT-BIH database records (116, 208, 210, 221, 228 and 233). Similarly to the approach of Millet *et al* (1997), there is no information on the criteria for record choice.

Al-Nashash (2000) and Maglaveras *et al* (1998) used neural networks for PVC classification. The first author reported 98.1% sensitivity and 94.7% predictivity from 14 MIT-BIH database records.

In the last two decades there has been an active interest in solving pattern recognition problems with the connectionist approach. In fact, the neural networks approach has been considered especially convenient in cases involving large databases. Multilayer feed-forward neural networks with the back-propagation algorithm have been used for the identification, classification and clustering of QRS complexes and ECG signals (Xue *et al* 1992, Bortolan *et al* 1996, Silipo *et al* 1999). Several versions of the back-propagation algorithm have been proposed in the literature for faster convergence and generalization properties. The learning phase of the simplest version updates the weights and biases in the direction where the performance function decreases most rapidly, the negative of the gradient (Rumelhart and McClelland 1986).

The PVC classification should be successful in ECG with artefacts—power-line interference, baseline wander, electromyogram noise, electrode displacement, etc.

We have developed a quantitative analysis of the pattern recognition parameters for PVC classification. 23 ECG and 3 VCG parameters were included: amplitudes of maximal positive and maximal negative peaks, area of the absolute values, area of positive values, area of negative values, number of samples with 70% higher amplitude than that of the highest peak, vectorcardiographic parameters and QRS width, etc. The measurements were performed separately on each channel, with the exception of the vectorcardiographic parameters, which include the combination of channels, and the beat complex width, where measurement in separate channels often leads to errors. Analysis of parameters for the PVC/N clustering was performed by neural networks. The aim is to rank the huge quantity of parameters. This ranking can be further used in real-time clustering methods, and is not within the scope of the current research.

2. Materials and method

2.1. ECG database

All 48 ECG recordings from the MIT-BIH arrhythmia database were studied. Each recording has a duration of 30 min and includes two leads—the modified limb lead II and one of the modified leads V1, V2, V4 or V5 (Mark and Moody 1988). The sampling frequency is 360 Hz and the resolution is 200 samples per 1 mV. Two cardiologists have annotated all beats in the database. Approximately 70% of the beats have been annotated as 'normal'. Since we focused only on the PVC classification, we followed the AHA records equivalent annotation, including some of the abnormal beats (left bundle branch block, right bundle branch block, aberrantly conducted beat, nodal premature beat, atrial premature beat, nodal or atrial premature beat, nodal escape beat, left or right bundle branch block, atrial ectopic beat and nodal ectopic beat) in the 'normal' group. In addition, fusion premature ventricular contractions, ventricular flutter waves, ventricular escape beats, blocked atrial premature beats, paced beats, missed beats and questionable beats were excluded from the study. No selection based on the quality of the signal was performed, thus the analysis was performed even in the presence of artefacts or noise in the ECG signal.

Forty-two of the MIT-BIH arrhythmia database recordings are of leads II and V1. The remaining are of leads II and V5 (100, 114, 123), V2 and V5 (102, 104), II and V4 (124).

2.2. Preprocessing

The preprocessing of the ECG signal was consistent with subsequent real-time application of the PVC/N clustering of the beat complexes, involving:

- Moving averaging samples in one period of the power-line interference; this filter is meant to eliminate the powerline interference. Its frequency response has a first zero at the interference frequency 60 Hz (50 Hz).
- Moving averaging of samples in 30 ms time intervals; this low-pass filter with a first zero at about 35 Hz suppresses the electromyographic noise.
- High-pass recursive filter for drift suppression (Daskalov *et al* 1998, Christov 2004); the phase characteristic of this filter is constant and the phase distortions introduced in the forward time direction are cancelled by a second-pass backward application. We did not use backward filtration because it is not applicable in real-time, and in our opinion the small distortions introduced do not impede PVC/N classification.

The high-pass recursive filter is given by the formula:

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

where *Yn* is the filtered sample sequence, *Xn* is the sample sequence of the original signal and *n* is the consecutive number of samples. The constants C_1 and C_2 are calculated using the formulae:

$$C_1 = \frac{1}{1 + \tan(F_c \pi T)} \qquad C_2 = \frac{1 - \tan(F_c \pi T)}{1 + \tan(F_c \pi T)},$$

where T is the sampling period and $F_c = 2.2$ Hz is the chosen cut-off frequency.

2.3. Pattern recognition parameters

Several heart beat parameters for pattern recognition were derived for each complex annotated as N or PVC in the MIT-BIH arrhythmia database. First, examining the two ECG leads, the onset and the offset of the complex were identified and the width (Width) was computed (see figure 1(a)). Then, from each ECG lead the following 11 parameters were derived: maximal positive peak (Pp), maximal negative peak (Pn), the area as sum of absolute values in the beat interval (Ar), the area of positive values in the same interval (ArP), the area of negative values in the interval (ArN), the sum of absolute velocity values in the interval (Av1), the number of samples with 70% higher amplitude than that of the highest peak (No), the time interval duration from the onset to the maximal positive peak (Ima), the time interval duration from the onset to the maximal negative peak (Imi), the QRS slope velocity between the beat onset and the first peak (S1), the QRS slope velocity between the first and the second peaks (S2).

From the VCG signal, the following parameters were considered: the maximum amplitude of the vectorcardiographic vector (VCGamp) in the plane formed by the two leads and the angle of the maximal amplitude vector (VCGang). The two parameters are presented in

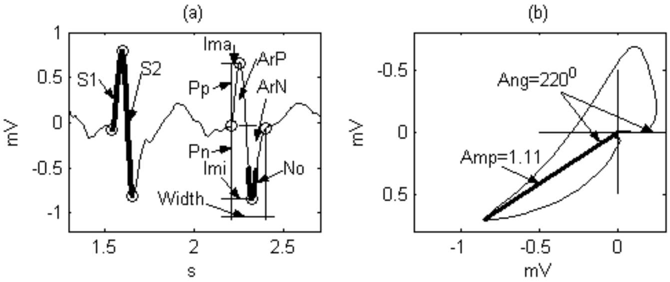

Figure 1. Some of the pattern recognition parameters obtained from the ECG leads (a) and from the VCG (b).

figure 1(b). For more relevant information on the classification task, the VCGang parameter was split into sine and cosine components (VCGsin, VCGcos). Therefore, 23 ECG and 3 VCG parameters were considered for the classification of normal and PVC beats.

2.4. Neural networks for parameter ranking

Two variations have been used in this study with the Matlab Neural Network Toolbox software:

- the Levenberg–Marquardt algorithm for faster speed of convergence (Hagan and Menhaj 1994),
- the Bayesian framework for improving the generalization (Mackay 1992).

The Levenberg–Marquardt algorithm was designed to approach the second-order training speed without having to compute the Hessian matrix, but with an approximation with the Jacobian matrix.

The Bayesian framework of David Mackay performs a regularization of the NN architecture, minimizing the size of network parameters (weights and biases) with statistical techniques. In fact, it is possible to improve the generalization property if the performance function were modified by adding a term that consists of the mean sum of squares of the network parameters (weights and biases). The process of Bayesian regularization minimizes a linear combination of squared errors and weights, determining the correct combination so as to produce a network with an improved generalization (Mackay 1992, Foresee and Hagan 1997).

An additional method for improving the generalization capacity of both algorithms was used, called early stopping (Nelson and Illingworth 1991). In this technique the dataset is divided into three subsets. The first set is the training set, which is used for the update process. The second subset is the validation set, which is monitored during the training phase. The third set is the test set, which is not used in the learning phase. The validation error normally decreases, like the training set error during the initial phase of training. When the network begins to overfit the data, the error on the validation set starts to rise. Consequently, the training is stopped when the validation error increases for a specific number of iterations.

During the clustering we used 40% of the beats for training, 20% for validation and 40% for testing. The general architecture used for this study is a feed-forward network with one input layer, one hidden layer of sigmoid neurons and one output layer of linear neurons. The number of input nodes is equal to the number of ECG/VCG parameters used for the experiment and it varies from N = 1 in the case of a single parameter to N = 26 considering all available ones. This architecture can be represented further by a triple N-5-1.

Table 1. Sensitivity (Se) and specificity (Sp) of each parameter for lead 1, lead 2 and leads 1 + 2.

	Lead 1		Lead 2		Leads 1 + 2	
	Se%	Sp%	Se%	Sp%	Se%	Sp%
Pp	99.3	48.9	99.6	68.5	99.5	84.4
Pn	99.6	84.3	99.6	69.1	99.8	89.2
Ar	99.4	83.7	99.4	74.3	99.6	91.9
ArP	99.1	76.4	99.4	70.3	99.4	87.2
ArN	99.7	76.5	99.6	70.1	99.5	89.9
Av	99.5	66.9	99.3	63.6	99.5	87.0
No	98.7	55.2	99.2	67.4	98.9	80.0
Ima	98.9	88.3	98.9	64.9	99.2	94.3
Imi	99.2	84.8	98.9	77.8	99.4	93.9
S1	99.1	78.3	99.3	81.2	99.5	92.9
S2	99.3	79.2	99.4	75.6	99.4	89.2
VCGamp					99.3	64.1
VCGang					99.7	91.3
Width					99.3	80.4

3. Results

A set of 48 ECG recordings from the MIT-BIH arrhythmia database was considered for this analysis. The indices used for the evaluation of the performance in the classification task were: the sensitivity (Se) or the classification accuracy of normal beats N, and the specificity (Sp) or the classification accuracy of PVC beats. In the first experiment, all 26 parameters were considered separately in the two ECG leads. The indices derived for each ECG lead, as well as for both leads are reported in table 1. For example the NN obtained from a learning process with only one parameter Ar in lead 1 (which corresponds to a NN architecture 1-5-1) is able to classify correctly 99.4% of normal beats and 83.7% of PVC beats. Considering the same parameter in lead 2 the accuracy is 99.4% and 74.3%, respectively. A NN that considers Ar in the two leads (which corresponds to a NN architecture 2-5-1) is able to obtain 99.6% and 91.9%.

Considering separate leads, the sensitivity is higher than 99.00% in almost all cases, but the specificity is higher than 80.00% with four parameters in lead 1 (Pn, Ar, Ima, Imi) and one parameter in lead 2 (S1). Taking into consideration lead 1 + lead 2, we obtained an improvement: the Sp was higher than 80% in all cases and higher than 90.00% with four parameters (Ar, Ima, Imi and S1).

Considering both leads, the seven ranked parameters for PVC clustering were: Ima, Imi, S1, Ar, VCGang, ArN and Pn, while for the N clustering they were: Pn, VCGang, Ar, Pp, ArN, Av and S1.

Another set of measurements was made to test the influence of the ECG/VCG parameters for the classification in the following five groups:

Amplitude: Pp, Pn
Area: Ar, ArP, ArN
Interval: No, Ima, Imi, Width
Slope: Av1, S1, S2
Vector: VCGamp, VCGsin, VCGcos.

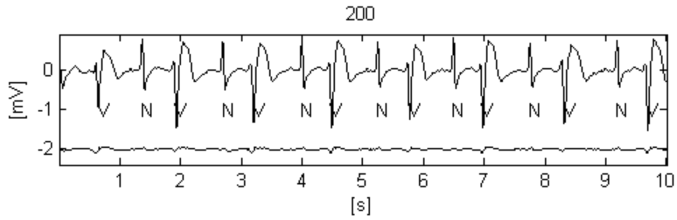

Figure 2. Very low amplitude in channel 2 (lower trace) compared to channel 1 (upper trace) of the MIT-BIH arrhythmia database record 200.

Table 2. Sensitivity (Se) and specificity (Sp) considering the parameters from lead 1, lead 2, leads 1 + 2 and from the five groups: amplitude, area, interval, slope, vector and from all parameters.

	Se%	Sp%
Amplitude	99.5	97.2
Area	99.4	95.5
Interval	99.3	96.0
Slope	99.3	96.9
Vector	99.9	93.6
Lead 1	99.7	98.4
Lead 2	99.6	94.0
Leads 1 + 2	99.7	98.5
All	99.7	98.5

Compound measurements for the 11 parameters in lead 1, lead 2, leads 1 + 2, and finally all 26 parameters, are reported in table 2. For example the area group is represented by six parameters, it produces a NN architecture with 6-5-1 nodes, and it obtains 99.4% sensitivity and 95.5% specificity. Taking into account all parameters in the NN clustering we obtained Se = 99.7% and Sp = 98.5%.

It can be observed that the amplitude is the group of highest specificity (97.2%), and lead 1 performs better than lead 2 (Sp of 98.4% and 94.0%, respectively). The good performance of lead 1 is not significantly improved by adding the parameters of lead 2 or all the remaining parameters.

The fact that lead 2 has lower PVC classification performance is justified and confirmed by the fact that some records of the MIT-BIH arrhythmia database include second leads of very low information value, and in some records (see figure 2) the axis of this lead is almost perpendicular to the maximum heart vector.

All experiments presented in table 1 were performed using the Levenberg–Marquardt algorithm, while those in table 2 were done using the Bayesian regularization method.

An additional specific study was performed for a quantitative analysis of the influence of the separate parameters in the classification task. The Bayesian regularization method was employed for this purpose. This method decreases the number of weights and biases in order to produce a 'minimal' network with an improved generalization. It also gives a measure of the number of network parameters (weights and biases) effectively used by the NN. In the resulting architectures the magnitude of the weights and biases has additional significance. For this analysis all the 26 ECG/VCG parameters were used. The effective number of parameters used by the network, considering that the total number of weights ($26 \times 5 + 5$) and biases ($5 + 1$) in this case is equal to 141. Figure 3 shows the corresponding histogram. It is evident that this number has a high variability.

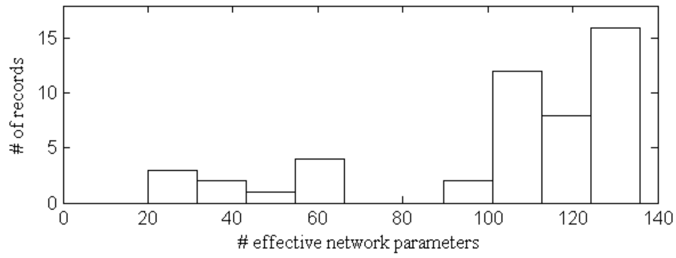

Figure 3. Histogram of the number of effective parameters (weights and biases) used by the network in the experiment with all 26 ECG/VCG parameters.

Table 3. Mean, median and standard deviation of the sum of absolute values of the weights connected with the 26 considered parameters in the experiment with all parameters. The ECG/VCG parameters are divided into five groups: amplitude, area, interval, slope and VCG.

ECG/VCG	Group	Parameter	Mean	Median	Standard deviation
ECG	Amplitude	Pp	1.03	0.47	1.87
Lead 1		Pn	0.77	0.38	0.88
	Area	Ar	0.67	0.43	0.73
		ArP	0.53	0.29	0.54
		ArN	0.65	0.50	0.61
	Interval	No	0.54	0.29	0.63
		Ima	0.42	0.30	0.45
		Imi	0.63	0.46	0.70
	Slope	Av1	0.54	0.37	0.52
		S1	0.75	0.33	1.00
		S2	0.46	0.35	0.49
ECG	Amplitude	Pp	0.58	0.40	0.59
Lead 2		Pn	0.57	0.40	0.61
	Area	Ar	0.52	0.27	0.79
		ArPArN	0.49	0.21	0.70
		ArN	0.49	0.27	0.67
	Interval	No	0.42	0.33	0.42
		ImaImi	0.38	0.21	0.55
		Imi	0.76	0.28	1.18
	Slope	Av1	0.78	0.40	1.12
		S1S2	0.91	0.31	1.58
		S2	0.89	0.34	1.21
ECG	Interval	Width	0.65	0.39	0.84
VCG	VCG	VCGamp	1.23	0.38	2.43
		VCGsin	1.16	0.49	1.36
		VCGcos	1.03	0.50	1.19

A further quantitative analysis was performed to consider the influence of the parameter groups (amplitude, area, interval, slope, vector) in the classification task. All weights and biases were monitored, connected with the input parameters of the 48 NN trained for every record of the MIT-BIH database. With the presence of only one hidden layer with five hidden nodes, each input node is connected by five weights. The mean values, median and standard deviation of the absolute values of weights of all 48 NN reported in table 3, allow qualitative analysis of the influence of the considered parameters. Low mean values imply a lower influence in the classification process, while higher values correspond to a higher capacity in the classification process. For example the weights connected with the parameter Pp-Lead 1, VCGamp, VCGsin and VCGcos (VCG) have the highest mean value. This is an indirect confirmation that the amplitude and VCG groups have good classification performance (table 2).

4. Discussion and conclusion

The results show that the vector group is sufficient (99.9%) for clustering the heart beats as normals. Additional parameters for this classification worsen the results (99.7% with the full set of parameters).

The PVC clustering is at the opposite pole. The best group for it—the amplitude parameters are quite insufficient (97.2%). Any additional group improves to some extent this result, reaching up to 98.5% with the full set.

The present study proves that the PVC clustering obtained from the two-channel ECG is 0.1–4.5% better than the one from only one channel.

The best classifier is obtained considering all 26 parameters. But with a low decrease of the accuracy, several NN classifiers can be detected with a limited number of parameters and with a more simplified architecture.

The good performance of a classifier depends on: (i) good preprocessing of the ECGs, (ii) the appropriate measurements and choice of parameter set for the corresponding clustering and (iii) the clustering method. In the clustering stage neural networks are used to study the influence of different parameters in the classification process. The article contributes by ranking a huge quantity of the parameters. Using the ranking it can clearly be said that there is not a 'golden' parameter set for both N and PVC clustering. The research contributes with the conclusion that each individual class has its individual set.

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