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IDENTIFICATION OF PVC BEATS BY NEURAL NETS

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Abstract

This paper describes the design, training and testing of an artificial neural network for classification of normal and abnormal premature ventricular contraction (PVC) beats in ECG signal. To carry out the classification task, we use the back-propagation (BP) learning algorithm. Two feature selections types were investigated with aim of generating the most appropriate input vector for the artificial neural network classifier (ANNC). The first selected information of each ECG beat is stored as 33-element vector; the second one is then reduced to a 10 dimensional vector using principal component analysis (P.C.A). The performance measures of the classifier will also be presented using as training and testing data sets from the MIT-BIH database.

***Keywords**: Neural networks, ECG signal, PVC beats, Feature selection, MIT-BIH database.*

Résumé

Cet article décrit la conception, l'entraînement et le test d'un réseau de neurones artificiels pour la classification des battements cardiaques normaux et anormaux (extrasystoles ventriculaires (ESV)) dans le signal ECG. Pour effectuer la tâche de classification, nous employons l'algorithme d'apprentissage de rétro-propagation. Deux types de sélection des caractéristiques ont été choisis dans le but de produire le vecteur d'entrée le plus approprié pour le classificateur (ANNC). La première information choisie de chaque battement d'ECG est présentée comme un vecteur à 33 éléments, le second est réduit à un vecteur de 10 éléments en utilisant l'analyse en composantes principales (A.C.P). Les mesures de performance du classificateur seront également présentées en utilisant comme données d'entraînement et de test la base de données MIT-BIH.

***Mots clés**: Réseaux de neurones, Signal ECG, Battements ESV, Sélection de caractéristiques, Base de données MIT-BIH.*

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ملخص

يصف هذا البحث طريقة تصميم وتدريب شبكة العصبونات الاصطناعية لتصنيف دقات القلب العادية والغير عادية (ذات انقباض بطيني مخدوج-قبل اوانه) من خلال الاشارة القلبية الكهربائية (ECG). ولتنفيذ مهمة التصنيف, نستعمل نظام الانتشار الارتجاعي. بحثنا عن نوعين لميزات مختارة قصد الحصول على شعاع لمدخل المصنف مبني على شبكة العصبونات الاصطناعية (A.N.N.C.) يمثل المجموعة الأولى للمعلومات المختارة لكل دقة قلب شعاع ذات 33 عنصر والمجموعة الثانية اختزلت في شعاع ذات 10 عناصر باستعمال تحليل المركبة الرئيسية (A.C.P.). قيمت كفاءة المصنف باستعمال قاعدة المعطيات العالمية (M.I.T.-B.I.H.) .

***الكلمات المفتاحية**: شبكات عصبونية – الاشارة القلبية الكهربائية (E.C.G.) - دقات ذات انقباض بطيني مخدوج (P.V.C.) - ميزات مختارة - قاعدة المعطيات B.I.H - (M.I.T).*

The Electrocardiogram (ECG) [1,2], as shown in figure 1, is the record of variation of bio-electric potential with respect to time as the human heart beats. Thus sufficient information is available in ECG signal to enable diagnosis of a number of cardiac abnormalities. The P wave is representative of atrial depolarization (cardiac stimulation), the QRS complex represents ventricular depolarization and the T wave represents the return of the ventricles to their resting state (repolarization).

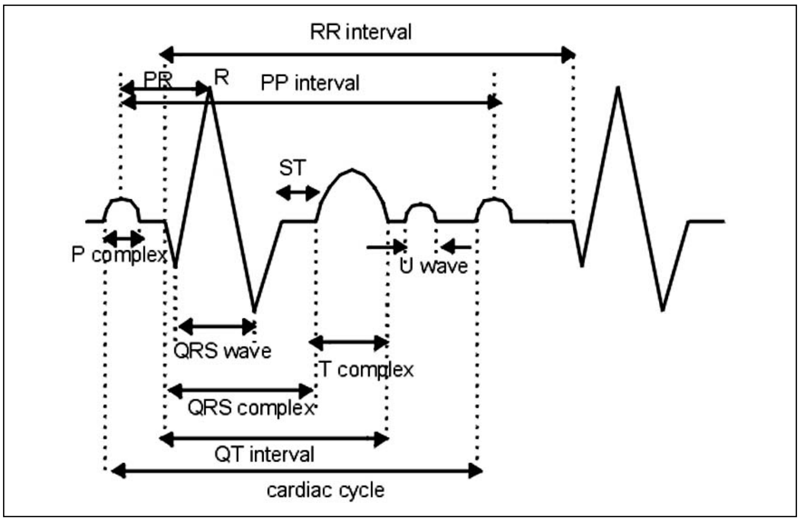

Figure 1: ECG cardiac cycle.

There is no visible waveform for atrial repolarisation as it is engulfed by ventricular depolarization. The goal of ECG classification is to classify the unknown recorded signal into one of a possible number of diagnostic classes, determining if the patients cardiac condition is 'normal' and may remain untreated, or whether the patient exhibits any cardiac abnormalities and requires a form of treatment. Automated ECG beat classification was traditionally performed using a decision-tree-like approach, based on various features extracted from an ECG beat [3-5]. The features used include the width and height of QRS complex, RR interval, QRS complex area, etc. One of the difficulties is that these features are susceptible to variations of ECG beat morphology and temporal characteristics. As such, the classification rate reported in these earlier efforts are rather moderate.

Recent advances in artificial neural networks have made them attractive for pattern recognition [6]. Neural networks have the potential for fast data-processing owing to their parallel architecture. When a neural network is used for pattern recognition, no assumption is needed about the underlying data probability distributions [7]. Once trained, it can be configured to perform adaptively to improve its performance overtime [8]. There have been many successful applications in biomedical signal processing. The purpose of the present work is to derive better parameters for reducing the size of the ANNC classifier while maintaining good classification accuracy. A prerequisite to this goal is to find parameters that represent each condition with acceptable discrimination capability. Therefore the QRS template is reduced using principal-component analysis. The instantaneous and average RR interval, the mean-square value, which can be thought of as the average signal power of the QRS complex segment, are used along with the reduced QRS template to provide another unique pattern feature of each ECG beat. Our study is subdivided into a number of processing steps:

- Data Preparation;
- Bandpass Filtering;
- Feature Extraction/Selection;
- Classification.

1- DATA PREPARATION

1.1- The data collection

In this work, we concentrate on the classification of normal and abnormal PVC beats. ECG records of eleven patients were selected from the MIT-BIH arrhythmia database [9, 10] shown in table 1. The sampling frequency of the ECG signals in this database is fs = 360Hz.

Records number	Number of Normal Beats	Number of PVC Beats
# 106	1507	520
# 116	2302	109
# 119	1543	444
# 203	2529	444
# 208	1586	992
# 213	2641	220
# 215	3196	164
# 219	2082	64
# 221	2031	396
# 228	1688	362
# 233	2230	831

Table 1: Evaluation data taken from the MIT-BIH arrhythmia database.

1.2- Bandpass filtering

In the MIT-BIH arrhythmia database, the analog outputs of the playback unit are filtered to limit analog-to-digital converter saturation and for anti-aliasing, using a bandpass analog filter with a passband from 0.1 to 100 Hz relative to real time. In this study, because of its simplicity and fidelity, an all integer coefficient digital bandpass filter, proposed by Lo and Tang [11], was used to remove noise caused by power line interference, respiration, muscle tremors, and spikes. Other types of filters have been developed for this use, such as in [12] and [13]. The integer coefficient bandpass filter was formed by combining a lowpass filter with a highpass filter, both based on a sampling frequency of fs = 360Hz. The transfer function of the lowpass filter is given as:

$$L(z) = (1-2z^{-6}+z^{-12})/(1-2z^{-1}+z^{-2})$$

The 3 dB point is at 20 Hz, and the first side-lobe zero amplitude is at 60 Hz. Therefore, power line interference at 60 Hz is completely eliminated, and high frequency muscle tremor noise is minimized, which is predominately a result of the bandlimited (anti-aliased filtered) data in the MIT-BIH arrhythmia database. Once the lowpass filter has removed the high frequency noise, one point from every two points in the output of the lowpass filter is presented as an input to the highpass filter. Thus, the data rate after the lowpass filter is half of the value before it. The transfer function of the highpass filter is given as

$$H(z)=z^{-127}-1/2^{14}(1-2z^{-128}+z^{-256})/(1-2z^{-1}+z^{-2})$$

where 2^{-14} is the normalization factor. The cutoff frequency of this filter is at 1 Hz, where the gain is unity. Thus, it successfully removes the drift caused by respiration at about 0.2 Hz.

1.3- Extraction of the QRS complex

In this study, we concentrate on the classification of normal and abnormal PVC beats. The eleven records selected from MIT-BIH ECG arrhythmia database are used for the development and evaluation of the classifier. The availability of annotated MIT-BIH database has enabled the evaluation of performance of the ANNC classifier. The QRS complexes were extracted from the bandpass filtered data based on the MIT-BIH arrhythmia database annotations. The QRS segments are obtained as 30 point templates. The position of annotation labels is used to identify the peak of the QRS waveform, and with 15 points on one side and the remaining on the other side with respect of the R peak were picked up to form the template.

1.4- Diagnostic feature selection

The aim of this work was to determine suitable input feature vectors which would discriminate between the normal and abnormal PVC beats. The principle effects of this technique results in the generation of a smaller descriptive feature vector and hence subsequently reducing the architecture of the network itself and increasing its generalisation ability [14], [15]. In this study, two sets of features were tested:

(1) The information of each beat is stored as 33-element vector, with the first 30 elements representing the QRS segment, the next two elements representing the temporal parameters such as the instantaneous and average RR interval. The instantaneous RR interval is calculated as the difference between the QRS peak of the present beat and the previous beat. The average RR interval is calculated as the average RR interval over the previous ten beats. The last element is the mean square value of each QRS segment, i.e :

$X^2 = E[x^2]$ (where E is the expectation operator and x ≡sample values in each segment). Thus, this set of 33 feature parameters for each ECG beat is utilized as input to the ANNC classifier.

(2) The information of each beat is represented by a 10-element vector, knowing that the 30-dimensional QRS template is reduced to a seven-dimensional vector using P.C.A. It is designed such that the data set may be represented by a reduced number of "effective" features and yet retains most of the intrinsic information content of the data, we may reduce the number of features needed for effective data representation by discarding those linear combinations that have small variances and retain only those terms that have large variances. The data vector x is then approximated with the m largest eigenvalues of the correlation matrix R, introducing an approximating error. Thus this 10-element vector was used as input to the ANNC classifier (second case).

2- ANNC CLASSIFIER ARCHITECTURE

2.1- Training and testing methods

Our experiments were performed using the neural network tool box in Matlab 5.3. During our experiment the limitations encountered with the use of the back-propagation algorithm are related to the lack of criteria for determining the optimum network structure, learning coefficient and momentum. These parameters depend on the nature, distribution and complexity of the input data. In the present study, they were determined by a trial-and-error approach. The number of neurons in the input layer was fixed by the number of elements in the input feature vector. Therefore the input layer had 33 neurons for the ANNC classifier (first structure) using the complete morphology of the QRS template and 10 neurons for the second structure using the reduced QRS template by applying P.C.A. The output layer was determined by the number of classes desired. In our study, the two neurons of the output layer correspond to the normal beats and PVC beats. In practice, the number of neurons in the hidden layer varies according to the specific recognition task and is determined by the complexity and amount of training data available. If too many neurons are used in the hidden layer, the network will tend to memorise the data instead of discovering the features. This will result in failing to classify new input data. Using a trial-and-error method, we tested hidden layers varying between two and 20 neurons. The optimum number of neurons in the hidden layer was found to be respectively six and three for the first and second structure of the ANNC classifier. Consequently, we used one network structure of thirty-three-six-two (i.e thirty-three neurons at the input layer, six at the hidden layer and two at the output layer), and an other structure of ten-two-two with the reduced QRS segment.

With large values of the learning coefficient and momentum, a network may go through large oscillations during training and may never converge. Smaller learning coefficient and momentum tend to create a more stable network but require a long training time. For a good compromise between training speed and network stability, the learning coefficient and momentum were selected in such a way that their values decreased with the increase of the training epoch. To generate an efficient network, different learning coefficients and momenta were selected for different layers. In the present work, the normlised root-mean-square (RMS) error of the output layer was used as a criterion to select these parameters. The selected learning coefficients and momenta correspond to the deepest slope of the normalised RMS error. Figure 2 shows the change in the RMS error during a training process.

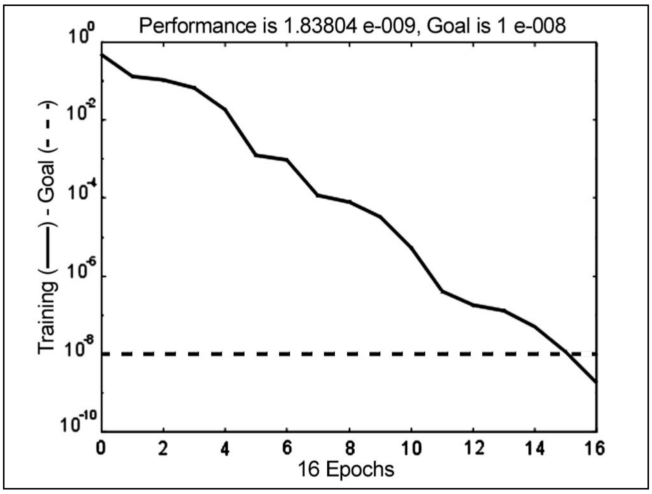

Figure 2: RMS error of the first classifier during the training process.

Using the hyperbolic tangent sigmoid as the neural transfer function, the input feature vectors were scaled to the range from –1 to +1 to fit into the dynamic range of this function. Before the training process was started, all the weights were initialised to small random numbers. This ensured that the classifier network was not saturated by large values of the weights. The threshold of convergence was set at 10^{-8} of the normilised RMS error. Training was stopped when the convergence threshold was reached or when the 2000^{th} epoch was encountered. In this experiment, we use the record (106) as the training data to develop the ANNC classifier and then tested from the remaining records.

2.2- Performance measure indices

The performance of the ANNC classifier for the structures was evaluated by computing the percentages of sensitivity (SE), specificity (SP) and correct classification (CC), the respective definitions are as follows:

- Sensitivity:[SE = 100xTP/(TP+FN)] is the fraction of real events that are correctly detected among all real events,
- Specificity: [SP = 100xTN/(TN+FP)] is the fraction of nonevents that has been correctly rejected,
- Correct classification: [CC=100x(TP+TN)/(TN+TP+FN+FP)] is the classification rate,

where TP was the number of true positives, TN was the number of true negatives, FN was the number of false negatives, and FP was the number of false positives. Since we are interested in estimating the performance of classifiers based on the recognition of PVC beats, the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are defined appropriately as shown below:

FP: classifies normal as PVC.
TP: classifies PVC as PVC.
FN: classifies PVC as normal.
TN: classifies normal as normal.

3- EXPERIMENTAL RESULTS

The results of the evaluation of the ANNC classifier for the two structures in terms of correct classification sensitivity and specificity are summarized in table 2 (actual number of beats) and table 3 (percentage).

These results show a good performance for normal and abnormal PVC beats classification using neural networks. The average results obtained by the two input vectors of the classifier were: 85,17 correct classification, 78,05 specificity and 98,61 sensitivity for the first case, in the other hand 76,40 correct classification, 75,65 specificity and 93,48 sensitivity for the second one.

The ANNC classifier performance results compare exceptionally well with other methods for PVC detection. For example Lin and Chang [16] reported that using linear prediction techniques resulted in 92 % sensitivity for PVC detection as compared to the ANNC classifier results shown above for the two feature selection types.

In our experiment, a threshold equal to 10^{-8} of the normalized RMS error of the output layer was used to stop training. This is a reasonable choice, because a larger threshold correspond to an unfulfilled network classifier, whereas a smaller threshold led to long training time and obtain a steady low RMS value, variable learning parameters (learning coefficient and momentum) were adopted in our experiments. This means starting with high values of the learning parameters and lowering them as training progresses. As mentioned previously, at present there is no algorithm to determine the best architecture for the neural network, learning coefficient and momentum for a given problem. Examining all possible combinations would be a very time-consuming and heavily computational task. Additionally, our present research on the ECG beats classification needs to select the optimum number of combination of the diagnostic features among a given set of feature candidates.

	1st Structure				2nd Structure			
Records	TP	FP	FN	TN	TP	FP	FN	TN
106	992	1570	0	15	903	39	0	1182
116	109	1	0	2299	101	0	1	1007
119	443	0	1	1541	439	719	5	756
203	444	1109	0	1418	433	862	2	1581
213	213	7	7	2632	67	1	9	119
215	162	481	2	2713	140	1736	6	1454
219	59	2	5	2078	17	1073	1	3
221	396	831	0	1198	274	7	3	1703
228	359	1	3	1685	312	0	8	1687
233	825	0	5	2229	171	0	101	756

Table 2: Beat–by-beat record-by-record testing result of the experiment.

	Correct Classification		Sensitivity		Specificity	
Records	1st Structure	2nd Structure	1st Structure	2nd Structure	1st Structure	2nd Structure
106	39.07	98.16	100	100	0.94	96.80
116	99.95	99.90	100	99.01	99.95	100
119	99.94	62.27	99.77	98.87	100	51.25
203	62.67	69.97	100	99.54	56.11	64.71
213	99.51	94.89	96.81	88.16	99.73	99.16
215	85.61	47.78	98.78	95.89	84.94	45.57
219	99.67	1.82	92.18	94.44	99.90	0.27
221	65.73	99.49	100	98.59	59.04	99.59
228	99.80	99.60	99.17	97.50	99.94	100
233	99.83	90.17	99.39	62.36	100	100

Table 3: Comparison of performance between the Two Structures of ANNC classifier. All entries are in percent (%).

CONCLUSION

In this paper, we developed an artificial neural network classifier (ANNC) to identify normal and abnormal premature ventricular contraction (PVC) beats in ECG. This study demonstrates the capability of automatic classification to distinguish between normal and abnormal PVC beats in ECG signals by neural networks, and how it was possible to reduce the input vector dimensions of the ANNC classifier using principle-component-analysis without a great loss of classification accuracy.

More investigations will be undertaken on how to perform features extraction from ECG beats by using other techniques such as linear prediction, linear segregation based on box plots, forward stepwise multiple linear regressions, wavelets, etc.

However, further investigation is required to a larger class of cardiac arrhythmias and automating the process for microcomputer system implementation.

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