CARDIAC ARRHYTHMIA CLASSIFICATION USING SUPPORT VECTOR MACHINES

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Abstract: A method for automatic arrhythmic beat classification is proposed. The method is based in the analysis of the RR interval signal, extracted from ECG recordings. Classification is made using support vector machines methodology to formulate a quadratic programming problem, subject to simple constraints, which is solved using the BOXCQP method. Four types of cardiac rhythms beats are classified: (1) beats belonging to ventricular flutter/fibrillation episodes, (2) premature ventricular contractions, (3) normal sinus rhythm and (4) beats belonging to 2º heart block episodes. The method is evaluated using the ECG recordings from the MIT-BIH arrhythmia database and results are presented.

Introduction

Automatic arrhythmia detection and classification, using the ECG and/or features extracted from it, is a critical task in clinical cardiology, especially when performed in real time. Several researchers have addressed this problem. The proposed techniques either perform beat-by-beat-classification or process ECG segments. In the first case, each beat is classified into several different rhythm types using various techniques: artificial neural networks [1,2], "mixture of experts approach" [3], hermite functions combined with self-organizing maps [4], fuzzy neural networks [5], AR models [6], artificial neural networks and fuzzy equivalence data [7], support vector machines [8], ECG morphology and linear discriminates [9] and time-frequency analysis combined with knowledge-based systems [10]. In the second case techniques such as artificial neural networks [11,12,13], time-frequency analysis [14,15], fuzzy adaptive resonance theory mapping [16], sequential detection algorithm [17], multiway sequential hypothesis testing [18], wavelet analysis [19], complexity measure [20], multifractal analysis [21], wavelet analysis combined with radial basis function neural networks [22] and non-linear dynamical modelling [23] are used. A combination of these two approaches, first beat-by-beat classification, using a rule-based system, and then arrhythmic episode detection has been proposed in [24]. Most of the techniques proposed in the literature process the entire ECG signal, extracting several features from it.

In this work a method for automated arrhythmic beat classification, which uses only the *RR* intervals extracted from the ECG recordings, is proposed. The method consists of four stages: (I) QRS detection and tachogram formulation, (II) support vector machines (SVM) for the formulation of the classification problem, (III) solution of the quadratic programming problem subject to simple constraints, using the BOXCQP method and (IV) multiclass classification. In the stages (II) and (III), the creation of a binary classifier is described, therefore, the stage (IV) is needed, where two techniques, the one-against-all and the all-against-all techniques, are used to combine several binary classifiers in order to create a single multiclass classifier. Following the above methodology four types of cardiac rhythm beats are classified: (1) ventricular flutter/fibrillation, (2) premature ventricular contractions, (3) normal sinus rhythm and (4) 2º heart block. The MIT-BIH arrhythmia database [25] is used in the evaluation of the proposed method and the results indicate high classification and generalization ability.

Materials and Methods

QRS detection and tachogram formulation: Arrhythmic beat classification is performed using only the tachogram (Fig. 1). Initially a QRS detection method

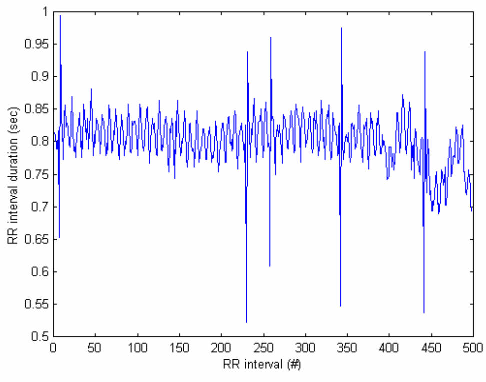

Figure 1: Tachogram

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proposed by Tompkins [26,27] is used to detect the R waves in the ECG signal and then the tachogram is formed measuring the time intervals between consecutive R waves. A three RR interval sliding window $([RR_1, RR_2, RR_3])$ is used to classify the middle RR interval (RR_2) into one of the four beat categories.

Support vector machines: The problem of empirical data modelling is present in many engineering applications. In empirical data modelling a process of induction is used to build up a model of the system, from which it is hoped to deduce responses of the system that have yet to be observed. Support vector machines have been developed by Vapnik [28] and are gaining popularity due to many attractive features, and promising empirical performance.

The classification problem can be restricted to the consideration of the two-class problem without loss of generality. In this case, having the data D:

$$D = \left\{ \left(x^1, c^1\right), \left(x^2, c^2\right), \ldots, \left(x^l, c^l\right) \right\}, \tag{1}$$

where x is a patern $\left(x \in \mathbb{R}^n\right)$, c its class $\left(y \in \{-1,1\}\right)$ and l the number of classes, the goal is to separate the two classes by a function of the form:

$$f(x) = w^T \cdot x + b, \tag{2}$$

where $w \in R^n$ and $b \in R$, which is induced from available examples (training set). The goal is to produce a classifier that will work well on unseen examples, i.e. it generalises well. In the example (Fig. 2) there are many possible linear classifiers that can separate the data, but there is only one that maximises the margin (maximises the distance between it and the nearest data point of each class). This linear classifier is termed the optimal separating hyperplane. Intuitively, this boundary is expected to generalise well as opposed to the other possible boundaries.

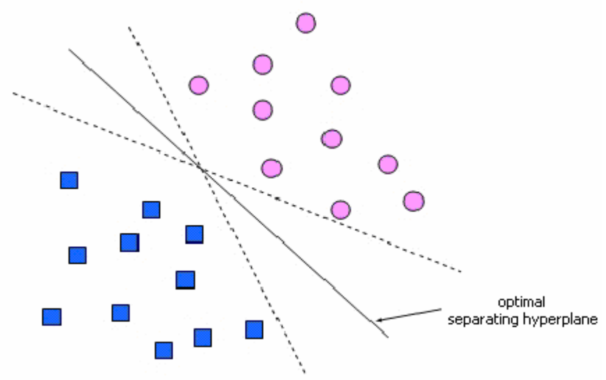

Figure 2: Optimal separating hyperplane.

The formulation of a maximum distance linear classifier is a convex quadratic problem with simple bounds on the variables:

$$\min_x \frac{1}{2} a^T Q a - a^T e, \quad \text{subject to: } 0 \le a_i \le C \tag{3}$$

where $e \in R^l$ and with $e_i = 1$, $Q_{ij} = y^i y^j K\left(x^i, x^j\right)$ and $K(x,y)$ is the kernel function performing the non-linear mapping into the feature space. The parameters $a \in R^l$ are the Lagrange multipliers. The kernel function is used for the case where a linear boundary is inappropriate and allows SVM to map the input vector, x, into a high dimensional feature space, z. By choosing a non-linear mapping a priori, the SVM constructs an optimal separating hyperplane in this higher dimensional space. Two well known kernel functions are the polynomial

$$K(x,y) = \left(x^T y + 1\right)^m, \tag{4}$$

and the Gaussian

$$K(x,y) = exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right). \tag{5}$$

For the solution of the quadratic problem in Eq. (1) the BOXCQP algorithm [29] can be used, which is described in more details bellow.

BOXCQP: Consider the quadratic programming problem subject to simple constraints:

$$\min_x \frac{1}{2} x^T B x - x^T d, \quad \text{subject to: } a_i \le x_i \le b_i, \tag{6}$$

where $x,d,a,b \in R^n$ and $B \in R^{n \times n}$ is a positive definite matrix. We construct the associated Lagrangian function

$$L(x,\lambda,\mu) = \frac{1}{2} x^T B x + x^T d - \lambda^T (x-a) - \mu^T (b-x) \tag{6}$$

The KKT (Karush-Kuhn-Tucker) necessary conditions at the minimum x^*, λ^*, μ^* require that:

$$\begin{aligned}
& Bx^* + d - \lambda^* + \mu^* = 0 \\
& \lambda_i^* \ge 0, \mu_i^* \ge 0, \forall i \in I \\
& \lambda_i^* \left(x_i^* - a_i\right) = 0, \forall i \in I \\
& \mu_i^* \left(b_i^* - x_i\right) = 0, \forall i \in I \\
& x_i^* \in \left[a_i, b_i\right], \forall i \in I
\end{aligned} \tag{7}$$

A solution to the above system can be obtained through an active set strategy described in detail in Algorithm BOXCQP.

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Algorithm BOXCQP

Initially set: $k=0$, $k=0, \lambda^{(0)}=\mu^{(0)}=0$ and $x^{(0)}=-B^{-1}d$.

If $x^{(0)}$ is feasible, **Stop**, the solution is: $x^{*}=x^{(0)}$.
At iteration k, the quantities $x^{(k)}, \lambda^{(k)}$ and $\mu^{(k)}$ are available.

1. Define the sets:
   $L^{(k)}=\left\{i: x_i^{(k)}<a_i \text{, or } x_i^{(k)}=a_i \text{ and } \lambda_i^{(k)}\geq 0\right\}$
   $U^{(k)}=\left\{i: x_i^{(k)}>b_i \text{, or } x_i^{(k)}=b_i \text{ and } \mu_i^{(k)}\geq 0\right\}$
   $S^{(k)}=\left\{i: a_i<x_i^{(k)}<b_i \text{, or } x_i^{(k)}=a_i \text{ and } \lambda_i^{(k)}<0,\right.$
   $\left.\text{or } x_i^{(k)}=b_i \text{ and } \mu_i^{(k)}<0\right\}$
   Note that $L^{(k)}\cup U^{(k)}\cup S^{(k)}=I$

2. Set:
   $x_i^{(k+1)}=a_i$, $\mu_i^{(k+1)}=0$, $\forall i\in L^{(k)}$
   $x_i^{(k+1)}=b_i$, $\lambda_i^{(k+1)}=0$, $\forall i\in U^{(k)}$
   $\lambda_i^{(k+1)}=0$, $\mu_i^{(k+1)}=0$, $\forall i\in S^{(k)}$

3. Solve:
   $Bx^{(k+1)}+d=\lambda^{(k+1)}-\mu^{(k+1)}$
   For the N unknowns:
   $x_i^{(k+1)}$, $\forall i\in L^{(k)}$
   $\mu_i^{(k+1)}$, $\forall i\in U^{(k)}$
   $\lambda_i^{(k+1)}$, $\forall i\in S^{(k)}$

4. Check if the new point is a solution and decide to either stop or iterate.
   If $x_i^{(k+1)}\in[a_i,b_i]$ $\forall i\in S^{(k)}$ and $\mu_i^{(k+1)}\geq 0$ $\forall i\in U^{(k)}$
   and $\lambda_i^{(k+1)}\geq 0$ $\forall i\in L^{(k)}$ **then**
   Stop, the solution is $x^{*}=x^{(k+1)}$.
   Else
   set $k\leftarrow k+1$ and iterate from **Step 1**.
   Endif

Multiclass Classification: The generalization from two-class classification to multiclassclassification is not straightforward. There are two different aproaches for this, direct, where the binary classification method is generalized to multiclass classification method, and indirect, where sereral binary classifiers are combined in order to produse a single multiclass classifier. In the present work an indirect approach is chosen to genetate the final classifier. The main ide is to combine multiple binary classifiers into a single multiclass classifier, can be matirialised with two differnt techniques, the one-against-all and all-against-all. In the case of the one-against-all technique (Fig. 3), a binary classifier is created for each class against all others, leading to C binary classifiers, if there are C different classes. The final decision is made choosing the class for which the corresponding classifier achieves the higher confidence.

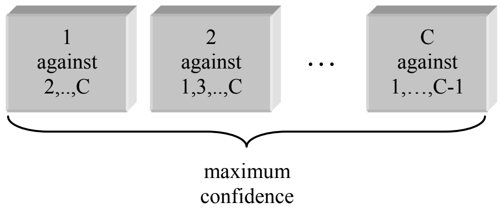

Figure 3: The one-against-all technique.

In the case of the all-against-all technique (Fig. 4), a binary classifier is trained for each pair of classes, leading to $C(C-1)/2$ binary classifiers and then their results are combined, with a voting procedure, in order to reach to the final decision.

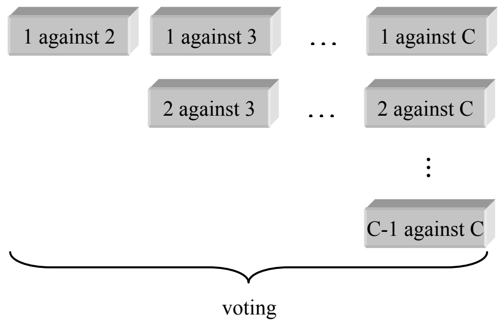

Figure 4. The all-against-all technique.

In this work both one-against-all and all-against-all techniques are evaluated.

Results

The MIT-BIH arrhythmia database is used for the evaluation of the proposed method. The tachogram is extracted from the ECG recordings of the database, and it is used to create windows of three consecutive RR intervals $([RR_1, RR_2, RR_3])$ and define their class c. Therefore, the dataset is defined as $D=\left\{x^l, c^l\right\}$, $l=1,...,K$, with $x^l=[RR_1, RR_2, RR_3]^l$, $d^l\in\mathbb{R}^3$ being a single pattern with 3 features, c^l is its class with 4 different classes, and K is the number of patterns. The class c^l is represented as $c^l=\{1,2,3,4\}$. All beats from all records from the database are included in the dataset D, excluding only 2 beats at the starting and at the end of each record due to the window length that is used in the method. The cardiac rhythm categories and the number of beats used in each of them, in dataset D, are presented in Table 1.

Table 1: Dataset, classes (cardiac rhythms) and number of beats used in each class.

Class	**Cardiac Rhythm**	**Number of beats in dataset *D***
1	Ventricular flutter/fibrillation (VF)	484
2	Premature ventricular contraction (PVC)	6,183
3	Normal (N)	102,793
4	2^o heart block (BII)	420
	Total	109,880

Both rhythm and beat annotations from the MIT-BIH arrhythmia database are used to specify the class of a window, as follows:

- If the middle beat of the window (RR_2) belongs to 2^o heart block episode (rhythm annotation BII in the database), then $c = 4$.
- Else if the middle beat of the window (RR_2) belongs to the starting of ventricular flutter/fibrillation, ventricular flutter/fibrillation wave or to the end of ventricular flutter/fibrillation (beat annotations [, !,], respectively, in the database), then $c^l = 1$.
- Else if the middle beat of the window (RR_2) is annotated as premature ventricular contraction (beat annotation V in the database) then $c^l = 2$.
- Everything else is considered as normal sinus rhythm, $c^l = 3$.

The third category is named normal sinus rhythm although it includes various types of cardiac rhythms, normal and arrhythmic. This "super category" is defined in order to include all beats from the remaining rhythm or beat annotations. In this way the classification is made for 3 cardiac arrhythmias and the remaining data, which is closer to real clinical conditions, where the data is a mixture of all possible cardiac rhythms and not just a close set of some specific types of rhythms.

To perform the training a training dataset (D_{train}) is needed, which is a randomly selected subset of D, containing equal number of patterns from each class. This number is set to 250 patterns, and thus the size of the training dataset is 1000. Although, the number of patterns of each class differs significant in D, the number of patterns selected from each class for the training set is equal. Thus, there is no bias for larger classes. The test dataset (D_{test}), which is used for the evaluation of the method, consists of the remaining patterns of D after selecting D_{train} ($D_{test} = D - D_{train}$).

Four SVMs are combined, using the one-against-all technique, and six SVMs using the all-against-all technique. All SVMs had Gaussian kernels. The confusion matrix, defined as:

$$X_{i,j} = \frac{\#\ of\ patterns\ in\ class\ j\ classified\ to\ class\ i}{total\ \#\ of\ patterns\ in\ class\ i}. \quad (8)$$

20 different pairs of D_{train} and D_{test} datasets were randomly created. The average confusion matrix for all 20 pairs is calculated and it is presented in Tables 2a and 2b, for the one-against-all and all-against-all techniques, respectively.

Table 2a: Confusion matrix of the classification (%), using the one-against-all technique.

		Database			
		VF	PVC	NSR	BII
Classification	VF	97.97	1.73	0.24	0.06
	PVC	1.98	88.21	9.77	0.03
	NSR	1.08	5.88	92.71	0.32
	BII	0.00	0.29	0.76	98.94

Table 2b: Confusion matrix of the classification, using the all-against-all technique.

		Database			
		VF	PVC	NSR	BII
Classification	VF	98.12	1.56	2.80	0.04
	PVC	2.06	88.27	9.77	0.03
	NSR	0.91	6.04	92.60	0.45
	BII	0.00	0.38	0.53	99.09

The accuracy of a classification method is also calculated:

$$Accuracy = \frac{1}{K}\sum_{i=1}^{C}\left(\#\ of\ patterns\ from\ class\ i\ classified\ to\ class\ i\right), \quad (9)$$

where K is the total number of patterns and C the number of classes. The mean accuracy, for all 20 pairs of D_{train} and D_{test} datasets, is 92.49%, when the one-against-all technique is used, and 92.41%, when the all-against-all technique is used.

Discussion

The presented results indicate high classification ability of the proposed method. The discrimination between the cardiac rhythms is very high for all classes. The largest misclassification rates are between the PVC and NSR classes (9.77 % NSR beats were misclassified as PVC and 6% PVC beats were misclassified as NSR). This is due to the fact that PVC and NSR classes present high similarity. The classification results for both VF and BII classes are almost 98% and 99%, respectively. There is no significant difference in the results between the one-against-all and all-against-all techniques, while the one-against-all technique was faster then the all-against-all technique..

A summary of the results obtained for arrhythmic beat classification by other methods is shown in Table 3. The works by Simon et al. [1], Hu et al. [3], Lagerholm et al. [4], Dokur et al. [2], Osowski et al. [5,8] Ge et al. [6] and de Chazal et al. [9] are based on the analysis of the ECG signal while the approaches proposed in [10,24] and in the present work is based on the analysis of the RR-interval signal only. All methods indicate high performance, 95%-98%. Simon et al. classify 5 beat categories, Lagerholm et al. sixteen, Dokur et al. ten, Osowski et al. seven in [5] and thirteen in [8], Ge et al. six, de Chazal et al. five and Tsipouras et al. classify four beat categories. Hu et al. classify four beat categories but they present results for only two of them (as shown in Table 6 in [3]). The methods proposed in [1], [2], [5], [6] and [8] are evaluated using very small datasets. In [3] initial labelling of the beats was required and there was no automatic QRS detection – the points of the database annotation were used. A similar approach was used in [9] for the fiducial points. In [4] all MIT-BIH arrhythmia database records were used for evaluation but the primary objective was to perform clustering with an expert performing the final beat classification. In the present work four beat categories are automatically classified, without any human interference, in contrast to [3] and [4]. The proposed approach uses only the RR-interval signal and not the entire ECG, therefore the number of the beat categories is smaller. All the MIT-BIH arrhythmia database records are used in the evaluation. There is no training stage, as in other approaches [1-3,5-9] because the classification is based on medical knowledge and no initial labelling of the beats is required, as in [3].

Conclusions

A method for automated classification of cardiac rhythm beats is proposed. The method utilizes only the RR intervals of the ECG, therefore is faster and more unaffected by the presence of noise than other proposed methods but also classifies a relatively small number of cardiac beats (four). The third category is named (NSR) includes various types of cardiac rhythms, normal and arrhythmic. This "super category" is defined in order to include all beats from the remaining rhythm or beat annotations, which is closer to real clinical conditions, where the data is a mixture of all possible cardiac rhythms and not just a close set of some specific types of rhythms. Class 3 can also be used for further classification into more types of cardiac rhythms (e.g. atrial flutter/fibrillation, premature atrial contractions etc), using ECG processing.

The proposed method is based on support vector machines methodology. The incorporation of BOXCQP method for the quadratic programming problem, results to a faster solution than other methods proposed for the specific problem. The presented results indicate high classification ability of the cardiac beats.

Table 3: Summary of previous methods for arrhythmic beat classification

Authors	Method	Dataset (beats)	Accuracy (%)
Simon & Eswaran [1]	decision based neural network	1,096	96.03
Hu et al. [3]	29 points from QRS and ECG features and mixture of experts	49,260	95.52[1]
Langerholm et al. [4]	Hermite functions and self organizing maps	108,963	98.49[2]
Dokur & Olmez [2]	DWT and intersecting spheres network	3,000	95.7
Osowski & Linh [5]	cumulants and fuzzy hybrid neural network	7,185	96.06
Ge et al. [6]	autoregressive modelling	856	96.84[3]
Osowski et al. [8]	support vector machines	12,785	95.91
Chazal et al. [9]	ECG morphology and linear discriminates	100,000	97.5
Tsipouras et al. [24]	knowledge-based system	109,880	94.26
this work	support vector machines	109,880	94.85

[1]Calculated from the results of Table VI of [3].
[2]Calculated from the results of Table VI of [4].
[3]Calculated from the results of Table 2 of [6].

Acknowledgements

This research is partially funded by the program "Heraklitos" of the Operational Program for Education and Initial Vocational Training of the Hellenic Ministry of Education under the 3rd Community Support Framework and the European Social Fund.

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