Combination of ECG Parameters with Support Vector Machines for the Detection of Life-Threatening Arrhythmias

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Abstract

Early detection of ventricular fibrillation (VF) and fast ventricular tachycardia (VT) is crucial for the success of the defibrillation therapy. A wide variety of detection algorithms have been proposed based on temporal, spectral, or complexity parameters extracted from the ECG. However, these algorithms are constructed by considering each parameter individually. This study aimed to analyze the performance of combining previously defined ECG parameters for the detection of life-threatening arrhythmias using support vector machines (SVM). A total of 11 *parameters have been computed, namely, TCI, STE, MEA, CM, VFleak, M, A2, FM, MAV, PSR and HILB. We studied two different binary detection scenarios: shockable (FV plus TV) vs nonshockable arrhythmias, and VF vs nonVF rhythms. We used the MITDB, the CUDB, and the VFDB to evaluate our algorithms. Sensitivity and specificity analysis show that the combination of parameters with SVM outperforms individual detection algorithms.*

1. Introduction

Sudden cardiac arrest (SCA) is a major health problem which accounts approximately for six millions deaths in Europe and in the United States [1]. SCA is a sudden, abrupt loss of heart function, most often caused by a rapid ventricular tachycardia (VT) that quickly degenerates into ventricular fibrillation (VF). Prompt detection of VT and VF episodes is crucial to deliver an electric shock therapy and in this way increase the probability of survival from a SCA incident. This has impelled the development automated external defibrillators (AED) which analyzes the surface electrocardiogram (ECG) signal and advise/deliver and electric shock if either fast VT or VF are detected. Although commercial AEDs have been extensively tested in-silico and in clinical trials [2], their real detection capabilities are still controversial [3].

Reliable detection of life-threatening arrhythmias, though extensively studied during the last decades, remains an open problem. A wide variety of detection algorithms have been developed based on temporal/morphological [4–8], spectral [9,10], or complexity parameters [11–14] extracted from the ECG. For each detector different separation scenarios have been considered [7], such as VF vs nonVF rhythms, VF plus VT vs nonVTVF, or VF vs VT, making it difficult to asses the real performance of the proposed algorithms. When compared in a standardized way [6], their performance is reduced from the claimed values presented in the original studies. Besides, the arrhythmia detection algorithms are constructed by considering each parameter individually, however the combination of ECG parameters have been suggested as a useful approach to improve detection efficiency [15,16].

This study aimed to analyze the performance of combining previously defined ECG parameters for the detection of life-threatening arrhythmias using support vector machines (SVM). SVM are statistical learning algorithms that have demonstrated an excellent performance in a number of classification problems [17]. We studied two different binary detection scenarios: shockable (FV plus TV) vs nonshockable arrhythmias, and VF vs nonVF rhythms. We used the MIT-BIH Arrhythmia Database (MITDB) [18], the Creighton University Ventricular Tachycardia Database (CUDB) [19], and the MIT-BIH Malignant Ventricular Arrhythmia Database (VFDB) [20] to evaluate our algorithms.

2. Materials and methods

2.1. ECG collection

We used the complete ECG signal recording files from the MITDB, the CUDB and the VFDB. The MITDB contains 48 files of slightly over 30 min length, 2 channels per file, sampled at 360 Hz. The MITDB includes 15 rhythm labels differentiating between VT, ventricular fluter (VFL), normal sinus rhythm (NSR), among other rhythms. The

CUDB contains 35 records of 8 min length from patients who experienced episodes of sustained VT, VFL and VF. Each record is sampled at 250 Hz and includes only two rhythm annotations: VF and nonVF. The VFDB contains 22 files of 30 min length, 2 channels per file, sampled at 250 Hz. As the CUDB, the VFDB includes patients who experienced episodes of sustained VT, VFL and VF. In this database, annotation labels contain 15 different rhythms such as VT, VF, VFL, and NSR.

2.2. Preprocessing

All ECG signals were preprocessed using the filtering process proposed in [6] which works in four successive steps: i) mean subtraction, ii) five-order moving average filtering, iii) high pass filtering with $f_c = 1$ Hz (drift suppression), and iv) low-pass Butterworth filtering with $f_c = 30$ Hz. Then, noise, asystole and low-quality episode segments were removed according to the corresponding annotation labels. Finally, only the first channel of the MITDB and the VFDB has been considered to avoid dependency of samples during the learning process.

2.3. ECG parameters

Each preprocessed ECG signal is divided in non-overlapping 8-seconds segments. This window length has demonstrated to give the best performance in a number of investigated detection algorithms [6]. For each 8-s segment, a set of 11 parameters were computed from the following existing methods: Threshold Crossing Interval (TCI) [4], Standard Exponential (STE) [6], Modified Exponential (MEA) [6], Complexity Measurement (CM) [11], VF filter (VFleak) [10], Spectral Algorithm (M and A2 parameters) [9], Median Frequency (FM) [21], Mean Absolute Value (MAV) [7], Phase Space Reconstruction (PSR) [12] and Hilbert Transform (HILB) [13]. A detailed description of each parameter can be found in the original manuscripts. For an 8-s segment we assigned the labels VF (including VFL), VT, or other rhythm (O) according to the mode of the annotation samples within the analyzed segment. Note that we used rhythm annotations, and therefore all samples contained in a VT/VF episode are considered as VT/VF respectively.

The parameterization of ECG signal segments resulted in a dataset of binary labeled data $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$, where $\mathbf{x}_i \in \mathbb{R}^d$ with $d = 11$ the number of computed parameters, $N = 17857$ the number of 8-s segments, and labels $y_i \in \{-1, +1\}$. Two binary detection scenarios were considered: VF episodes vs nonVF, and shockable (VF plus VT) vs nonshockable rhythms. Both constitute unbalanced datasets with the following prior probabilities: VF vs nonVF, ($p_{+1} = 95.2\%$, $p_{-1} = 4.8\%$); shockable vs nonshockable, ($p_{+1} = 91.5\%$, $p_{-1} = 8.5\%$).

2.4. SVM classifiers

In recent years, SVM classification algorithms have been used in a wide number of practical applications [17]. SVM binary classifiers are sampled-based statistical learning algorithms which construct a maximum margin separating hyperplane. Given a training dataset $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$, where $\mathbf{x}_i \in \mathbb{R}^d$ and $y_i \in \{-1, +1\}$, SVM solves a quadratic optimization problem:

$$\begin{aligned} &\min_{\mathbf{x},b,\xi_i} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N}\xi_i, \qquad (1)\\ &\text{s.to} \;\; y_i\left(\langle\phi(\mathbf{x}_i), \mathbf{w}\rangle + b\right) - 1 + \xi_i \geq 0,\\ &\qquad \xi_i \geq 0,\; i = 1, \ldots, N, \end{aligned}$$

where $\phi(\mathbf{x}_i)$ is a nonlinear transformation that maps training data to a higher dimensional space, ξ_i represent the losses, and C is a regularization parameter that represents a trade-off between margin and losses. By using Lagrange multipliers, (1) can be rewritten into its dual form, and then, the problem consists of solving

$$\max_{\alpha_i} \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{N}\alpha_i y_i \alpha_j y_j K(\mathbf{x}_i, \mathbf{x}_j), \qquad (2)$$

constrained to $0 \leq \alpha_i \leq C$ and $\sum_{i=1}^{N}\alpha_i y_i = 0$, where α_i are the Lagrange multipliers corresponding to primal constraints. $K(\mathbf{x}_i, \mathbf{x}_j) = \langle\phi(\mathbf{x}_i), \phi(\mathbf{x}_j)\rangle$ is the kernel function, which allows us to calculate the dot product of pairs of vectors transformed by $\phi(\cdot)$ without explicitly knowing neither the nonlinear mapping nor the higher dimensional space. We used the Gaussian kernel in our experiments:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2\right). \qquad (3)$$

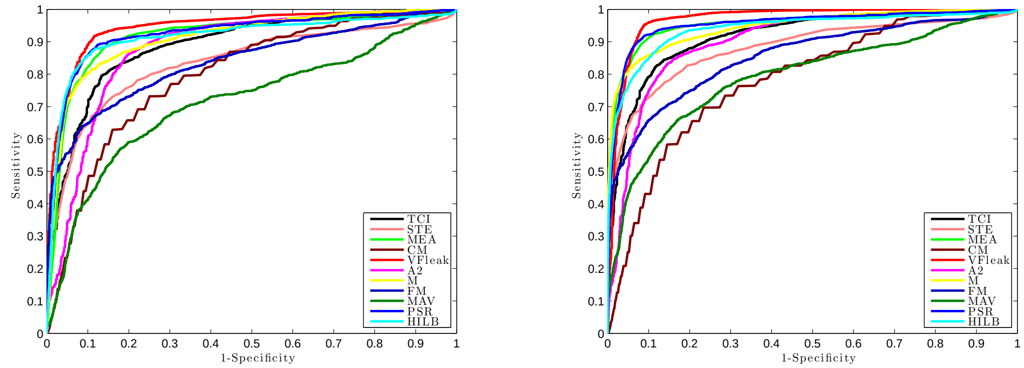
After obtaining the Lagrange multipliers, the SVM classification for a new sample $\mathbf{x}$ is simply given by

$$y = \text{sgn}\left(\sum_{i=1}^{N}\alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b\right). \qquad (4)$$

The free parameters of the SVM model γ and C have to be settled a priori. Methods such as cross-validation or bootstrap resampling can be used for this purpose.

3. Results

First, we test the discrimination ability of the computed parameters by analyzing the receiver operating characteristics (ROC) curve. Figure 1 shows the ROC curves obtained using the complete database. The performance of the detection parameters were assessed in terms of the area under the ROC curve (AUC) and evaluating the sensitivity (SE),



(a) (b)

Figure 1. ROC curves for the (a) VF vs nonVF problem, and (b) shockable vs nonshockable scenario.

i.e the proportion of correctly detected VF/Shockable observations, and the specificity (SP), i.e the proportion of correctly identified nonFV/nonShockable samples. The results of the ROC analysis are presented in Table 1. In all cases, the best performance corresponds to VFleak parameter, which is consistent with previous studies [2, 6]. The performance of PSR and HILB differs from the original investigations [12, 13], but it is similar to other studies [5].

Table 1. ROC analysis for the computed parameters using the complete dataset

	VF vs nonVF			Shock vs nonShock		
Param	AUC	SE[a]	SP[b]	AUC	SE[a]	SP[b]
TCI	0.89	49	68	0.92	65	76
STE	0.83	48	47	0.88	62	58
MEA	0.92	70	83	0.95	80	91
CM	0.80	23	47	0.78	25	37
VFleak	0.95	73	89	0.97	82	93
A2	0.88	34	74	0.90	51	72
M	0.91	71	72	0.95	81	82
FM	0.84	56	41	0.85	56	53
MAV	0.72	24	18	0.79	43	26
PSR	0.92	74	85	0.95	85	92
HILB	0.92	75	80	0.94	76	86

[a] Sensitivity(%) for a 95% specificity.
[b] Specificity(%) for a 90% sensitivity.

3.1. SVM performance

The parametrization dataset of the ECG signal was used as the input to the SVM detector. A random subset of the input space (70%) was used for training while the remaining data was used as test set. Given that the datasets were unbalanced, we used the balanced error rate (BER) [22] as metric to set the free parameters (C,γ) of the SVM by following a 5-fold cross validation strategy. The performance of the SVM detector was assessed using the ROC analysis in terms of SE, SP and AUC, and benchmarked against the VFleak parameter, as presented in Figure 2 and Table 2. In both scenarios under analysis, the SVM detector outperforms individual parameters in terms in SE and SP. This difference is enhanced in the case of shockable rhythms.

Table 2. ROC analysis of the SVM detector (test set)

	VF vs nonVF			Shock vs nonShock		
	AUC	SE[a]	SP[b]	AUC	SE[a]	SP[b]
SVM	0.96	81	85	0.99	96	99
VFleak	0.95	73	89	0.97	82	93

[a] Sensitivity(%) for a 95% specificity.
[b] Specificity(%) for a 90% sensitivity.

4. Discussion and conclusions

The overall performance of the computed parameters are in accordance with previous studies [5, 6], in which VFleak, HILB and PSR provide the best detection results. Differences in SE and SP values can be attributed to the ECG databases. Here we included the VFDB whereas the American Heart Association database is not used.

In this work, a novel detection detection algorithm has been presented that combines ECG parameters with SVM to identify VF/shockable arrhythmias, thus showing that the use of machine-learning techniques can improve the efficiency for the detection of life-threatening arrhythmias. In these detection schemes, where the number of ECG parameters can be easily increased, it would be of interest to incorporate efficient feature selection techniques for assessing the discriminatory properties of the selected variables. This, besides of improving the accuracy of VF detectors, might help researchers to provide a better understanding of the underlaying mechanisms responsible for the generation of life-threatening arrhythmias.

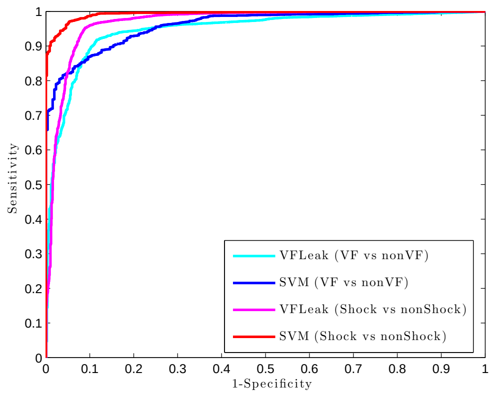


Figure 2. ROC curves for the SVM detector vs VFleak parameter.

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