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SVM BASED LIFE THREATENING ARRHYTHMIAS DETECTION WITH THE COMBINATION OF ECG PARAMETERS

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Abstract: - Correct detection and classification of ventricular fibrillation (VF) and rapid ventricular tachycardia (VT) is crucial for the success of the defibrillation therapy in automatic external defibrillator and patient monitoring. A huge variety of detection algorithms have been proposed based on temporal, spectral and time frequency parameters extracted from the surface ECG signal by considering each parameter individually. In this study a novel life threatening arrhythmias detection algorithm combining 14 ECG parameters on different domain using machine learning algorithm has been used to improve detection efficiency. To analyze which parameter affects the performance, a novel FS algorithm based on SVM classifiers is used and the proposed methodology was evaluated in two different binary detection scenarios: shockable (FV plus VT) versus nonshockable arrhythmias, and VF versus nonVF rhythms, using the information contained in the medical imaging technology database, the Creighton University ventricular tachycardia database, and the ventricular arrhythmia database. Sensitivity (SE) and Specificity (SP) are analyzed and our proposed algorithm significantly improves the performance by improving the efficiency for detection of life-threatening arrhythmias.

Keywords: - Feature selection (FS), support vector machines (SVM), ventricular fibrillation (VF) detection.

I. Introduction

Sudden cardiac arrest (SCA) is a major health problem that accounts approximately about six millions mortality in the western countries like Europe and United States. 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). Approximately one third of these patients could survive with the timely deployment of a defibrillator. Thus 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 of Automated External Defibrillators (AED) as an emergency paramedic than the manual defibrillator.

AEDs are devices that analyze the electrocardiogram (ECG) of the patient and recognize whether a shock should be delivered or not, e.g., in case of ventricular fibrillation (VF). It is of vital importance that the ECG analysis system used by AEDs differentiates well between VF and a stable but fast sinus rhythm (SR). An AED should not deliver a shock to a collapsed patient not in cardiac arrest. On the other hand, a successfully defibrillated patient should not be defibrillated again. AED analyzes the surface electrocardiogram (ECG) signal and advise/deliver an electric shock if either rapid VT or VF is detected. However, though extensively tested and studied during the last decades both by the industry and by the scientific community, reliable detection of life-threatening arrhythmias remains an open problem. The quality of the mathematical algorithms for detection of ventricular fibrillation (VF) used by these devices is of vital importance.

In order to effectively offer high-energy defibrillation to ventricular fibrillation (VF) and low-energy cardio version to ventricular tachycardia (VT), automatic external defibrillators (AED's) and implantable cardioverter defibrillators (ICD's) should be able to distinguish, reliably and accurately, shockable VT and VF rhythms from nonshockable cardiac rhythms, including sinus rhythm (SR), supraventricular tachycardias (atrial flutter and fibrillation) and idioventricular rhythms, etc.

For this purpose, various VT and/or VF detection methods have been developed, such as probability density function method, rate and irregularity analysis of peaks in the short-term autocorrelation function, sequential hypothesis testing algorithm, correlation waveform analysis, four fast template matching algorithms, VF-filter method, spectral analysis, and time-frequency analysis. All these methods exhibit advantages and disadvantages, some being too difficult to implement and compute for AED's and ICD's, some having low specificity in differentiating shockable and nonshockable arrhythmias. Hence, more sophisticated signal processing techniques are necessary to fully describe and characterize VT and VF that will allow development of new detection schemes with high level of accuracy or, equivalently, low false-positive and false-negative performance statistics.

A wide variety of detection algorithms have been developed based on temporal, morphological, spectral, or complexity parameters extracted from the ECG signal. For each detector, different separation scenarios have been considered, such as VF versus nonVF rhythms, VF plus VT versus nonVTVF, or VF versus VT, making it difficult to assess the real performance of the proposed algorithms. When compared in a standardized way, their real performance is reduced from the values presented in the original investigations. The combination of ECG parameters using machine learning techniques, such us neural networks, or support vector machines (SVM), has been suggested as a useful approach to improve the detection efficiency. This strategy, however, raises additional requirements to be considered. First, the need of feature selection (FS) techniques to select those relevant and informative parameters in order to increase the efficiency of the learning task, to improve the performance of the detection process, and to better understand how data affect the learning process. And second, the evaluation and comparison of the proposed algorithms should be assessed over the out of sample test set. Broadly, this task has been carried out over the entire or the validation datasets, making it difficult to compare different detection strategies.

II. Feature Construction

This section illustrates the process of building the input space data to feed the SVM classifier from the ECG raw data signals.

A. ECG Collection

We used the complete ECG signal recording files from the MITDB, the CUDB, and the VFDB, which are available at the PhysioNet repository. The MITDB contains 48 Holter recording files of slightly over 30-min length, two channels per file, sampled at 360 Hz. The MITDB includes 15 rhythm labels differentiating between VT, ventricular fluter (VFL), normal sinusrhythm(NSR), amongotherrhythms. The CUDB contains 35 Holter 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, namely, VF and nonVF. The VFDB contains 22 files of 30-min length, two 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, including VT, VF, VFL, NSR, among other rhythms.

B. Preprocessing

All ECG signals were preprocessed using the filtering process proposed in, which works in four successive steps: 1) mean subtraction; 2)five-order moving average filtering; 3)high-pass filtering with fc = 1 Hz (drift suppression); and 4) low-pass Butterworth filtering with fc = 30 Hz. Then, noise, asystole, and low-quality (artifacts) 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 redundancy of samples during the learning process.

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C. ECG Parameters

Each preprocessed ECG signal is divided in nonoverlapping 8-s segments. This window length has demonstrated to give the best performance in a number of investigated detection algorithms. For each Le = 8 s segment, a set of 13 previously defined parameters were computed. These can be broadly classified in three major categories.

1) *Temporal/Morphological Parameters:* are defined in the time domain.

- *Threshold crossing interval (TCI*) is the time interval between consecutive pulses (threshold crossings) within a 1-s ECG segments. TCI requires a 3-s window to be computed. On a Le duration episode, TCI is evaluated by averaging Le−2 consecutive values. Threshold crossing sample count (TCSC) refers to the number of samples that cross a given threshold V0 within a 3-s ECG interval. On a Le duration episode, TCSC is evaluated by averaging Le −2 consecutive TCSC values.

- *Standard exponential (STE)* is calculated as the ratio between the number of crossing points of the ECG signal with a decreasing exponential curve centered at the time instant where maximum amplitude value occurs, and the time duration of the considered ECG segment Le.

- *Modified exponential (MEA*) first adjusts a decreasing exponential function positioned at the peak values of an ECG segment. Then, MEA is computed as ratio between the number of liftings, and the time duration of the considered ECG segment Le.

- *Mean absolute value (MAV)* is the MAV of 2-s ECG segments. On a Le duration episode, MAV is obtained by averaging Le −1 consecutive 2-s values.

2) *Spectral parameters*: are calculated in the frequency domain.

- *VFfilter(VFleak)* is a measure of the residue after applying a narrow band elimination filter centered at the mean signal frequency of the considered ECG signal segment.
- *Spectral algorithm (M, A1 and A2parameters)* analyzes the energy content in different frequency bands by means of Fourier analysis. Let F be the peak frequency (component with largest amplitude) in the range of 0.5–9 Hz. Then, M measures of the frequency content between 0 and the minimum of (20 F,100 Hz), while A2 measures the frequency content between 0.7 and 1.4 F.

- *Median frequency (FM)* is the central frequency of the spectral mass contained in the power spectrum of the considered ECG signal segment.This parameter was defined to estimate the duration of the cardiac arrest, and therefore it has not been usually use for detection purposes. However, since it provides information about the duration of the VF episode, we included it here to analyze its discriminatory properties.

3) *Complexity parameters*: provide with different measures of the complexity of the ECG signal
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- *Complexity measurement (CM)* is the normalized value of the Lempel-Ziv complexity measure of a binary sequence extracted from the ECG signal segment.

- *Phase space reconstruction (PSR)* measures the sparsity of the phase plot representation when considering the original ECG signal segment and a time-delayed version of it.

- *Hilbert transform (HILB)* measures the sparsity of the phase plot representation when considering the original ECG signal segment and its HILB signal.

- *Sample entropy (SpEn)* is a measure of similarity within an ECG signal segment. A lower value of SpEn indicates more self-similarity. Thus, VF/VT rhythms are characterized by higher values os SpEn.

After computing all the aforementioned parameters, labels were assigned to each 8-s segments. In order to analyze the VF versus nonVF, and the shockable versus nonshockable problems, we considered three types of rhythms labels: VF (including VFL), VT, and other rhythms (O). Labels were assigned according to the mode of the annotation samples within the analyzed segment. For instance, in a transition ECG segment in which 40% of samples are labeled as NSR and the remaining samples are labeled as VF, then we labeled the whole segment as a VF.
The parameterization of the ECG signal segments resulted in a dataset of binary labeled data {(x1,y1),...,(xN ,yN)}, where xi ∈Rd, with d = 13 (number of computed parameters), N = 17857 (number of 8-s segments), and labels yi ∈ {+1,−1}. Two binary detection scenarios were considered: VF episodes versus nonVF, and shockable (VF plus VT) versus nonshockable rhythms. Both problems resulted in unbalanced datasets with the following prior probabilities: VF versus nonVF, (p+1 = 4.8%, p−1 = 95.2%); and shockable versus nonshockable, (p+1 = 8.5%, p−1 = 91.5%). Before the classification process, each input feature example x(j) ∈RN was scaled so that 0⩽x(j) ⩽1.

III Svm Classifiers

Two different SVM classifiers are used to discriminate VF versus nonVF rhythms, and shockable versus nonshockable (from now on Shock versus nonShock) episodes by using the dataset of parameters extracted from the ECG signals. This briefly reviews the SVM algorithm formulation and the boot strap resampling method to estimate the performance of the SVM classifiers.

A. SVM Formulation

In recent years, SVM algorithms have been successfully used in a wide number of practical classification problems, due to their good generalization capability derived from the structural risk minimization principle. SVM binary classifiers are sampled-based statistical learning algorithms that construct a maximum margin separating hyperplane. Given a training dataset $\{(x_1,y_1),...,(x_N ,y_N)\}$,where $x_i \in R^d$ and $y_i \in\{-1,+1\}$, SVM solves a quadratic optimization problem

$$\min_{x,b,\varepsilon} = \frac{1}{2}||w||^2+C\sum_{i=1}^{N}\varepsilon_I$$

$$\text{Subject to } y_i((\emptyset(x_i),w)+b) - 1 + \varepsilon_i \geq 0,$$

$$\varepsilon_i \geq 0,\ i=1,\ldots,N \qquad (1)$$

where $\varphi(x_i)$ is a nonlinear transformation that maps training data to a higher dimensional space, ε_i represent the losses C is a regularization parameter that represents a trade-off between the margin and the losses.

By using Lagrange multipliers, can be rewritten into its dual form, and then, the problem consists of solving

$$\max_{\alpha_i} \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{N}\alpha_i y_i \alpha_j y_i K(x_i , x_j) \qquad (2)$$

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, $K(x_i,x_j)=\varphi(x_i),\varphi(x_j)$ is the kernel function, which allows us to calculate the dot product of pairs of vectors trans- formed by $\varphi(\cdot)$without explicitly knowing neither the nonlinear mapping nor the higher dimensional space. The Gaussian kernel is used in our experiments

$$K(x_i,x_j) = \exp(-\gamma||x_i - x_j||^2) \qquad (3)$$

After obtaining the Lagrange multipliers, the SVM classification for a new sample x is simply given by

$$Y = \operatorname{sgn}(\sum_{i=1}^{N}\alpha_i y_i K(x_i,x) + b \qquad (4)$$

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

B. Bootstrap Resampling

Bootstrap resampling is a computer-based method for nonparametric estimation of the distribution of statistical magnitudes, and it can be used to estimate the performance of SVM classifiers. Let $V = \{(x_1,y_1),\ldots,(x_N ,y_N)\}$ be a set of data in a classification problem. A bootstrap resample $V^* = \{(x^*_1,y^*_1),\ldots,(x^*_N ,y^*_N)\}$ is a new dataset drawn at random with replacement from sample V. Let us consider a partition of V in terms of their sample, given by $V = (V^*_{in}, V^*_{out})$, being V^* in and V^*_{out} the subsets of samples included and excluded in the resample, respectively. For the resample r, the SVM classifier can be trained with V^* in and its performance $P^*(r)$ can be estimated by using V^*_{out}, in terms of a predefined metric such as the accuracy, or the error probability. Then, given a collection of R independent resamples, $\{V^*(1),V^*(2),\ldots,V^*(R)\}$,the performance density function can be estimated by the histogram built from replicates $P^*(r)$, where r =1,...,R. A typical choice for R is from 100 to 500 resamples.

IV Feature Selection

Performance of supervised learning algorithms can be strongly affected by the number and relevance of input variables. FS techniques aim to find the best describing subset of the input variables, compared to the original set of features. FS techniques can be divided into three major categories, namely, filter, wrapper, and embedded methods.

Here the relevance of the computed parameters by applying a combination of filter-type FS procedures is estimated. Filter methods are general FS procedures that rank the features according to a predefined evaluation criterion, which is independent of the machine learning classifier. Examples of filter methods include correlation criteria, classical test statistics (χ^2-test, F-test, t-test), principal/independent component analysis, mutual information techniques, classification trees, self-organizing trees, or fuzzy clustering.

A. Combined Filter Methods Procedure

Following a similar approach as in, consider a combined strategy of filter methods, accounting for correlation- based methods (correlation criterion and the maximum separability Fisher criterion), and mutual information methods (minimal redundancy maximal relevance – mRMR - criterion)

1) Correlation criterion

Correlation criterion asses the degree of dependence of an individual parameter with the outcome. For the jth feature $x^{(j)}$ with labels y, the linear correlation coefficient is defined as

$$P(j) = \frac{\left(\sum_{i=1}^{N}(x_i^{(j)} - \mu_j)(y_i - \bar{y})\right)}{\left(\sqrt{\sum_i (x_i^{(j)} - \mu_j)^2 \sum_i (y_i - \bar{y})^2}\right)} \qquad (5)$$

where μ_j represents the mean value for samples of feature $x^{(j)}$,
$\bar{y}$ is the average of outcomes.

Note that $-1 \leq \rho \leq 1$. Larger absolute values of ρ indicate higher linear correlation between $x^{(j)}$ and y, whereas they are uncorrelated if ρ approaches to zero.

2) Fisher criterion

Fisher criterion measures the ability of the j^{th} feature to separate between two sets of labeled data (positive and negatives instances) by computing the F-score as

$$F(j) = \frac{(\mu(y_+)^2 + \mu(y_-)^2)}{\sigma^2(y_+) + \sigma^2(y_-)} \qquad (6)$$

Where $\mu(y_\pm) = \mu_{j,\pm} - \mu_j$ represents the difference between the average of jth feature for the positive/negative classes $\mu_{j,\pm}$ and the whole set of samples μ_j.

In the denominator, $\sigma^2(y_+)$ is the sample variance of the positive/ negative instances and can be calculated as

$$\Sigma^2(y_\pm) = \frac{1}{n_\pm - 1} \Sigma_{i=1}^{n_\pm} x_{i,\pm}^{(j)} - \mu_{j,\pm})^2 \qquad (7)$$

,

being n_+ the number of positive/negative samples. The larger the value of F(j) the more likely this feature is discriminative.

3) mRMR Criterion

Both correlation and Fisher criteria are computationally easy and fast, but they do not reveal mutual information among features (apart from linear correlation). Therefore, the mRMR criterion is applied, which aims at maximizing the mutual information between the outcomes and the feature distribution while minimizing the redundancy between features, according to the following expression:

$$\max_{x^{(j)}} \left\{ \frac{1}{|S|} \sum_{x^{(j)} \in S} MI(x^{(j)}, y) - \frac{1}{|S|^2} \sum_{x^{(j)}, x^{(k)} \in S} MI(x^{(j)}, x^{(k)}) \right\} \quad (8)$$

where MI(x,y) accounts for the mutual information among variables x and y, and |S| represents the size of the feature set.

B. FS with SVM Classifiers

The above mentioned filter FS procedure and SVM algorithms are combined in order to build a high-performance classifier. A backward selection procedure is applied to the list of ranked features starting from the completed dataset, progressively eliminating the less relevant feature and then estimated the performance of the SVM classifier using bootstrap resampling (set R = 500). The performance of the SVM classifier for different subsets of ranked features can be estimated.

V Results

A Individual Parameters Performance

The performances of the detection parameters were assessed in terms of the area under the ROC curve (AUC) and by evaluating the sensitivity (SE), i.e., the proportion of correctly detected VF/Shockable observations, and the specificity (SP), i.e., the proportion of correctly identified nonVF/nonshockable samples. SE and SP are calculated as

$$SE = \frac{TP}{TP + FN} \qquad (9)$$

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$$SP = \frac{TN}{TN + FP} \qquad (10)$$

where TP represents the number of true-positive decisions, FN the number of false-negative decisions, TN the number of true- negative decisions,FP the number of false-positive decisions.

B Svm Performance

In this experiment, we aimed to analyze the performance of the SVM algorithm when using the complete set of ECG parameters. Thus, the complete dataset was used as the input to the SVM detector. A random subset of the input space (70%) as used for training while there maining data were used as test set. Given that the datasets associated with the two problems under analysis were unbalanced, weights were assigned to each class. In addition, we used the balanced error rate (BER) as the metric to set the free parameters (C,γ) of the SVM by following a fivefold cross-validation strategy over the training set. The performance of the SVM detector was assessed using the ROC analysis in terms of SE, SP, AUC and of the positive predictivity (PP), the accuracy (ACC) and the BER calculated over the test set as

The performance of the SVM detector was assessed using the ROC analysis in terms of SE, SP, AUC and of the positive predictivity (PP), and the accuracy (AC) calculated over the test set as

$$PP = \frac{TP}{TP + FP} \qquad (11)$$

$$AC = \frac{TN + TN}{PC + NC} \qquad (12)$$

where PC = TP+FN and NC=TN+FP

Average value of the parameters extracted after calculation from all the three databases such as VFDB, CUDB, MITDB is shown in Table Average value of the parameters extracted after calculation from all the three databases such as VFDB, CUDB, MITDB is shown in Table I

TABLE I

ROC ANALYSIS FOR THE COMPUTED PARAMETERS USING THE COMPLETE DATASET

Parameters	**VFDB**	**CUDB**	**MITDB**	**Average values**
TCI	0.918	0.800	0.8294	0.8496
TCSC	0.842	0.818	0.7092	0.7901
STE	0.936	0.904	0.8248	0.8887
MEA	0.824	0.860	0.8613	0.8489
MAV	0.929	0.937	0.8772	0.9147
VFleak	0.862	0.937	0.8579	0.8861
M	0.949	0.913	0.8847	0.9156
A1	0.771	0.922	0.8765	0.8567
A2	0.815	0.801	0.9035	0.8400
MF	0.832	0.794	0.8527	0.8266
CM	0.838	0.871	0.8896	0.8665
PSR	0.837	0.850	0.9491	0.8790
HILB	0.906	0.902	0.9505	0.9198
SpEn	0.867	0.764	0.8027	0.8116

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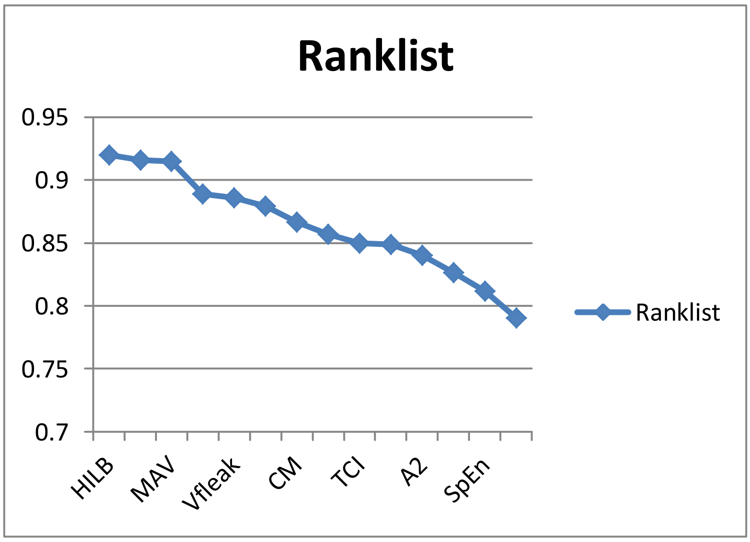
After calculating the average value of the parameters the next process is to rank it according to their values from the highest to the lowest. The rank list thus obtained after averaging is shown in Table II

TABLE II

RANK LIST OBTAINED AFTER AVERAGING

Rank	Parameters	Values
1	HILB	0.9198
2	M	0.9156
3	MAV	0.9147
4	STE	0.8887
5	VFleak	0.8861
6	PSR	0.8790
7	CM	0.8665
8	A1	0.8567
9	TCI	0.8496
10	MEA	0.8489
11	A2	0.8400
12	MF	0.8266
13	SpEn	0.8116
14	TCSC	0.7901

Graphical representation of the ranklist after averaging is shown in Figure



The final average value for Accuracy, Sensitivity and Specificity obtained from all the three databases are shown in Table III

TABLE III

AVERAGE VALUES OF ACCURACY, SENSITIVITY AND SPECIFICITY

Parameters	VFDB	CUDB	MITDB	Average
Accuracy	0.9366	0.9384	0.9336	**0.9362**
Sensitivity	0.8733	0.8769	0.8673	**0.8725**
Specificity	1	1	1	**1**

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VI. Summary And Conclusions

A. Summary

In this work, a SVM based machine learning approach technique is used by combining 14 different parameters that is extracted from ECG signal. ECG signal is collected from three different databases such as MITDB, VFDB, CUDB. These collected signals are first preprocessed and the required features are extracted from those ECG signal. Then these extracted ECG parameters are combined together and given as the input to the SVM classifier for discriminating the signal into VF vs NonVF and Shockable vs non shockable. Feature selection technique is performed along with SVM classifier to give a better accuracy, specificity and sensitivity values.

B. Conclusion

In this work, a Machine learning algorithm such as SUPPORT VECTOR MACHINE algorithm along with feature selection techniques are used in order to increase the accuracy in detecting and discriminating VF from nonVF. Instead of using single parameters to detect VF, the combination of parameters with SVM gives a better result. Feature selection technique performed along with SVM classifier gives a better accuracy, specificity and sensitivity values when compared to the results obtained only with SVM. Thus this work improves the detection efficiency of VF in patients by implementing it in automatic external defibrillators.

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