Improved recognition of sustained ventricular tachycardia from SAECG by support vector machine

Stanislaw Jankowski, Zbigniew Szymanski, Ewa Piatkowska-Janko**, Artur Oreziak****

From Institutes of Electronic Systems, *Computer Science and **Radioelectronics, Warsaw University of Technology, Warsaw
***Ist Department of Cardiology, Medical University of Warsaw, Warsaw, Poland

ABSTRACT

Objective: We present the improved method of recognition of sustained ventricular tachycardia (SVT) based on new filtering technique (FIR), extended signal-averaged electrocardiography (SAECG) description by 9 parameters and the application of support vector machine (SVM) classifier.

Methods: The dataset consisted of 376 patients (100 patients with sustained ventricular tachycardia after myocardial infarction (MI) labelled as class SVT+, 176 patients without sustained ventricular tachycardia after MI and 77 healthy persons, 50% of data were left for validation. The analysis of SAECG was performed by 2 types of filtration: low pass four-pole IIR Butterworth filter and FIR filter with Kaiser window. We calculated 3 commonly used SAECG parameters: hfQRS (ms), RMS40 (μV), LAS<40 μV(ms) and 6 new parameters: LAS<25 μV(ms) - duration of the low amplitude <25μV signals at the end of QRS complex; RMS QRS(μV) – root mean square voltage of the filtered QRS complex; pRMS(μV) - root mean square voltage of the first 40ms of filtered QRS complex; pLAS(ms) - duration of the low amplitude <40μV signals in front of QRS complex; RMS t1(μV) - root mean square voltage of the last 10ms the filtered QRS complex; RMS t2(μV) - root mean square voltage of the last 20ms the filtered QRS complex. For the recognition of SVT+ class patients we used the SVM with the Gaussian kernel.

Results: The results confirmed good generalization of obtained models. The recognition score (calculated as correct classification/total number of patients) of SVT+patients on data set containing 3 standard parameters (Butterworth filter) is 92.55%. The same score was obtained for data set containing 9 parameters (Butterworth filter). The best score (95.21%) was obtained for data set based on 9 parameters and FIR filter.

Conclusion: Our approach improved risk stratification up to 95% based on SAECG due to the application of FIR filter, 6 new parameters and efficient statistical classifier, the support vector machine. *(Anadolu Kardiyol Derg 2007: 7 Suppl 1; 112-5)*

Key words: ventricular tachycardia, signal-averaged electrocardiography

Introduction

Signal-averaged electrocardiography (SAECG) involves computerized analysis of segments of a standard surface electrocardiogram (1). It is used for detecting ventricular late potentials (VLP). Ventricular late potentials in patients with cardiac abnormalities, especially coronary artery disease or following an acute myocardial infarction (MI), are associated with an increased risk of ventricular tachyarrhythmias and sudden cardiac death.

The American College of Cardiology (ACC) (1) stated that signal-averaged electrocardiography (SAECG) had established value in the risk stratification of development of sustained ventricular arrhythmias (SVT) in patients recovering from MI who are in sinus rhythm without ECG evidence of bundle branch block or intraventricular conduction delay (QRS complex >120 ms). The ACC document (1) also stated that SAECG had value in identifying patients with ischemic heart disease and unexplained syncope who are likely to have inducible SVT (sVT+).

The Agency for Health Care Policy and Research (2) published a Health Technology Assessment of SAECG, concluding that clinical studies of SAECG consistently demonstrated a very high negative predictive value (76-100%), variable sensitivity (35-83%) and specificity (47-91%), and poor positive predictive value (8-48%) when performed in patients with cardiomyopathy or following MI. The high negative predictive value (NPV) may spuriously suggest the test's utility for identifying those patients who may not require antiarrhythmic therapy. It is more likely that the high NPV reflects the fact that sudden cardiac death, already relatively uncommon in the first year post-infarction, has continued to decline due to the use of beta-blockers, thrombolytic therapy and aspirin.

The objective of our study is the improvement of the recognition of patients after MI with risk of (SVT) by the application of: FIR filter, 6 new parameters and the efficient statistical classifier - support vector machine (SVM).

Methods

Our study is based on a data set performed at the Department of Cardiology, Medical University of Warsaw. The data set consists of 378 patients divided into three following groups upon the medical diagnosis:

- patients with sustained ventricular tachycardia (sVT+) after MI - 100 patients;
- patients without sustained ventricular tachycardia (sVT-) after MI - 199 patients;
- persons without cardiovascular diseases – 77 patients.

Address for Correspondence: Dr. Stanislaw Jankowski, Institute of Electronic Systems Warsaw University of Technology ul. Nowowiejska 15/19, 00-660 Warsaw, Poland
E-mail: sjank@ise.pw.edu.pl

Filtration

There are two methods of body-surface ECG signal-averaging: time-domain and frequency-domain. Time-domain averaging is a computer-driven sequential digital process based on the vector analysis of three orthogonal ECG leads (X, Y, and Z) that separates and extracts high-frequency late potentials from lower frequency ST segments by the use of directional filters, enabling filter output to correspond in time to signal input. The noise is reduced by electrically isolated amplifiers, shielded lead systems, and filters to reduce aberrant noise to <1 μV.

The signal-averaged ECG signals were recorded using a system with a sampling frequency of 1 kHz. Standard bipolar X, Y, Z leads were used. The time domain analysis of the signal-averaged ECG was performed using two type of filtration:

1. 40Hz high-pass and 250 Hz low pass four-pole IIR Butterworth filter (1, 3)
2. FIR filter with Kaiser window 45-150Hz (4).

A mean number of 150 beats were used for signal averaging, for achieving mean noise level 0,7μV. After filtering each lead, x(t), y(t), z(t), the resulting vector magnitude is calculated from the standard equation $(x^2 + y^2 + z^2)1/2$.

Time domain parameters

The QRS complex of the three bipolar leads were combined into vector magnitude (Fig. 1). For both types of filtration we calculated 3 commonly used SAECG parameters (5):

- hfQRS - the total duration of the filtered QRS complex;
- RMS40 -the root mean square (rms) voltage of the last 40 ms of the filtered QRS complex;
- LAS<40 μV - the duration of the low amplitude signals at the terminal portion of the QRS complex;

and 6 new parameters:

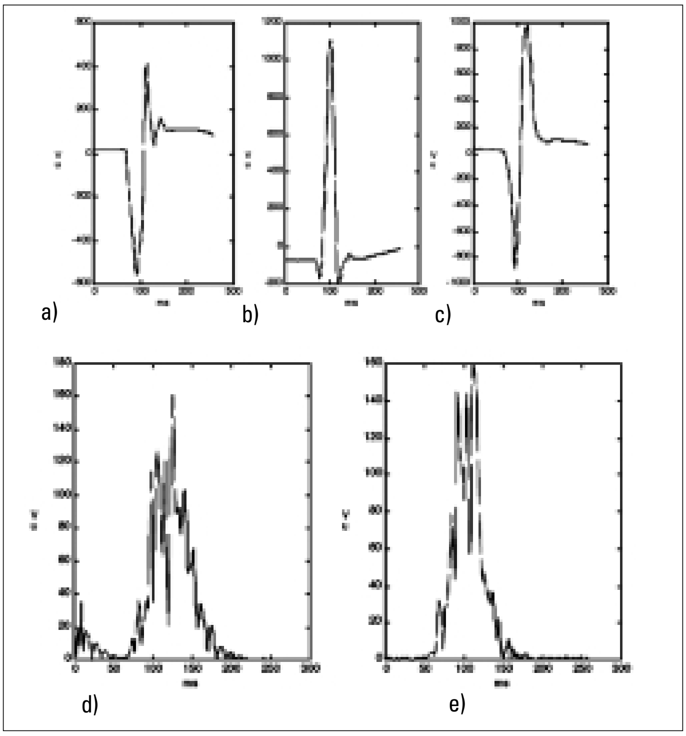

Figure 1. SAECG of a patient after MI with SVT+ : a) lead X, b) lead Y, c) lead Z and the vector magnitude obtained by d) four-pole IIR Butterworth filter; e) FIR filter with Kaiser window 45-150Hz.

MI- myocardial infarction, SAECG– signal-averaged electrocardiogram, SVT– sustained ventricular tachycardia

- LAS<25 μV(ms) – the duration of the low amplitude <25μV signals at the terminal portion of QRS complex;
- RMS QRS(μV) - rms voltage of the filtered QRS complex;
- pRMS(μV) - rms voltage of the first 40ms of filtered QRS complex;
- pLAS(ms) – the duration of the low amplitude <40μV signals in front of QRS complex;
- RMS t1(μV) - rms voltage of the last 10ms the filtered QRS complex;
- RMS t2(μV) - rms voltage of the last 20ms the filtered QRS complex.

Support vector machine classifier

Support vector machine (6-8) is a widely used large margin classifier with excellent generalization ability. The input of the classifier has the form of feature vector $x=(x_1,...,x_n)$ and its output is real-valued function f: $X \subset R^n \rightarrow R$. If $f(x) \geq 0$ the input x is assigned to the positive class and otherwise to the negative class. This is a supervised learning system that can find the separating surface between two classes of the training set. The basic notion of the SVM theory is the margin ρ – the distance of each data point from the decision boundary separating the two considered classes. In case of non-linear separating boundary the non-linear kernel functions can be applied due to specific properties of the support vector machines. We used the Gaussian kernel of width s.

$$k(\mathbf{x}_i,\mathbf{x}_j) = \exp\left(\|\mathbf{x}_i-\mathbf{x}_j\|^2 /(2\sigma^2)\right) \quad (1)$$

The optimal separating hypersurface realizes the maximal-minimum margin, hence the classification problem is formulated as a quadratic program. If the data belonging to the two classes are not separable, the soft-margin is introduced by defining some non-negative variables $\xi_i \geq 0$ (slack variables). A slack variable is greater than the margin for points that are misclassified. For the sake of clarity, we recall the basic notion of SVM classifier. The Lagrangian of the data set is equal

$$L(\mathbf{w},b,\xi,\alpha) = \frac{1}{2}(\mathbf{w}\cdot\mathbf{w}) + \frac{C}{2}\sum_{i=1}^{l}\xi_i^2 - \sum_{i=1}^{l}\alpha_i[y_i((\mathbf{w}_i\cdot\mathbf{x}_i)+b)-1+\xi_i] \quad (2)$$
$$0 \leq \alpha_i \leq C$$

where: w – weight vector determining the margin width, *b* – bias, *C*– regularisation term, ξ -slack variables, α- Lagrange multipliers, *l* – number of examples.

The results of SVM classification strongly depend on the choice of two hyperparameters *C* and σ.

The Lagrangian *L* has to be minimised with respect to the primal variables **w** and *b* and maximised with respect to the dual variables α_i - a saddle point has to be found.

The decision rule of classification is

$$h(\mathbf{x}) = \mathrm{sgn}(f(\mathbf{x})) = \mathrm{sgn}\left(\sum_{i=1}^{l} y_i\alpha_i k(\mathbf{x},\mathbf{x}_i)+b\right) \quad (3)$$

In this expression only these points are involved that lie closest to the hyperplane because corresponding Lagrange multipliers are non-zero. These points are called support vectors and lie exactly on the margin, i.e. at the distance *p* from the separating boundary. The support vectors at *C*, i.e. whose Lagrange multipliers are equal, lie inside the margin. The value of *C* determines the trade-off between the margin width and the number of classification errors.

The fact that only a subset of the Lagrange multipliers is non-zero is referred to as sparseness and means that support vectors contain all the information necessary to construct the optimal separating hypersurface. The fewer number of support vectors the better generalisation can be expected.

The SVM classifiers were successfully applied to other recognition tasks in cardiology (9, 10).

Results

During the study the three data sets were used comprising:

- 3 standard parameters (hfQRS, RMS40, LAS<40) – calculated from signal filtered by 40Hz high-pass and 250 Hz low pass four-pole IIR Butterworth filter,
- 9 parameters (3 standard parameters and LAS<25, RMS QRS, pRMS, pLAS, RMS t1, RMS t2) – calculated from signal filtered by 40Hz high-pass and 250 Hz low pass four-pole IIR Butterworth filter,
- 9 parameters (3 standard parameters and LAS<25, RMS QRS, pRMS, pLAS, RMS t1, RMS t2) – calculated from signal filtered by FIR filter with Kaiser window 45-150Hz

Each data set consists of three classes: SVT+, SVT- and normal. For every data set three independent SVM classifiers were prepared, which recognized examples from different classes. Overall, 50% of the data were left out (test data) for validation of obtained models. Table 1 presents classification results of those test data sets. In order to validate the classifier false positive (FP), false negative (FN) and true positive (TP) parameters were calculated.

The data set was divided into 2 subsets:

a) training set of 188 patients (50 of group I, 100 of group 2 and 38 of group 3);

b) test set of 188 patients (50 of group 1, 99 of group 2 and 39 of group 3).

In our approach we performed a set of one-against-all SVM classifiers.

The results confirmed good generalization of obtained models. The recognition score (calculated as correct classification/total number of patients) of SVT+ patients on data set containing 3 standard parameters (Butterworth filter) is 92.55%. The same score was obtained for data set containing 9 parameters (Butterworth filter). The best score (95.21%) was obtained for data set based on 9 parameters and FIR filter. Table 2 contains the number of support vectors the model is based on. The number of support vectors is a good indicator of the complexity of the model. High SV count usually means the separating hypersurface has complex shape. High number of support vectors at C indicates the classes are difficult to separate because they overlap each other.

The same score for data sets consisting of 3 and 9 parameters suggests not all parameters used for sVT+ classification are significant and further study is needed.

Only 76 patients from the first group (patients with SVT after MI) fulfilled the common criteria of the late potential existence.

Discussion

We describe the classification method applied for better stratification of patients with high risk of ventricular tachyarrhythmias. Our results showed that by using SVM classifier we can correctly classify more than 92% patients with SVT+ even for commonly used type of filtration and three parameters.

For FIR filtration and 9 parameters we can properly classify more than 95%, as compared to 75% score based on 3 critical values of the conventional parameters (1).

This result suggests that the classification method can improve risk stratification based on SAECG. The application of statistical learning systems for classification yields the flexible recognition systems that can adapt to the specific clinical conditions, as hardware and software as well as environmental conditions that affect local population susceptibility to cardiac diseases.

The presented method can be also applied to other cardiologic problems, as e.g. for a group of patients with bundle branch block or for prediction of serious ventricular arrhythmias in hypertensive patients with different forms of the left ventricular geometry (11).

Sudden cardiac death is a significant problem, especially in patients after the MI. Only one-third of patients dying suddenly can be identified prior to the event. Properly recognition of the high-risk patients can save them life. The SAECG is one of the non-invasive tests, which can be use to the risk stratification in patients who suffered myocardial damage. To make the most of this method we suggest the increase the number of ventricular SAECG parameters to better evaluation pro-arrhythmic substrate. In our opinion the new parameters and other digital filters used to filtration of ventricular SAECG are more efficient than the conventional criteria of VLP in prediction of SVT. This is particularly important in view of the fact that high-risk patients with sustained tachyarrhythmias can be saved by implantable cardioverter defibrillator implantation.

Table 1. Classification results of the test data set

	3 parameters Butterworth				9 parameters Butterworth				9 parameters FIR			
Class	FP	FN	TP	Score, %	FP	FN	TP	Score, %	FP	FN	TP	Score, %
SVT+	8	6	174	92.55	2	5	174	92.55	2	7	179	95.21
SVT-	33	15	140	74.47	13	17	154	81.91	13	5	170	90.43
Normal	5	30	153	81.38	3	6	172	91.49	3	10	175	93.09

FN- false negative, FP- false positive, SVT- sustained ventricular tachycardia, TP- true positive

Table 2. Number of support vectors in SVM models

Class	No. of examples	3 parameters Butterworth		9 parameters Butterworth		9 parameters FIR	
		SV	SV at C	SV	SVs at C	SV	SVs at C
SVT+	50	24	14	28	8	28	8
SVT-	100	89	81	67	43	67	43
Normal	38	67	57	48	32	48	32

C- regularisation term, SV- support vector, SVM- support vector machine, SVT- sustained ventricular tachycardia

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