Predicting Transthoracic Defibrillation Shocks Outcome in the Cardioversion of Atrial Fibrillation Employing Support Vector Machines

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Abstract

In this work, we use support vector machines (SVM) to predict if a defibrillation shock is likely to be successful or not in the cardioversion of persistent AF patients. The ECG signals of 47 patients elected for electrical cardioversion treatment were collected at the Royal Victoria Hospital in Belfast city, NI-UK.

Signal processing was performed on ECG segments prior each shock. Three electrocardiographic indexes were extracted and used as input: the dominant atrial fibrillatory frequency, the mean and the standard deviation of the R-R interval time series of the ECG segments. We trained SVM using about 40% of the data.

SVM could predict the outcome of 89% of low-energy shocks $\leq$ 100 [J], with a sensitivity (SE) of 87.50% and specificity (SP) of 98.8%. As a remarkable result, the outcome of higher energy shocks ($\geq$ 150 [J]) could be predicted with 100% exactitude.

1. Introduction

Atrial Fibrillation (AF) is the most common cardiac arrhythmia, affecting 1% of the world population [1], with a prevalence of approximately 5.5% in people more than 55 year of age [2].

Transthoracic cardioversion is a common therapy for restoring sinus rhythm in patients with this arrhythmia. A high effectiveness (between 88 and 99%) has been reported for this technique [3]. However, patients could receive between one and four defibrillation shocks before reversing AF back to sinus rhythm, and in some cases, some patients may not revert to sinus rhythm despite using high energy shocks. Then, to predict in whom and when a shock will be success represents a challenge.

The success of electric cardioversion (ECV) depends on a number of factors, including the duration of the arrhythmia, the transthoracic impedance, the employed waveform and the position of the pads. The surface electrocardiogram (ECG) analysis has shown to be a useful non-invasive tool to predict the success of an electrical cardioversion [4, 5].

ECG digital signal processing like the combination of machine learning techniques, as neural networks and support vector machines (SVM), have been used in the prediction of spontaneous termination of paroxysmal atrial fibrillation [6-8], and the success of electric shocks in the intracardiac low energy cardioversion of patients with atrial fibrillation. We hypothesize that SVM could be an useful tool in a similar way, predicting in this case, the success or not of the transthoracic shocks for the cardioversion of atrial fibrillation.

The objective of this work is to evaluate a non invasive predictor based on SVM for electric shock outcomes in the ECV of AF before it is attempted.

2. Methods

2.1. Study population

ECG analysis was performed on ECG segments of 47 patients with a history of persistent AF, referred for ECV at the Royal Victoria Hospital, in Belfast, UK. All patients were fully anticoagulated as per AHA/ACC guidelines and baseline characteristics were recorded (Table 1). These characteristics reflect current clinical practice with a mean age of 66 years and a considerable number of patients having undergone a previous electrical cardioversion.

2.2. Defibrillation protocol

All cardioversions were carried out using the Heartstream XL (Philips Medical Systems). This uses an impedance compensated biphasic waveform. Pads were positioned in the right infraclavicular and left apical position. Defibrillation was carried out using an incremental energy protocol (100J, 150J, 200J, 200J). In very thin or small structured patients (very low basal metabolic index), defibrillation protocol began with a shock energy below 100J (50J minimum), followed by a 100J, then increments of 50J until a maximum of 4 shocks. Success was defined as the restoration of sinus rhythm for a minimum period of 30 seconds.

Table 1. Patients clinical characteristics.

Characteristics	Total
Age	66 ± 12
Male	35 (68%)
Hypertension	21 (41%)
Coronary Artery Disease	37 (72%)
Left Atrial Enlargement (> 47 mm)	20 (39%)
Pacemakers	7 (13%)
Implantable Defibrillator	1 (2%)
Previous Antiarrhythmia Agents	45 (88%)
Previous Cardioversion	11 (21%)

2.3. ECG recording and signal preprocessing

The ECG signal (lead II), was recorded continuously from the analog output of a Siemens SC7000 monitor. Digitization was carried out at a sample frequency of 1 KHz and 16 bits resolution. Recordings were performed during ECV procedure for a mean duration of 14 minutes and 49 seconds, including at least 60 seconds of ECG prior to the first shock and 4 minutes after the last one.

Three electrocardiographic indexes were extracted: the dominant atrial fibrillatory frequency (DAFF), and the mean and the standard deviation of the R-R interval time series of the ECG segments (RR_MN and RR_SD respectively).

ECG analysis was performed using Matlab® version 6.5 (The Mathworks Ins., Natick, MA, USA). Signal processing was performed on ECG segments (between 55 and 60 s) prior each shock. In order to reduce signal wandering due to respiratory activity and high frequency noise, a bidirectional filter (zero phase), order 100, with pass band 0.5Hz-50Hz was used.

Following this, atrial activity extraction from the ECG signal was performed. The signal was first upsampled at 1024 Hz, to obtain a better definition. Once QRS detection was carried out, there was a chosen time period with a fixed numbered of data samples before and after the fiducial point, thus capturing the QRST complex. Thereafter the AF reduction process was performed [9].

The QRST complexes were classified according to their morphology, applying a cross correlation technique between an individual beat (QRST complex) and the average of all the complexes. Averaging takes place with beats of a same class. The adopted technique was very similar to that used by Cantini and Coworkers [10], but instead of cross correlation technique for the QRST complexes classification and subtraction, they employed what they called a L1 distance with wiggling and vertical shifting.

A template was created with the QRST segments averaged, and the transitions between successive QRST complexes were filled with the mean of corresponding intervals of the original signal. With the template signal, the QRST complexes were cancelled employing a recursive least square adaptive filter (filter order 5, memory factor λ=0,99) to produce a residual atrial activity signal (RAAS). The method described by Haykin [11], for the weight adaptation of the RLS filter, was employed.

Figure 1 shows a block diagram of the process employed for the extraction of the residual atrial activity signal (RAAS).

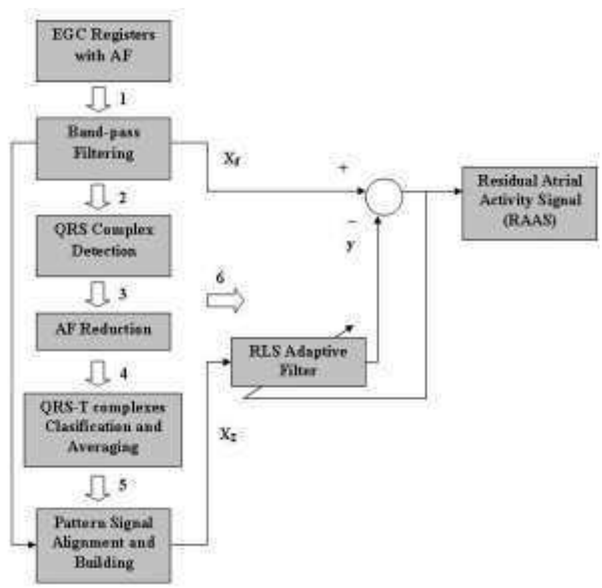

Figure 1. Block diagram of the QRS-T cancellation process

2.4. Spectral analysis

RAAS was down-sampled to 256 Hz. The power spectrum of the residual signal was calculated by 4096 points windowed FFT, 1024 points Gaussian window and 768 points overlap. The DAFF was estimated as the frequency component with maximum power amplitude within the 3.5-10 Hz band.

Spectral analysis of the atrial activity has been shown to have temporal variability [12]. Frequency analysis was carried out over whole segments (DAFF_L) and over 10 seconds segments (DAFF_S) of the RAAS immediately before electric discharges, for computing the dominant atrial fibrillatory frequency.

2.5. Classification and statistical analysis

Those shocks which reverted AF to sinus rhythm were considered as positive shocks, and the others failed in revert AF, as negative shocks.

A radial basis function, support vector machine was employed for the classification problem. SVMs were trained using learning sets, formed by combination of the computed variables from a half of records previous to positive shocks and a quarter of those negative ones. Multiples learning sets were randomly formed. The rest of the data represented the test set.

SVMs with high classification exactitude in the training phase were chosen for evaluating with the corresponding test set.

The SVMs were implemented using libraries designed by the Taiwan University [13]. Equation 1 represents the radial basis function employed for the SVM implementation.

$$e^{\left(-\varphi|U-V|^2\right)} \quad (1)$$

In the equation 1, U and V represent the vectors of variables, and φ is an arbitrary coefficient for setting the SVM. We adjusted φ=1 for building the SVMs.

Sensitivity (SE), specificity (SP), and positive predictive value (PPV) were computed for the predictive models of the built support vector machines.

3. Results

Electric cardioversion was successful in 41 (87%) and unsuccessful in 6 patients (13%). A total of 107 shocks were delivered to the 41 successful cases. Only 2 patients could be cardioverted with a shock less than 100 [J] (one of them with 50 [J], and the other with 70 [J]). Cumulative number and percentage of patients according to energy level are shown in table 2.

Table 2. Cardioverted patients accumulative percentage.

Energy level	% of patients
< 100 [J]	4 % (2/47)
≤100 [J]	53 % (25/47)
≤150 [J]	85 % (40/47)
≤200 [J]	87 % (41/47)

Employing the data of the shocks ≤100 [J], it was possible to predict the outcome of these shocks with 83% of exactitude, when the SVM were trained using the variables: RR_MN, RR_SD and DAFF_S. A better performance (89% of exactitude) was obtained when the variables RR_MN, RR_SD and DAFF_L were used for training the SVM.

A 100 % of the shocks of energy ≤150 [J] were correctly predicted using RR_MN, RR_SD and DAFF_L in the training of the SVM. Other combinations of the variables did not improve the performance of the SVM in the classification of the shocks. Table 3 presents a summary of the best prediction results obtained for the built support vector machines, for shocks ≤100 and ≤150 [J]. Sensitivity, specificity and positive predictive value about the prediction, are also show in table 3.

Table 3. Performance of the SVM for different combinations of the variables used in the training. Exactitude (EX), SE, SP, and PPV are presented in %.

Variables for SVM training	EX	SE	SP	PPV
Shocks ≤100 [J] (N=73)				
RR_MN, RR_SD, DAFF_S	83.56	91.67	79.59	68.75
RR_MN, RR_SD, DAFF_L	89.04	87.50	89.80	80.77
Shocks ≥150 [J] (N=34)				
RR_MN, RR_SD, DAFF_S	85.29	85.71	85.00	80.00
RR_MN, RR_SD, DAFF_L	100	100	100	100

4. Discussions and conclusions

In this study, we analyzed the ECG signal to assess the power of SVM in the prediction of successful external defibrillation shocks. RR_MN, RR_SD, and DAFF_L variables resulted in the best classification power for shocks ≥ 150 J. Longer ECG segments (> 10 s) analysis improve SVM classification power, probably because a better frequency resolution for DAFF_L. Despite a serious limitation using just one lead (DII) and the errors associated to average beat subtraction method (heart axis variation), SVM were able to predict shock success with excellent results mainly for shocks ≥ 150 J including DAFF_L in the analysis; we could speculate here that our limitation in the number of analysed patients (N = 47) made possible such a success classification for shocks ≥ 150 J (N = 34), and that a consideration of a greater test group probably will result in a reasonably but not perfect classification and a better discrimination between energy levels, in a way that a patient could, not only be classified for cardioversion but also recommended for an specific energy level, avoiding unnecessary shocks.

SVM´s can be used with remarkable success for ECV shocks outcome prediction, efforts should be directed to weight variables information contribution, extended data sets, and software development for clinical use.

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