Nonlinear energy operators for defibrillation Shock Outcome Prediction

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Abstract

Accurate prediction of shock success would avoid futile defibrillation attempts that may damage the myocardium, and would help optimizing treatment decisions for out-of-hospital cardiac arrest (OHCA) patients. This work applies the Smoothed Nonlinear Energy Operator (SNEO) to analyze the energy content of the pre-shock ventricular fibrillation (VF) waveform adquired by automated external defibrillators (AED).

A database of 419 shocks was analyzed and shock outcome predictors were calculated in the a 5-s pre-shock ECG segment. The SNEO was compared to some classical VF features. For each feature a detector of successful shocks was designed minimizing the Balanced Error Rate (BER). Finally, using SNEO as shock outcome predictor the minimun pre-shock segment duration was determined. The SNEO has proven to be a good shock outcome predictor even for 2-s segments and it could be used to optimize treatment decisions for OHCA patients.

1. Introduction

In sudden cardiac arrest (SCA) two early interventions are key for the survival of the patients, early defibrillation and early cardiopulmonary resuscitation (CPR). Useless interruptions or ineffective chest compressions (CC) during CPR, in addition to delays in CPR or in the access to the automated external defibrillator (AED) may adversely affect patients' survival. The survival rate also decreases with every futile defibrillation attemp due to damage to the myocardium produced by shocks. Consequently an accurate prediction of optimal therapy, defibrillation or continuation of CPR, is of mayor relevance.

Predicting defibrillation success, i.e the development of accurate shock outcome predictors, would help optimizing timing of defibrillaion. A noninvasive approach to shock outcome prediction is ECG analysis of the VF waveform, through which many predictors/features have been developed over the years [1–3].

In this work, we present the Smoothed Nonlinear Energy Operator (SNEO) [4] as a shock outcome predictor. SNEO is based on the analysis of the local energy content of the VF-waveform and in this work we also compare it to other classical shock outcome prediction features. After that, we determine the minimun ECG pre-shock segment duration for an accurate shock outcome prediction using SNEO.

2. Methods

2.1. Data collection and annotation

A dataset of 1009 out of hospital cardiac arrest (OHCA) cases was used for this study. The OHCA patients were treated by the basic life Support (BLS) services of the Basque Health Service (Osakidetza) between January 2013 and June 2015. The Emergency service of the Basque Autonomous Community is a two-tier system, where BLS is the first at scene and the patients were treated with automated external defibrillators (AED). Data from the following AEDs were collected: LifePack 1000 (Physio-Control, Redmond, WA, USA), ZOLL AED PRO (ZOLL Medical, Chelmsford, MA, US) and Philips Medical Systems Heartstart FR2 (Philips Medical Systems, Andover, MA). The ECG resolution and sampling frequencies of the devices were: 4.8/4.8/2.5 μV and 125/250/200 Hz, respectively. The ECG data was recorded in the three AEDs, but only using LifePack 1000 the thoracic impedance (TI) was recorded. Using the manufacturer's custom tools all data and the messages from the devices were exported to a common MATLAB format. The signals were resampled to a common sampling rate of 250 Hz. Shocks were identified using the messages from the AEDs, and a 30-s pre-shock ECG interval for analysis, and a 70-s post-shock interval to annotate the outcome were extracted. Shocks were considered successful if sustained QRS complexes (rate$>$ $30\,\mathrm{min}^{-1}$) appeared within one minute. Cases where there was no ECG signal, it was corrupted by CC-artefacts

or any other noise, or the rhythm annotation was not possible were removed. The 5-s preshock VF segments 1-s prior the defibrillation were extracted. The final dataset contained a total of 419 shocks from 163 patients, 107 of which (65 patients) were successful and 312 (125 patients) unsuccessful.

2.2. Shock outcome predictors

The segments of the database were preprocessed using a 4th-order bandpass elliptic filter with 1 dB of passband ripple, 30 dB of stopband attenuation and a typical AED passband of 0.5-30 Hz. The filter suppressed high frequency noise and baseline oscillations. The non-linear Teager-Kaiser Energy Operator (TKEO) [5,6] was applied to the ECG segments. TKEO ($\psi_k[x(n)]$) is expressed in the discrete domain as the Equation (1), where the constant k is the lag parameter and $x(n)$ is the VF-segment:

$$\psi_k[x(n)] = x^2(n) - x[n-k]x[n+k] \tag{1}$$

Then TKEO was convolved with a Kaiser window, to obtain the Smoothed Nonlinear Energy Operator (SNEO):

$$\psi_{S,L}[x(n)] = \psi_k[x(n)] \otimes w_L(n) \tag{2}$$

were $\otimes$ denotes convolution and $w_L(n)$ represents the smoothing Kaiser window of length $L + 1$. The Kaiser window is defined by:

$$w[n] = \frac{I_0\left(\beta \cdot \sqrt{1 - (2n/L - 1)^2}\right)}{I_0(\beta)} \tag{3}$$

where I_0 is the zero order modified Bessel function. In SNEO, the window length is associated to the lag parameter by $L = 4k + 1$.

The parameter β of the kaiser window can be adjusted to approximate the most common windowing functions [7], as shown in Table 1.

SNEO was computed also for different sampling frequencies: 250, 125, 85, 62 and 50 Hz. Therefore SNEO depends on the k, β and f_s. Finally the shock outcome predictor based on SNEO was obtained by computing SNEO's median value, as it is customarily done for the amplitude or slope [2].

To benchmark the performance of the new predictor several classial predictors were computed: average Peak-to-Peak amplitude (PPA) in the time domain [2, 8], Median Slope (MdS) in the slope domain, Amplitude Spectrum Analysis (AMSA) [1, 9] and Power Spectrum Analysis (PSA) in the spectral domain. To compute the spectral features, a hamming window and a 2048-point FFT were applied.

Type of window	β
Rectangular	0
Barlett	1.33
Hanning	3.86
Hamming	4.86
Blackman	7.04

Table 1. Values of β and window equivalences
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2.3. Data Analysis

The optimization of the SNEO predictor was performed minimizing the Balanced Error Rate (BER) defined as:

$$\text{BER} = 1 - \tfrac{1}{2} \cdot (\text{Se} + \text{Sp}) \tag{4}$$

where sensitivity, Se, was defined as the percentage of successful shocks correctly classified, and specificity, Sp, the unsuccessful shocks correctly classified.

The optimal working point was determined using a Leave one patient out cross validation (LOPCV) scheme for each feature. Results for every predictor were given in terms of Se, Sp, BER, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and the Area Under the Curve (AUC), from the Receiving Operating Curve (ROC), analysis.

3. Results

3.1. Optimization of SNEO

To find the optimum working point the SNEO was computed for $k = 1$ up to 15, for $f_s = 250, 125, 85, 62$ and 50 Hz, and for $\beta = 0$ up to 12, increasing β in 0.1. Figure 1 summarizes the results obtained for this simulation for a value of $\beta = 1.33$. As shown in the figure reducing f_s and L (or k) yields similar results, i.e. a lag of 8 for $f_s = 250$ Hz is equivalent to a lag of 4 for $f_s = 125$ Hz.

Figure 2 shows the effect of the shape of the window (β). For each β the BER plotted corresponds to the optimal value of k. As shown in the figure differences in BER are small so the choice of window does not affect the accuracy of the feature, and sampling frequencies should be kept above 80 Hz. Figure 3 shows the effect of k in terms of the mean BER (averaged over all values of β), for $f_s = 250$ Hz. The optimal lag was $k = 8$ for this sampling frequency, but reducing f_s should be accompanied by a proportional reduction of k. To analyze the effect of the window shape the analysis of Figure 3 was replicated for different shapes of the window, as shown in Figure 4. Optimal values of β were around 9, which confirm the results shown in Figure 2.

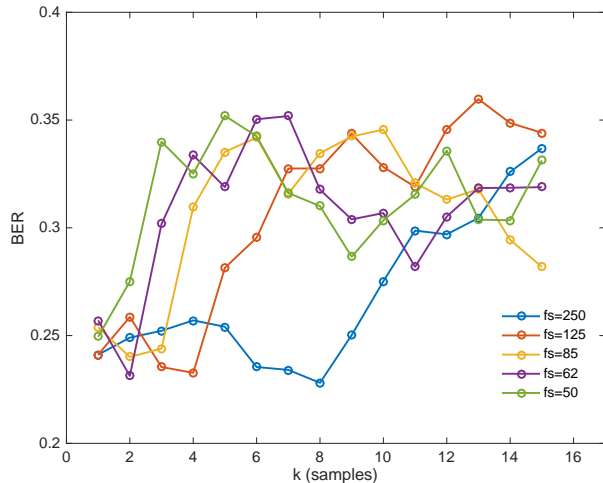Finally we explored the possibilty of reducing the analysis segment, as shown in Figure 5. The values were

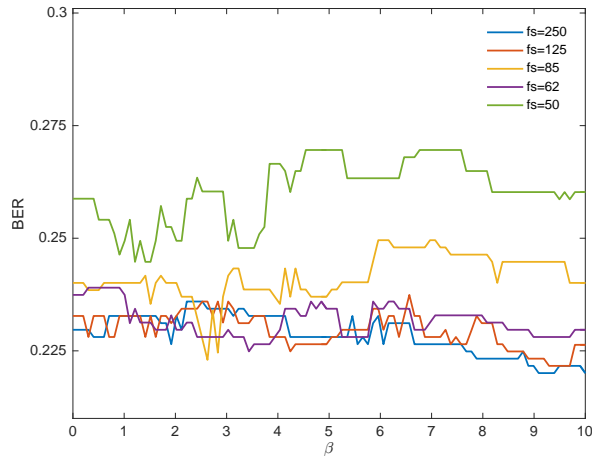Figure 1. BER for the different sampling frequencies in function of k, with $\beta = 1.33$.

Figure 2. BER in terms of β. The BER is the minimum value obtained for each β (so k may differ for each point).

Figure 3. Mean values of BER for every k considering $f_s = 250Hz$ averaged for $\beta = 0 : 12$.
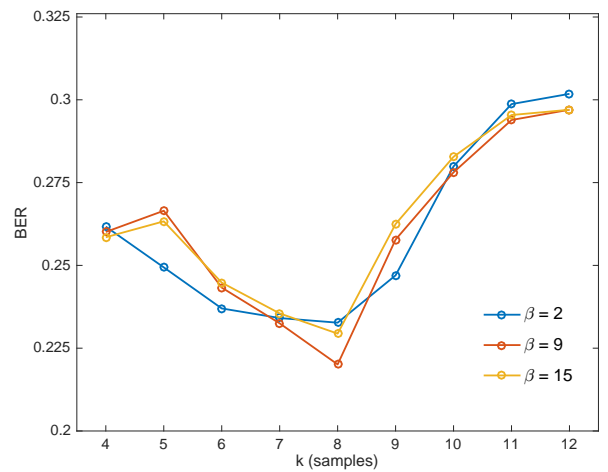
Figure 4. BER curves in function of k and β

Figure 5. BER, Se and Sp in function of the segment duration.

obtained for $f_s = 250$ Hz, $\beta = 9$ and $k = 8$, and they show that segment lengths as short as 2-s can be used without significant losses in accuracy.

3.2. Comparison with classical predictors

We compared the AUC for our new classifier (optimal working point) with the classical predictors as described in literature [3]. Results are shown in Table 2 and in Table 3.

The SNEO showed the best results with a BER of 0.22, Se of 81.3% and Sp of 74.7% as shown in Table 3. These results correspond to the best results obtained with $k = 8$, $\beta = 9$ and $fs = 250Hz$, as shown in Figure 4.
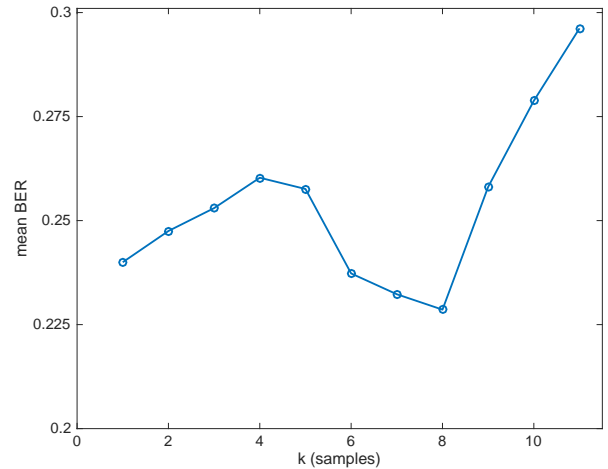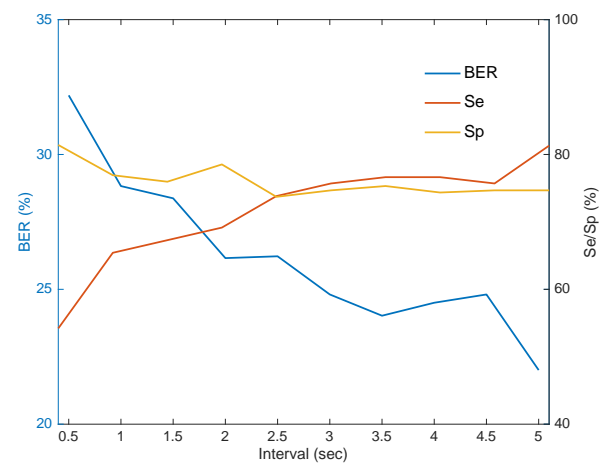
Feature	Se (Sp=90)	Sp (Se=90)	AUC
PPA	42.1	53.5	0.814
MdS	49.5	55.4	0.826
AMSA	53.3	53.2	0.814
PSA	43.9	52.6	0.816
SNEO	37.4	55.1	0.808

Table 2. ROC analysis of the shock outcome prediction features, using 5-s segments, in terms of Se, Sp and AUC

Feature	Se	Sp	PPV	NPV	BER
PPA	78.5	72.8	49.7	90.8	0.244
MdS	75.7	75.3	51.3	90.0	0.245
AMSA	71.0	76.9	51.4	88.6	0.260
PSA	73.8	74.4	49.7	89.2	0.259
SNEO	81.3	74.7	52.4	92.1	0.220

Table 3. Analysis of optimal working point of the shock outcome prediction features using 5-s segments in terms of Se, Sp, PPV, NPV and BER

4. Conclusions

We introduced the SNEO as a new shock outcome predictor and we have compared its results with four classical VF-waveform features. We have used a database of 419 shocks extracted from OHCA cases treated by the BLS services. The SNEO with $fs = 250Hz$, $k = 8$ and $\beta = 9$ showed the lowest BER. In addition, for segments as short as 2-s SNEO showed similar Se and Sp values. We conclude that the SNEO could be useful to optimize treatment decisions for OHCA patients.

Acknowledgements

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