

# Sample Entropy as a Shock Outcome Predictor during Basis Life Support

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## Abstract

*Optimizing defibrillation times may improve survival from ventricular fibrillation (VF) cardiac arrest. VF waveform analysis is one of the best non-invasive decision tools for shock outcome prediction. This study introduces a VF-waveform feature based on the computation of the sample entropy (SmpEnt) for shock outcome prediction.*

*A database of 255 shocks were analyzed, using a 5 s preshock ECG segment. 14 classical VF waveform features measuring amplitude, slope, complexity and spectral characteristics were computed in addition to SmpEnt. An optimal detector of successful shocks was designed for each feature minimizing the Balanced Error Rate. Finally, the minimum preshock segment duration assuring an accurate shock outcome prediction was determined for SmpEnt.*

*SmpEnt is an improved shock outcome predictor, even for VF-segments as short as 1.5-s, and it could be used as a decision support tool to guide optimal timing for defibrillation.*

## 1. Introduction

Many factors contribute to poor outcomes from cardiac arrest including delays in cardiopulmonary resuscitation (CPR), frequently interrupted or ineffective chest compressions (CC), and delayed access to electrical defibrillation [1]. Unnecessary CC interruptions adversely affect to the probabilities of survival of the patient [2]. Repetitive and futile defibrillation shocks decrease the chances of survival because shocks may produce myocardial damage [3]. Consequently, the decision of whether to defibrillate or continue with CCs may be critical for the survival of the patient. Ideally, the patient would only be shocked when defibrillation has a good prognosis, and this involves the development of tools for shock outcome prediction.

Among all non-invasive decision guides, ECG analysis of the ventricular fibrillation (VF) waveform might be one of the best ways to decide whether or not to interrupt CCs

to deliver a defibrillation shock [4]. Over the years many VF-waveform features [5,6] and decision algorithms based on the features [7] have been introduced for shock outcome prediction. Authors have proposed features based on the time-domain, slope and spectral analyses of the ECG, and on complexity measures of the VF-waveform [8].

In this study we introduce a new shock outcome predictor based on the sample entropy (SmpEnt) analysis of the VF-waveform, and we compare it to previously presented features. We then analyze the minimum ECG segment duration needed for an accurate prediction based on SmpEnt. The analysis is based on data obtained from out-of hospital cardiac arrest (OHCA) patients treated by the Basic Life Support (BLS) services of the Basque Health Service, Osakidetza.

## 2. Methods

### 2.1. Data collection and annotation

Data were collected from 511 patients who suffered OHCA in the Basque Autonomous Community between January 2013 and December 2014. The Basque Emergency Service is a two-tier system and data corresponded to patients in which BLS was first at scene, and therefore the patients were connected to automated external defibrillators (AED). The ECG and thoracic impedance (TI) data was recorded using Lifepack 500/1000 defibrillators (Physio-Control, Redmond, WA, USA) with resolutions and sampling frequencies of 4.8  $\mu$ V/0.81 m $\Omega$  and 125/60 Hz, respectively. ECG and TI data, defibrillator messages and CC-instant information data was converted to an open matlab format using PhysioControl's LIFENET research tool and all signals were resampled to a common 250 Hz sampling frequency.

Shocks were automatically identified using the messages from the defibrillator, and 100 s records of the ECG/TI signals were extracted with 30 s preshock for VF waveform analysis and 70 s postshock to analyze the outcome. The TI signal was used to identify intervals during CCs in which the waveform cannot be analyzed or the resulting rhythm cannot be accurately determined. Successful shocks were

those that restored an ECG with sustained QRS complexes and a minimum rate of 30 bpm within the post-shock interval [4]. Figure 1 shows examples of (un)-successful shocks.

From the 511 patients analyzed only 143 presented shockable rhythms, and a total of 411 shocks were delivered. In some cases the resulting rhythm was impossible to annotate (end of record), there was noise before defibrillation, shocks were inappropriate, or the analysis was conducted during CCs. These shocks were discarded leaving a total of 255 shocks from 92 patients for analysis, 65 (43 patients) were successful and 190 (67) unsuccessful.

## 2.2. Shock outcome predictors

ECG shock outcome predictors were computed using a 5-s ECG segment ending 1-s before the shock annotation. The ECG signal was preprocessed using an order 4 bandpass elliptic filter with 1/30 dB passband/stopband ripple, and a typical AED bandwidth of 0.5-30 Hz. A backward-forward filtering scheme was used to avoid phase distortion, and the filter eliminated base line distortion and high frequency noise while preserving all the VF spectral components. The preprocessed segments were used to compute the following VF-waveform features grouped by analysis domains (see [5, 6] for a detailed mathematical description of the features):

- **Time Domain.** The features computed were: Amplitude Range (AR), average peak-to-peak amplitude (PPA) and Mean Amplitude (MA).
- **Slope domain.** The slope was defined as the first difference of the preprocessed ECG, and the following features were computed: Mean Slope (MS) and the Median Slope (Mds).

- **Spectral Domain.** A Hamming window was applied and a 2048-point FFT of the ECG segment was computed, spectral amplitude was defined as the modulus of the FFT and the power spectral amplitude as the square of the modulus. The computed features included: Amplitude Spectrum Analysis (AMSA), Peak Frequency (PF), Centroid Frequency (CF), Energy (ENRG), Max Power (MP), Centroid Power (CP) and Power Spectrum Analysis (PSA).
- **Complexity Domain.** Two measures of complexity were computed: Spectral Flatness Measure (SFM) and Spectral Entropy (SpecEnt).

In addition SmpEnt is introduced as a shock outcome predictor. SmpEnt is a useful tool to analyze the regularity and complexity of a time series, in our case of the VF waveform [9]. The basic hypothesis is that a VF with more complex rhythm dynamics corresponds earlier phases of VF and a better state of myocardial tissue, and should therefore be more amenable to electrical defibrillation. Sample Entropy is the negative logarithm of the conditional probability that two sequences similar for  $m$  points remain similar for  $m + 1$  points, excluding self-matches. To compute SmpEnt the ECG was downsampled by a factor of 4 ( $f_s = 62.5$  Hz),  $m = 3$  and the tolerance for matches was set to  $r = 0.2 \cdot std$ , with a minimum value of  $r = 0.05$ . The minimum value of  $r$  avoids confusing high frequency noise with VF spectral components in very low amplitude VF.

## 2.3. Data analysis

Shock outcome prediction was first evaluated in terms of sensitivity (Se) and specificity (Sp), defined as the proportion of correctly identified successful and unsuccessful shocks, respectively. A receiver operating

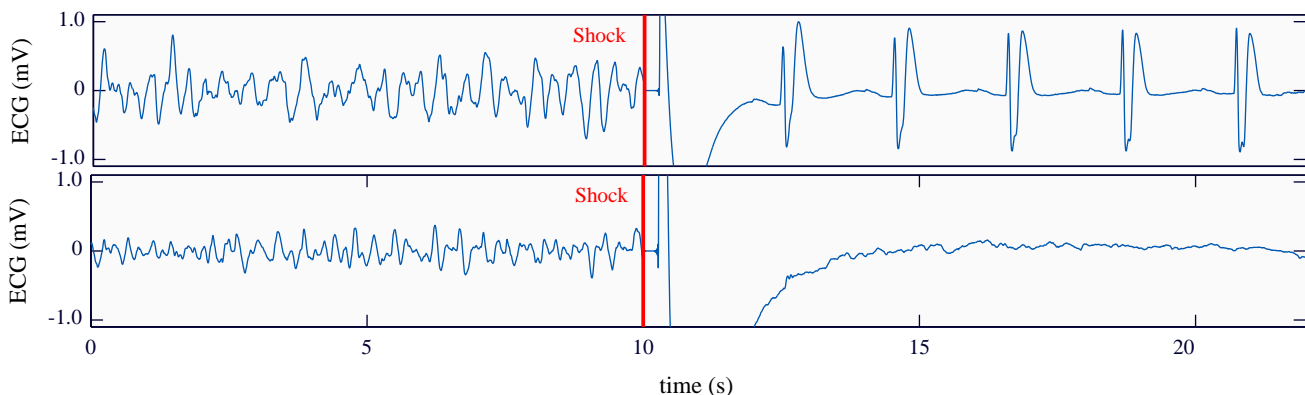


Figure 1. Examples of ECG signals corresponding to successful (top) and unsuccessful (bottom) shocks. In the first example the VF waveform presents a higher fibrillation frequency and larger amplitude, and QRS complexes appear immediately after the shock. In the second case, VF frequency and amplitude are lower, and the shock results in the lack of electrical activity (asystole).

characteristics (ROC) analysis was conducted, and the area under the curve (AUC) was determined as a global measure of the features' discriminative power. Two cut-off points were defined, the Se for a 90% Sp and the Sp for a 90% Se. In all analyses the successful/unsuccessful samples from each patient were weighted, so all patients within a group contributed in the same way to the analysis.

Then a single feature support vector machine (SVM) classifier was fitted to determine the optimal working point for each feature. The performance for the optimal working point was estimated using a leave one patient out cross validation (LOPCV) scheme. Optimal classifiers were determined in each fold by minimizing the Balanced Error Rate (BER), defined as:

$$BER = 1 - \frac{1}{2} \cdot (Se + Sp)$$

The same LOPCV scheme was used to compute the following measures of performance: Se, Sp, positive predictive power (PPV), negative predictive power (NPV) and BER. The same methodology was applied to develop a multi-feature SVM classifier using both sequential forward and backward feature selection (SFS/SBS).

Finally the minimum ECG segment length was determined for an accurate shock outcome prediction based on SmpEnt. For an analysis segment ending 1-s before the shock, the segment length was gradually increased from 0.5-s up to 5-s, an optimal SVM classifier was fit and Se/Sp and BER were determined.

Feature	Se (Sp=90)	Sp (Se=90)	AUC
AR	44.6	50.3	0.800
MA	38.8	42.5	0.792
PPA	33.9	67.6	0.837
MS	41.1	64.0	0.842
MdS	39.5	69.7	0.844
AMSA	51.6	57.1	0.835
PF	14.0	40.8	0.700
CF	12.8	28.1	0.668
ENRG	39.2	48.9	0.789
MP	28.8	42.5	0.729
CP	26.4	43.5	0.727
PSA	52.0	61.3	0.837
SFM	13.6	25.5	0.624
SpecEnt	20.5	19.9	0.604
SmpEnt	38.1	59.7	0.840

Table 1. ROC analysis of the VF detection features computed using 5-s segments in terms of sensitivity (Se), specificity (Sp) and AUC

### 3. Results

Table 1 shows the results for the ROC analysis. The table shows several features (from all analysis domains) with AUCs well above 0.8, including PPA, MS, MdS, AMSA, PSA and SmpEnt. When an LOPCV analysis was conducted to determine the optimal working point for each feature, SmpEnt showed the best performance with a BER of 0.18, as shown in Table 2. The combined Se/Sp values for the optimal working point were 83.6% and 79.7%, respectively. A multi-feature SVM classifier did not improve the BER results. In fact a SFS approach resulted in a classifier based only on SmpEnt. The SBS approach on a classifier based on MA, PPA, MdS, AMSA, ENRG, MP and CP with an under performing BER of 0.22. So, classification based only on SmpEnt yielded the best results.

Finally, figure 2 shows how shock outcome prediction based on SmpEnt changes as a function of the length of the analysis interval (segment). The figure shows the BER but also how Se and Sp change for different segment durations. For segment durations over 1.5-s the BER is consistently under 0.22, so 1.5-s was considered the minimum segment duration for an accurate shock outcome prediction based on SmpEnt.

### 4. Discussion

In this study we have introduced SmpEnt as a shock outcome predictor, and compared its performance to 14 previously reported VF-waveform features, using a

Feature	Se	Sp	PPV	NPV	BER
AR	42.7	87.0	67.9	70.3	0.351
MA	39.2	84.0	61.1	68.3	0.384
PPA	80.1	76.1	68.2	85.6	0.219
MS	78.9	77.6	69.4	85.2	0.217
MdS	81.2	77.4	69.7	86.5	0.207
AMSA	73.0	78.2	68.2	81.9	0.244
PF	47.1	70.6	50.7	67.5	0.412
CF	40.4	83.9	61.7	68.7	0.379
ENRG	36.9	89.6	69.5	68.9	0.367
MP	20.5	95.6	75.2	65.2	0.419
CP	14.7	96.4	72.4	63.8	0.444
PSA	55.3	84.2	69.2	74.6	0.302
SFM	9.3	96.5	63.2	62.4	0.471
SpecEnt	13.6	88.6	43.3	61.5	0.489
SmpEnt	84.3	79.7	72.7	88.8	0.180

Table 2. Analysis of optimal working point of the VF detection features computed using 5-s segments in terms of Se, Sp, PPV, NPV and BER

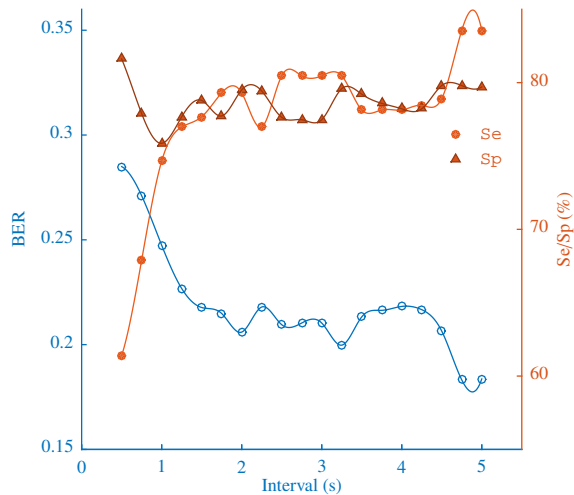


Figure 2. Evolution of BER and Sp/Se as a function of the segment duration.

database of 255 shocks extracted from patients treated by BLS personnel. For a single feature classifier, SmpEnt had the lowest BER of all the features, and the addition of features did not improve the classifier's performance. Furthermore, SmpEnt showed improved detection performance for segments as short as 1.5-s. During BLS, SmpEnt could be used as a decision support tool to guide optimal timing for defibrillation.

Our results match those of Firoozabadi et al. [6], except for SFM and CF which in our data had much poorer performance. The AUC values and the Se/Sp values are in line with most studies based on classical parameters such as AMSA or MdS [4, 8]. SmpEnt provides a marginal prediction improvement when compared to classical features. Our results also suggest that combining features does not improve shock outcome prediction based on SmpEnt, although a recently published study [7] reported improved shock outcome prediction results for an SVM classifier based AMSA, MdS and amplitude (SmpEnt was not studied). In general most VF-features analyzed showed very large correlation coefficients on our data ( $R_{ij} > 0.9$ ), which suggests that these features may be equivalent approaches to quantifying the same underlying physiological state of the VF rhythm. A possible approach to improve outcome prediction may then be the addition of information derived from other signals, such as the capnogram [7], or the inclusion of data on the state of resuscitation efforts (CPR quality, arrival times, ...).

Finally, shock outcome was defined in terms of the appearance of QRS complexes after the shock, in line with most previous studies [4, 8]. Other definitions of shock outcome, to better match the clinical outcome of the

patient, were left for future studies. These criteria may include hospital admission, restoration of spontaneous circulation during resuscitation or neurological outcome at hospital discharge. These studies require matching clinical data from the patients to the analysis conducted in the present study.

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