Prediction of Countershock Success in Patients Using the Autoregressive Spectral Estimation

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Ventricular fibrillation, prediction, countershock success, autoregressive spectral estimator

Summary
Objectives: Ventricular fibrillation (VF) is a life-threatening cardiac arrhythmia and within minutes of its occurrence, optimal timing of countershock therapy is highly warranted to improve the chance of survival. This study was designed to investigate whether the autoregressive (AR) estimation technique was capable to reliably predict countershock success in VF cardiac arrest patients. Methods: ECG data of 1077 countershocks applied to 197 cardiac arrest patients with out-of-hospital and in-hospital cardiac arrest between March 2002 and July 2004 were retrospectively analyzed. The ECG from the 2.5 s interval of the precountershock VF ECG was used for computing the AR based features Spectral Pole Power (SPP) and Spectral Pole Power with Dominant Frequency weighing (SPPDF) and Centroid Frequency (CF) and Amplitude Spectrum Area (AMSA) based on Fast Fourier Transformation (FFT). Results: With ROC AUC values up to 84.1% and diagnostic odds ratio up to 19.12 AR based features SPP and SPPDF have better prediction power than the FFT based features CF (80.5%; 6.56) and AMSA (82.1%; 8.79). Conclusions: AR estimation based features are promising alternatives to FFT based features for countershock outcome when analyzing human data.

1. Introduction
Ventricular fibrillation (VF) is a life-threatening cardiac arrhythmia that leads to sudden cardiac death unless being treated within minutes of its occurrence [1]. Electrical defibrillation is the treatment of choice [2], but optimal timing is vitally important as the chance of survival decreases dramatically with prolonged duration of VF with increased likelihood of asystole, pulseless electrical activity or persistent VF following the countershock [3]. Moreover, thermal injury to the heart should be reduced by minimizing the total cumulative energy and number of electrical shocks delivered during the cardiopulmonary resuscitation (CPR) attempt [4]. In recent years, a variety of VF parameters have been investigated to assist physicians guiding countershock therapy [5–10].

2. Methods
2.1 Dataset
The present patient data were part of retrospective observational studies of patients with out-of- and in-hospital cardiac arrest between March 2002 and July 2004 with details published elsewhere [9]. The studies were approved by the Regional Committee.

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for Research Ethics and the Norwegian Data Inspectorate and by the Institutional Review Board of the University of Chicago Hospitals respectively. Patient suffering from cardiac arrest were treated by emergency medical services according to the 2000 international CPR guidelines [15]. Heart-start 4000 defibrillators (Laerdal Medical) were used for countershock therapy and for simultaneous online ECG recording with a sampling frequency of 500 Hz. Corresponding demographic data were documented in an Utstein style database [16]. The data have been used in previous countershock prediction studies [9, 17]. Small differences in patient numbers can be attributed to different focus on ECG traces between the studies.

Of a total of 1077 countershocks applied to 197 cardiac arrest patients, 343 were excluded due to non-shockable rhythms or artefacts. The ECG from the 2.5 s interval immediately pre-countershock was used to compute the prediction features. As in our previous studies countershock was regarded as successful when VF was converted to a supraventricular rhythm within the first 10 s post-countershock and generated a pulse without continuing CPR, regardless of the duration. Sixty-three (= 8.5%) of 734 countershocks resulted in a Return Of Spontaneous Circulation (ROSC). All the other resulting rhythms were merged in a group with No Return Of Spontaneous Circulation (NoROSC). Data of both groups were split at random in equal parts into a training and a testing set, respectively. That means that the training set consists of 31 ROSC and 335 NoROSC data sets and the testing set was assembled by 32 ROSC and 336 NoROSC data sets.

2.2 Signal Processing

First of all, a downsampling and a fourth order 3–40 Hz Butterworth bandpass filter was applied to all signals for avoiding aliasing effects. After these preprocessing stages, the different prediction features with AR estimation and FFT were calculated.

2.2.1 Autoregressive Modeling

The AR model can briefly be described as a linear adaptive filter system with a zero-mean-Gaussian white noise as input signal and order p [18]. The filter parameters, called AR parameters, are adjusted so that the output signal corresponds to the VF ECG signal (Fig. 1).

Different approaches for assessing the AR parameters are all based on the central condition that the optimal estimator for this linear prediction problem has the smallest quadratic forward prediction error with respect to the AR parameters. Here, the recursive estimation of the parameters is assigned through the Yule Walker method which uses the auto-correlation matrix for parameter adjustment [18].

As the AR estimation results always depend on the optimal model order, this choice can be rather crucial. Three different model selection criteria (Akaike Information Criterion (AIC), Final Prediction Error (FPE) and Minimal Description Length (MDL)) are used for comparing the results. The description of the different criteria can be found in [19].

2.2.2 Pole Frequency and Pole Power

Based on the AR parameters calculations, the entire Power Spectral Density (PSD) of the AR process can be subdivided into bell-shaped curves. The characteristics of these curves can be obtained from the position of the poles in the unity circle [20]. The number of poles corresponds to the number of the model order p. The pole frequency and power calculations are illustrated in Figure 2 where a 2.5 s VF ECG signal segment (Fig. 2A) and its PSD (Fig. 2C, solid line, model order 12) can be seen.

By knowing the pole distribution inside the unit circle (Fig. 2B, note that only six of 12 poles are displayed, see below), the centre frequency of each peak, called pole...
frequency $f_{\text{pole}, i}$ of the PSD can be calculated from the phase $\Phi_i$ of each peak $i$ (i.e. the angle of the pole location in Fig. 2B):

$$f_{\text{pole}, i} = 2 \cdot \pi \cdot \Phi_i = 2 \cdot \pi \cdot \tan^{-1} \left( \frac{\text{Im}(z_i)}{\text{Re}(z_i)} \right),$$

where $z_i$ are the poles.

With the help of the residues [20],

$$r_i = z^{-1} \cdot (z - z_i) \cdot H(z) \Big|_{z = z_i},$$

where $H(z)$ is the model transfer function of the AR estimation model in the $z$-domain, the pole power $P_{\text{pole}, i}$ of the $f_{\text{pole}, i}$ can be calculated in the case of complex conjugate pole pairs as

$$P_{\text{pole}, i} = 2 \cdot \text{Re}(r_i) \cdot \sigma^2,$$

and in the case of a real pole as

$$P_{\text{pole}, i} = r_i \cdot \sigma^2.$$

This indicates that each spectral component of the PSD can be characterized by the pole frequency and its pole power [12]. In Figure 2C three of these bell-shaped curves calculated from the pole frequencies and characterized by the three pole pairs of greatest power (◊ in Fig. 2B) can be seen (dotted, dash-dot and dashed line). The nearer the pole is located to the unity circle, the greater is the amplitude of the bell-shaped curve. Here, the pole pair at 9.9 Hz in Figure 2B produces the highest peak in the PSD (Fig. 2C). Thus, it is possible to describe a complex signal and its spectral distribution with only a few characteristic parameters, whose number corresponds to the number of $P_{\text{pole}, i}$.

### 2.3 Prediction Features Based on AR Estimation

#### 2.3.1 Spectral Pole Power (SPP)

SPP represents a combination of all $f_{\text{pole}, i}$ and $P_{\text{pole}, i}$ of each PSD and was calculated as follows:

$$\text{SPP} = \sum_{i=1}^{T} (f_{\text{pole}, i} \cdot P_{\text{pole}, i}),$$

where $T$ corresponds to the number of $P_{\text{pole}, i}$. Note the physical analogy of its calculation compared to the Amplitude Spectral Area (AMSA) parameter, whose calculation is FFT based and will be described in Section 2.4.2.
2.3.2 Spectral Pole Power with Dominant Frequency (DF) Weighing (SPPDF).

SPPDF was calculated by multiplying the SPP with the DF, which was defined as the frequency of the pole pair with the maximal power, because the distribution of the PSD and the DF might have predictive power concerning countershock outcome [21].

$$SPPDF = DF \cdot \sum_{i=1}^{T} (f_{pole, i} \cdot P_{pole, i})$$

where T corresponds to the number of $P_{pole, i}$.

2.4 Prediction Features Calculated by FFT

For comparison and testing purposes of SPP and SPPDF, two established FFT based features were investigated.

2.4.1 Centroid Frequency or Median Frequency (CF)

CF is calculated as the point of mass in the spectrum [22, 23], so that the low-frequency contents of the VF ECG are highlighted:

$$CF = \frac{\sum_{j=1}^{N} (A_j \cdot f_j)}{\sum_{j=1}^{N} P_j}$$

where $P_j$ is the relative power, $f_j$ is the frequency to this relative power and N is the number of samples.

2.4.2 Amplitude Spectrum Area (AMSA)

AMSA, first published by Marn-Pernat et al. for countershock outcome prediction, represents the whole area under the PSD curve [24]. It has been shown that AMSA has the potential for guiding the countershock therapy without interrupting CPR and ventilation [25]. The parameter is calculated as follows:

$$AMSA = \sum_{j=1}^{N} (A_j \cdot f_j)$$

where $A_j$ is the amplitude, $f_j$ is the corresponding frequency and N is the number of samples, respectively.

2.5 Statistical Analysis

In analogy to former investigations, the receiver operating characteristic (ROC) curve and the underlying area under the curve (AUC) were used to compare the predictive power of the VF features investigated [7, 17, 19]. The ROC curve describes the relationship between the sensitivity and specificity for whether a feature can predict countershock success. There are non-parametric and parametric methods for obtaining the AUC ROC curve [26–28]. Here a non-parametric kind of calculation was chosen that uses the trapezoidal rule [28], where the AUC value is calculated by using an average of a number of trapezoidal approximations built by sensitivity and specificity at different operating points.

An AUC area of 1.0 indicates perfect discrimination ROSC and NoROSC, while an AUC area of 0.5 indicates completely stochastic prediction without any discrimination. Here, sensitivity is defined as the proportion of correctly predicted ROSC and the number of all ROSC data sets. Specificity is the rate of correctly predicted NoROSC and real NoROSC data.

Moreover, the likelihood ratio (LR) and the diagnostic odds ratio were calculated for evaluating the performance of the different prediction parameters [29]. The higher the positive LR and the diagnostic odds ratio and the smaller the negative LR, the better is the diagnostic evidence of the prediction parameter [29]. In every case the confidence interval was set to 95%.

### Table 1: Threshold of the prediction features

<table>
<thead>
<tr>
<th>Prediction Feature</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPP</td>
<td>0.08 mVHz</td>
</tr>
<tr>
<td>SPPDF</td>
<td>0.3 mVHz²</td>
</tr>
<tr>
<td>CF</td>
<td>0.3 mV</td>
</tr>
<tr>
<td>AMSA</td>
<td>400 mVHz</td>
</tr>
</tbody>
</table>
3. Results

3.1 Predictive Power of AR and FFT-based Features in the Training Set

For the AR-based prediction features, a mean model order of 25.5 (range 6 to 50) was obtained by AIC and FPE and a mean model order of 10 (range 5 to 50) by MDL. Based on the training set results calculated with AIC, the threshold levels of all four prediction features were defined in such a way that the ratio between correctly predicted successful shocks and nonessential shocks is best (Table 1), so that only a few necessary shocks are missed and many nonessential shocks can be avoided.

The sensitivities and the specificities of the prediction parameters are summarized in Figure 3. With sensitivities of 0.839 the AR based predictors yielded specificities up to 0.736 for SPP and 0.689 for SPPDF, vs. sensitivities of 0.677 and 0.774 and specificities of 0.757 and 0.692 for the FFT based predictors.

For evaluating the performance of the prediction features the ROC AUC values, the LR values and the diagnostic odds ratio with its confidence intervals (CI) can be seen in Table 2. For getting an overview of the function of a ROC curve, Figure 4 shows the ROC curves of all four parameters in case of the training set. Based on such a ROC curve with 100 steps the AUC value can be calculated.

As the ROC AUC values (up to 82.6 %) as well as the LR (3.173 and 2.700; 0.219 and 0.234) and the odds ratios (10.44 to 16.47) in Table 2 show, the best prediction features were those calculated with AR spectral estimation (SPP and SPPDF). Especially when comparing odds ratios, a great difference between the FFT based and the AR based parameters can be found (6.56 and 7.71 vs. 10.44 – 16.47).

3.2 Predictive Power of AR and FFT-based Features of the Testing Set

For the testing set, a mean model order 25.4 (range 5 to 50) was calculated by AIC and FPE and a mean model order of 9.6 (range 5 to 43) by MDL. The ROC AUC values of the prediction parameters including their specificities are summarized in Figure 5.

Table 2

<table>
<thead>
<tr>
<th>Parameter</th>
<th>ROC AUC [%]</th>
<th>Odds ratio</th>
<th>Odds CI</th>
<th>LR+</th>
<th>pLR CI</th>
<th>LR−</th>
<th>nLR CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPP</td>
<td>81.6</td>
<td>14.47</td>
<td>5.406 to 38.752</td>
<td>3.173</td>
<td>2.521 to 3.994</td>
<td>0.219</td>
<td>0.098 to 0.49</td>
</tr>
<tr>
<td>MDL</td>
<td>81.7</td>
<td>16.47</td>
<td>5.406 to 38.754</td>
<td>3.173</td>
<td>2.521 to 3.996</td>
<td>0.219</td>
<td>0.098 to 0.51</td>
</tr>
<tr>
<td>SPPDF</td>
<td>82.6</td>
<td>11.54</td>
<td>4.321 to 30.82</td>
<td>2.700</td>
<td>2.174 to 3.354</td>
<td>0.234</td>
<td>0.105 to 0.524</td>
</tr>
<tr>
<td>MDL</td>
<td>81.6</td>
<td>10.44</td>
<td>3.912 to 27.877</td>
<td>2.523</td>
<td>2.04 to 3.121</td>
<td>0.242</td>
<td>0.108 to 0.541</td>
</tr>
<tr>
<td>CF</td>
<td>80.5</td>
<td>6.56</td>
<td>2.977 to 14.453</td>
<td>2.793</td>
<td>2.064 to 3.781</td>
<td>0.426</td>
<td>0.255 to 0.712</td>
</tr>
<tr>
<td>AMSA</td>
<td>81.4</td>
<td>7.71</td>
<td>3.227 to 18.406</td>
<td>2.514</td>
<td>1.969 to 3.21</td>
<td>0.326</td>
<td>0.169 to 0.628</td>
</tr>
</tbody>
</table>

Fig. 4 ROC curves of the training set. (SPP...Spectral Pole Power, SPPDF...Spectral Pole Power with Dominant Frequency weighing, CF...Centroid Frequency, AMSA...Amplitude Spectrum Area)
The same threshold levels as obtained from the training set were used.

The sensitivities and the specificities of the prediction parameters can be seen in Figure 5. The results of the training set can be verified here, because the values of sensitivities and specificities don’t change much: The AR-based estimators yielded sensitivities at 0.839 vs. Sensitivities of 0.677 and 0.774 for the FFT-based predictors. Also the specificities show the same trend (0.736 and 0.689 vs. 0.757 and 0.692).

For evaluating the performance of the prediction features the ROC AUC values, the LR values and the diagnostic odds ratio with its confidence intervals (CI) can be seen in Table 3 again.

Here again, the AR-based parameters have a better predictive power than the FFT-based ones. The ROC AUC values are 83.8 % and 84.1 % for SPP and SPPDF, whereas the ROC AUC values are only 79.8 % and 82.1 % for CF and AMSA, respectively. When comparing the diagnostic odds ratios, the AR based parameters have better evidence with up to 19.12 than CF and AMSA (6.05 and 8.79).

4. Discussion

This study indicates that in patients with in- or out-of hospital VF cardiac arrest, countershock success can be predicted from AR estimation, which therefore might be valuable for optimizing countershock therapy. In particular, the predictive power of AR-based parameters SPP and SPPDF exceeded that of the FFT based features CF and AMSA. The data were subdivided at random into a training and a testing set with only minimal differences in the predictive power in these similarly distributed, independent sets. Hence, it appears that the threshold was well chosen with stable results over different data sets.

Countershock success prediction has previously mostly been based on spectral VF ECG analysis using FFT with little clinical impact so far, probably due to limited predictive accuracy. [5 – 7]. In an effort to improve the accuracy, various methods such as analysis of chaotic behaviour [30], selfsimilarity [31], scaling exponent [23] wavelet transformation [32] or feature combination using neural networks [9] have been investigated in the recent years. Many of these have resulted in higher sensitivity and specificity than previously published features or feature combina-

![Fig. 5](image-url) The sensitivities and specificities of the prediction features 2.5 s before countershock induction in the testing set of the human data. (AIC…Akaike Information Criterion, FPE…Final Prediction Error, MDL…Minimal Description Length, SPP…Spectral Pole Power, SPPDF…Spectral Pole Power with Dominant Frequency weighing, CF…Centroid Frequency, AMSA…Amplitude Spectrum Area)

<table>
<thead>
<tr>
<th>Method</th>
<th>ROC AUC [%]</th>
<th>Odds ratio</th>
<th>Odds CI</th>
<th>LR+</th>
<th>pLR CI</th>
<th>LR−</th>
<th>nLR CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPP</td>
<td>AIC &amp; FPE</td>
<td>83.4</td>
<td>17.12</td>
<td>6.401 to 45.793</td>
<td>3.519</td>
<td>2.781 to 4.453</td>
<td>0.206</td>
</tr>
<tr>
<td></td>
<td>MDL</td>
<td>83.2</td>
<td>19.12</td>
<td>6.401 to 45.795</td>
<td>3.519</td>
<td>2.781 to 4.455</td>
<td>2.206</td>
</tr>
<tr>
<td>SPPDF</td>
<td>AIC &amp; FPE</td>
<td>84.1</td>
<td>13.47</td>
<td>5.053 to 35.928</td>
<td>2.949</td>
<td>2.367 to 3.674</td>
<td>0.219</td>
</tr>
<tr>
<td></td>
<td>MDL</td>
<td>84</td>
<td>13.12</td>
<td>5.923 to 34.977</td>
<td>2.894</td>
<td>2.326 to 3.6</td>
<td>0.221</td>
</tr>
<tr>
<td>CF</td>
<td></td>
<td>79.8</td>
<td>6.05</td>
<td>2.809 to 13.044</td>
<td>2.737</td>
<td>2.007 to 3.731</td>
<td>0.452</td>
</tr>
<tr>
<td>AMSA</td>
<td></td>
<td>82.1</td>
<td>8.79</td>
<td>3.692 to 20.948</td>
<td>2.705</td>
<td>2.12 to 3.451</td>
<td>0.308</td>
</tr>
</tbody>
</table>

Table 3 ROC AUC, diagnostic odds ratio, positive LR (LR+) and negative LR (LR−) with its CI of testing set
tions. Although nonlinear analysis can add complementary information to frequency based measures, these methods require considerable computing power including sophisticated hardware and software. In particular, the time delay due to increased computing time requirement of nonlinear techniques is a critical obstacle to use the resulting features as an on-line guide for countershock therapy. Therefore, analytic tools with high predictive power while requiring short computing time are highly warranted.

AR spectral estimation is computationally fast and has been used successfully for e.g. investigating heart rate variability [20], fetal heart rate from cardiotocographic recordings [12], and for studying event-related EEG data [33].

The higher specificities of the AR based features SPP and SPPDF than the FFT based features CF and AMSA at the same sensitivity both in the training and the testing set in the present study agree with the results for SPP and SPPDF vs. CF and AMSA in a porcine model of VF cardiac arrest [19]. These experiments were performed in healthy pigs under tight laboratory control, however, while the clinical data were collected under variable circumstances in- and out-of-hospital from patients with variable factors that can alter the VF power spectrum such as coronary artery disease [34], cardiomyopathy [35], cardiac channelopathies (such as long QT syndrome [36]), medication or technical factors. At the same sensitivity level, the specificity of the AR estimators SPP and SPPDF obtained in patients was equal (SPPDF) or even above (SPP) the corresponding values in the porcine setting [19]. Thus, it appears that the AR based prediction features are relatively robust.

As high specificity is of clinical value as unsuccessful shocks damaging the heart could be avoided and the opportunity for a successful shock should not be missed, it is important to have both – a high sensitivity and specificity – here. So for choosing the best threshold the ratio between sensitivity and specificity was made with a weighting for sensitivity. This means that almost all successful shocks are correctly predicted.

As the LR and the diagnostic odds ratio are valuable statistical tools for comparing the evidence of a diagnostic test beside ROC AUC [37–39], it was found in this study that SPP and SPPDF have more prediction power than the FFT-based ones used here. Not only in the training but also in the testing set, the odds ratio yielded better results in opposite to the FFT based features (6.5 – 8.7 vs. 10.4 – 19.12). Also the positive and the negative LR of AR based features are better than the FFT based features. The negative LR value is smaller for the AR based features (<0.25) in opposite to the FFT based features (0.4 and 0.3) that means that many unsuccessful shocks are recognized. Thus, the damage of the heart because of obsolete shocks can be minimized. Thus, it seems that SPP and SPPDF are valuable tools for guiding countershock therapy.

Although not calculated in the human database the computing time of an AR-based feature was less than half the time required to calculate FFT-based features in the porcine experiments [19]. This is the other feature that is clinically important.

As the results with AR estimation often depend on the choice of the model order [18], this choice can be very crucial. Different model order selection criteria and their effects on the prediction power were therefore investigated. Whereas AIC and FPE tended to overestimate the model order [18], MDL mostly underestimated the order resulting in a mean model order of less than half the mean order defined by the other two methods. However, the predictive power of the features calculated with different selection criteria methods was minimally affected by the model order in both datasets. We found that the three pole pairs with the highest power contain average of 94.3% (AIC and MDL) and 99.6% (MDL) of the total signal power. Thus, there are typically only two or three peaks in the VF ECG spectrum. The remaining pole pairs are of low power and modulate the shape of the peaks which are not symmetric. The marginal influence of model order selection on predictive power of the SPP and SPPDF parameter enhanced their technical practicability [19].

Several study limitations should be pointed out. First the fraction of countershocks resulting in ROSC was low compared to the fraction with NoROSC outcome. However, this imbalance reflects the clinical situation where the majority of countershocks fail to restore spontaneous circulation. Secondly, data collection was performed in three emergency medical services and one hospital in four different countries, which may have influenced the results. Although generality of the results is assessed by independent testing, a larger multicentre trial performed in a prospective manner would provide better results. Third, a period of CPR performed prior to defibrillation has been shown to change the VF waveform [22], but this does not affect this study as most of the countershocks analysed here were applied after periods of CPR. Fourth, there are various approaches for developing countershock outcome prediction features. This study deals with prediction features based on spectral estimation, so feature parameters calculated with other methods are beyond this study.

5. Conclusion

The AR estimation method is an interesting alternative for countershock outcome prediction with predictive power of the developed AR based parameters higher than the FFT based features. Reduced computational effort might facilitate its implementation in defibrillators.

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