Removal of Resuscitation Artefacts from Ventricular Fibrillation ECG Signals Using Kalman Methods

K Rheinberger[1], M Baubin[2], K Unterkofler[1], A Amann[2]

[1]Research Center Process and Product Engineering, Vorarlberg University of Applied Sciences, Austria
[2]Department of Anesthesiology and Critical Care Medicine, Innsbruck Medical University, Austria

Abstract

Removing cardiopulmonary resuscitation (CPR) related artefacts from human ventricular fibrillation (VF) ECG signals would provide the possibility to continuously detect rhythm changes and estimate the probability of defibrillation success. This would avoid "hands-off" analysis times which diminish the cardiac perfusion and thus deteriorate the chance for a successful defibrillation attempt. Our approach consists in representing the CPR-corrupted signal by a seasonal state-space model. This allows for a stochastically changing shape of the periodic signal and also copes with time-dependent periods. The residuals of the Kalman estimation can be identified with the CPR-filtered ECG signal. Preliminary results using only a small pool of human VF and animal asystole CPR data show that the seasonal model is not as effective as models using reference signals, but it might be useful in combination with them.

1. Introduction

During CPR, chest compressions and ventilations cause artefacts in the ECG. In order that the rhythm detection algorithms of automated external defibrillators work properly, the international guidelines [1] prescribe a so-called "hands-off interval" for the time of analysis. During this period, CPR is stopped and the ECG signal is thus artefact free. However, as a consequence of this, myocardial blood flow drops and both the success of a subsequent defibrillation attempt [2] and the probability of success [3, 4] decrease. Thus, it would be desirable to remove CPR artefacts from the ECG signal continuously during CPR. Thereby, continuous rhythm detection would be possible and would provide minimal "hands-off" delay before the delivery of an electric countershock. Furthermore, in the case of VF, CPR removal algorithms would allow for continuous monitoring of the myocardial metabolism of the heart through parameters derived from the artefact cleaned ECG signal [5]. CPR artefact removal is thus a crucial step towards diagnostic based defibrillation and has the potential of dramatically improving the survival rate of cardiac arrest patients.

The human heart fibrillates at frequencies that overlap with the characteristic frequencies of CPR artefacts [6]. Furthermore, in real life situations, the rates and amplitudes of chest compressions and ventilations, and therefore the shape of the CPR ECG artefacts can change in the course of time. Thus, CPR artefact removal is a delicate signal processing problem and needs sophisticated adaptive algorithms.

In contrast to the large amount of literature about algorithms to detect and analyse VF signals [7, 5], there are surprisingly only few and recent publications addressing the problem of removing CPR artefacts: Ruiz et al. [8] use Kalman filters assuming that the CPR artefact as well as the VF signal can be modeled by sinusoidal functions of known angular frequencies. Klotz et al. [9] propose a methodology based on time-frequency methods and local coherent line removal. The Norwegian research group of Eftestol et al. [10, 11, 12] apply an adaptive filtering approach using reference signals (thoracic impedance, compression depth, etc.), which correlate with the CPR artefact signal.

2. Methods

2.1. Data and evaluation methods

Seven porcine asystole ECG signals containing CPR artefacts (the noise), and seven human artefact free VF ECG signals (the signal) are added pairwise with specific signal-to-noise ratios (SNR). All of the resulting 49 signals have 5 seconds duration. After separation of the mixture by means of a removal algorithm the restored SNR [10, 8]

$$\text{rSNR} := 10 \cdot \log_{10}\left(\frac{Var(\text{signal})}{Var(\text{signal-estimation})}\right)$$

reflects the mean squared estimation error of the reconstruction in comparison with the signal variance, c.f. Fig. 1. For the purpose of CPR artefact removal by means

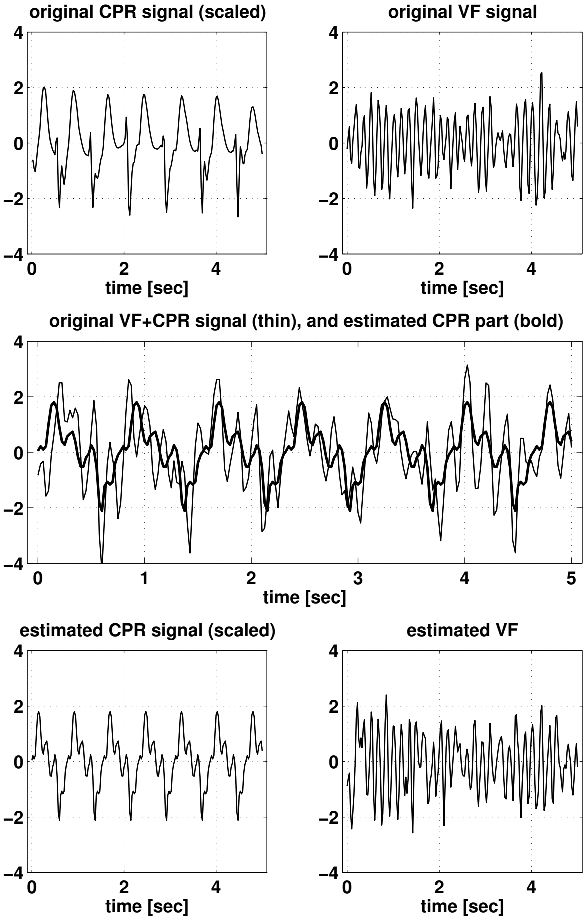

Figure 1. Adding and separating a CPR artefact ECG signal (the noise) and an artefact free VF ECG signal (the signal) by means of the seasonal model.

of our model, it suffices to work at a sampling frequency of approx. 20-50 Hz, which usually covers the frequencies contained in the CPR artefact signal. This is because our model estimates the CPR artefact signal and handles the VF part as residuals. Therefore, the following procedure can be applied:

1. Down-sample the CPR and VF signals from their original sampling frequencies to a sampling frequency $f \in [20, 50]$ Hz, which results in the two signals VF_f and CPR_f.
2. Normalise VF_f and CPR_f, and scale CPR_f such that a desired SNR is accomplished.
3. Estimate the CPR part of the mixture by means of the model and the chosen optimisation procedure resulting in the signal CPR_f^{est}
4. Assuming that all frequencies of the CPR artefact signal are contained in $[0, f/2]$, the restored SNR can be computed by calculating the difference between the scaled true CPR signal CPR_f and its estimate CPR_f^{est}.
5. In order to get an estimate of the VF part (including as much frequencies as possible), one up-samples CPR_f^{est} to the original VF sampling frequency (375 Hz for our data), and subtracts it from the CPR+VF mixture at this sampling frequency.

Besides evaluating a CPR removal algorithm with the restored SNR, one can compare the values of a typical ECG parameter, such as the mean frequency [5], for the artefact free VF signal and its estimate.

2.2. The seasonal state-space model

We propose Kalman state-space methods [13, 14, 15] for CPR artefact removal, because:

- The Kalman recursions provide a numerically fast and adaptive way to compute estimates of the CPR part of the CPR corrupted signal.
- The underlying state space models include all classical time series models, can be combined in a straightforward way, and allow for integration of reference signals (thoracic impedance, compression depth, etc.).
- There exist established optimisation techniques for the estimation of model parameters.

Our approach consists in representing the CPR-corrupted signal by a seasonal state-space model [15, p.266f]. This model is motivated by the idea that CPR artefacts form a roughly periodical signal, whereas the VF ECG signal is not periodical, or at least at a much higher rate. The residuals of the Kalman-estimation can be identified with the CPR-filtered ECG signal.

A classical seasonal time series $\{Y_t\}$ with constant period d and period mean zero fulfils

$$Y_{t+d} = Y_t, \text{ and } \sum_{t=1}^{d} Y_t = 0.$$

Combining these equations, we see that such a time series is governed by the recursions

$$Y_{t+1} = -Y_t - \ldots - Y_{t-d+2}. \tag{1}$$

In order to allow for random variations from strict periodicity, one introduces a white noise term $\{S_t\}$ with mean zero in equation (1):

$$Y_{t+1} = -Y_t - \ldots - Y_{t-d+2} + S_t.$$

This allows for a stochastically changing shape of the periodic signal.

The states $\{X_t\}$ of the corresponding $d-1$ dimensional state-space model including observation noise are formed by the vectors

$$X_t = (Y_t, Y_{t-1}, \ldots, Y_{t-d+2})^T.$$

The observations $\{Y_t\}$ are recovered from the states by the observation equation

$$Y_t = G_t X_t + W_t,$$

where W_t is the observation noise and $G_t = (1, 0, \ldots, 0)$. Finally, the state equation is given by

$$X_{t+1} = F_t X_t + V_t,$$

with $V_t = (S_t, 0, \ldots, 0)^T$ and

$$F_t = \begin{pmatrix} -1 & -1 & \ldots & -1 & -1 \\ 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & 1 & 0 \end{pmatrix}.$$

2.3. Time-dependent period

To cope with time-dependent periods $d(t)$, a state-space with dimension $\max\{d(t)\}$ is used, and in the first row of the transition matrix F_t the first $d(t) - 1$ entries are set to -1, and the rest are set to zero. We estimate the (time-dependent) period $d(t)$ by means of the (windowed) sample autocorrelation function of the CPR corrupted signal $\{Y_t\}$.

2.4. Optimisation

The seasonal model presented above is a structural state-space model [14], where the transition and observation matrices are known. Thus, it is determined by giving

- the variance of the state noise S_t,
- the variance of the observation noise,
- the initial state predictor, and
- the initial error covariance matrix.

We determine the optimal values of these parameters for given observations by reduced maximum likelihood estimation (RMLE) [15, p.278ff], which basically amounts to applying the Kalman predictor recursions repeatedly. However, after the RMLE any of the three types of Kalman recursions (prediction, filtering, and fixed-point smoothing) can be applied to the optimal model during evaluation.

3. Results

For each of the 49 mixed signals (sampling frequency $f = 40$ Hz) and each SNR= -10, -5, 0, 5, 10 dB an optimal seasonal model was determined via RMLE, where a constant period was estimated. Every optimal model was then evaluated using the Kalman predictor recursions. Fig. 1 shows the original and estimated CPR and VF parts for an example signal with SNR= 0 dB. For each of the 49 mixed signals the restored SNR at the original sampling frequency and the difference between the true and the estimated VF mean frequency were computed. The results are depicted in Fig. 2 and 3.

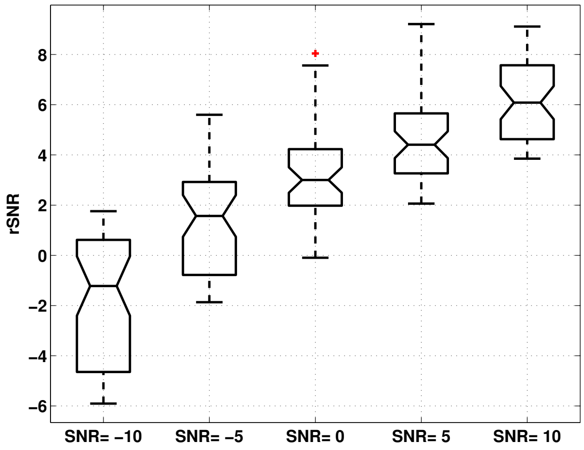

Figure 2. Boxplots of the restored SNR.

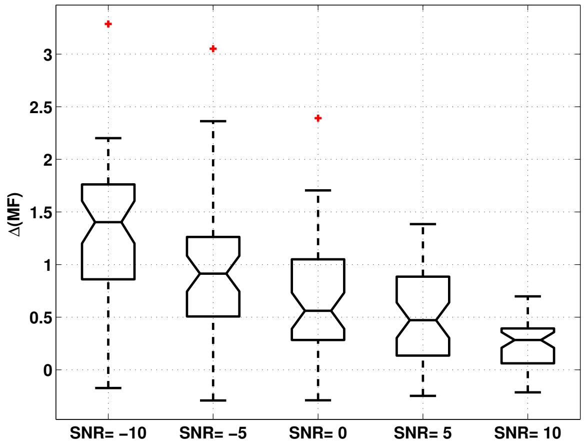

Figure 3. Boxplots of the differences between the true and the estimated VF mean frequency.

4. Discussion and conclusions

The restored SNR of the proposed CPR artefact removal algorithm does not attain as good values as the algorithm of Eftestol et al. [10, 11, 12], which uses reference signals correlating with the CPR artefacts. However, they observed large and spiky ECG artefacts without a similar shape in the reference channels, c.f. Fig. 1. These artefacts could thus not be reconstructed by a regression on the reference channels.

Our approach does not have the additional information of reference signals and estimates the CPR artefact part from the corrupted signal only, thus is not that effective. The seasonal model, however, can model periodic signals of any shape (Fig. 1), and therefore might be useful to improve the performance of a regression model on reference signals. In case the regression model is formulated in state-space terms, it can be easily combined with the seasonal model.

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Address for correspondence:

Klaus Rheinberger
Research Center Process and Product Engineering,
Vorarlberg University of Applied Sciences,
Hochschulstr. 1, 6850 Dornbirn, Austria
email: klaus.rheinberger@fhv.at