Removing CPR Artifacts from the Ventricular Fibrillation ECG by Enhanced Adaptive Regression on Lagged Reference Signals

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Abstract

Removing cardiopulmonary resuscitation (CPR) related artifacts 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 estimating the CPR-part of a corrupted signal by an adaptive regression on lagged copies of a reference signal which correlate with the CPR artifact signal. The algorithm is based on a state-space model and the corresponding Kalman recursions. The preliminary evaluation based on a small pool of artifact-free VF and asystole CPR data outperform comparable previous studies. In comparison with ordinary least-squares (OLS) regression the proposed algorithm shows improvements for low SNR corrupted signals and yields better estimates of the mean frequency of the true VF ECG signal.

1. Introduction

The international guidelines 2005 emphasize high quality CPR [1, 2]: Rescuers should push hard, push fast, allow full chest recoil, minimize interruptions in compressions, and defibrillate promptly when appropriate. During CPR, however, chest compressions and ventilations cause artifacts in the ECG. In order that the rhythm detection algorithms of automated external defibrillators work properly, the international guidelines prescribe a so-called "hands-off interval" for the time of analysis. During this period, CPR is stopped and the ECG signal is thus artifact free. However, as a consequence of this, myocardial blood flow drops and both the success of a subsequent defibrillation attempt [3] and the probability of success [4, 5] decrease. Thus, it would be desirable to remove CPR artifacts from the ECG signal continuously during CPR. 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 artifact cleaned ECG signal [6]. CPR artifact 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 international guidelines therefore encourage defibrillation manufacturers to develop defibrillators that are capable of analyzing the heart rhythm during uninterrupted chest compressions [2].

The human heart fibrillates at frequencies that overlap with the characteristic frequencies of CPR artifacts [7]. Furthermore, in real life situations, the rates and amplitudes of chest compressions and ventilations, and therefore the shape of the CPR ECG artifacts can change in the course of time. Thus, CPR artifact 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 analyze VF signals [8, 6], there are surprisingly only few and recent publications addressing the problem of removing CPR artifacts: Ruiz et al. [9] use Kalman filters assuming that the CPR artifact as well as the VF signal can be modeled by sinusoidal functions of known angular frequencies. Klotz et al. [10] propose a methodology based on time-frequency methods and local coherent line removal. The Norwegian research group of Eftestol et al. [11, 12, 13] apply an adaptive filtering approach using reference signals (thoracic impedance, compression depth, etc.), which correlate with the CPR artifact signal. Rheinberger et. al. [14] propose a seasonal state-space model for the CPR signal.

This study enhances a state-space model of adaptive regression on lagged copies of a reference signal presented in [15].

2. Methods

2.1. Data and cross-validation

A learning data set and a different test data set of CPR corrupted signals are used, first to optimize some parameters of the algorithms and then to evaluate the optimal algorithms. Each data set consists of seven porcine asystole ECG signals c during CPR and seven human artifact-free VF ECG signals v which are added pairwise at signal-to-noise ratios

$$\mathrm{SNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{Var}(v)}{\mathrm{Var}(c)}\right).$$

of -10, -5, 0, 5, and 10 dB. Each CPR artifact recording includes an arterial blood pressure signal, lagged copies of which are used as reference signals, i.e., regressors in the regression models. All signals have a length of 10 seconds. The human ECG-data were collected using a Welch Allyn PIC 50 defibrillator.

2.2. Preprocessing

The reference signal is band-pass filtered between 0.1 and 15 Hz, detrended and normalized to standard deviation one. For the purpose of CPR artifact removal by means of our models, it suffices to work at a sampling frequency of approx. 40 Hz, which usually covers the frequencies contained in the CPR artifact signal. This is because our models estimate the CPR artifact signal and handle the VF part as residuals.

2.3. Models

In many cases it is appropriate not only to regress on one reference signal, which was recorded synchronously with the CPR corrupted ECG signal, but also to regress on lagged copies of the reference signal, cf. Figure 2.

2.3.1. OLS regression models

Let $\{y_t\}_{t=1,\ldots,T}$ denote the observations of a CPR corrupted ECG signal $y = v+c$ and $(R_{t,k})_{t=1,\ldots,T}^{k=1,\ldots,M}$ the matrix of M lagged copies of the reference signal at the T sampling time points. OLS corresponds to finding a column vector $\hat{\beta} \in \mathbb{R}^M$, such that the Euclidean norm $||y - R\hat{\beta}||$ is minimal for all $\beta \in \mathbb{R}^M$. The OLS estimate $\hat{y} = R\hat{\beta}$ is an estimate of the CPR part of a corrupted ECG signal, whereas the residuals $y - \hat{y}$ are an estimate of the artifact removed VF ECG signal.

We considered models differing in the sampling frequency f, the time interval δ between two adjacent lagged copies of the reference signal and the minimal and maximal lag times l_{min} and l_{max}.

Figures 1 and 2 show the result of an OLS regression on lagged copies of the arterial blood pressure signal. Negative lags (shift towards the past) and positive lags (shift towards the future) are used. In both directions the OLS regression coefficients are non-zero. Thus also future parts of the reference signal can be useful for estimating the CPR artifact part of a corrupted signal. This fact is not a hindrance for practical on-line application as it leads only to a short time delay.

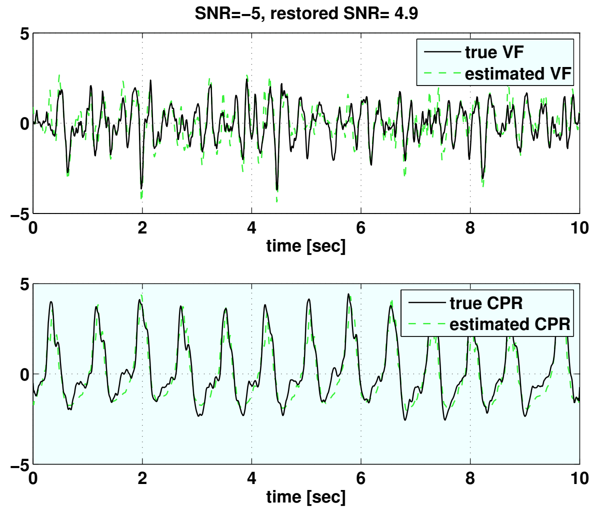

Figure 1. Results of an OLS regression of a CPR corrupted VF ECG signal on lagged copies of the arterial blood pressure signal showing the true and estimated CPR and VF part. The regression coefficients are plotted in Figure 2.

2.3.2. State-Space models

As already pointed out, the coupling between the ECG and chest compressions as well as the shape of the CPR ECG artifacts can change in the course of time. An adaptive regression model can handle these features. We propose a state-space regression model - called ALR (Adaptive Lagged Regression) - whose states are time-varying regression coefficients and whose observations are the CPR corrupted ECG signal. This is a generalization of the above OLS model having constant coefficients. The observation equation reads $Y_t = G_t X_t + W_t$, where $G_t = (R_{t,1}, \ldots, R_{t,M})$, and W_t is observation noise, which models the artifact removed ECG signal and has variance σ_w^2. The state equation is given by $X_{t+1} = F_t X_t + V_t$, where each state transition matrix F_t is the $M \times M$ identity matrix. The state noise vector V_t has covariance matrix Q. The case $Q = 0$ reproduces the OLS regression model, since the regression coefficients do not change in the course of time. A state noise covariance matrix $Q \neq 0$ allows for a dynamic evolution of the states, i.e., for adap-

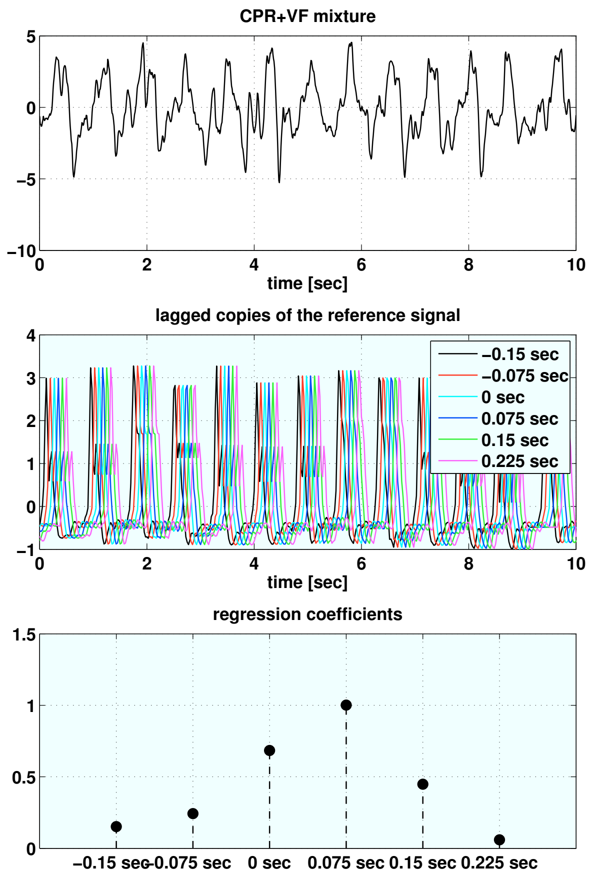

Figure 2. The CPR corrupted VF ECG signal as the sum of a CPR and a VF part, lagged copies of the reference signal and OLS regression coefficients corresponding to Figure 1. A lag of e.g. -0.15 seconds means that the original reference signal is shifted 0.15 seconds towards the past, in other words, the reference signal values of 0.15 seconds ahead are used.

tive regression coefficients. The OLS regression coefficients were used as initial state and the initial error covariance matrix was computed using the estimator statistics of the OLS regression coefficients. We set $Q = \alpha R^2 ||y||^2$, where the constant α was found by optimization on the learning data set and R^2 denotes the coefficient of determination of the OLS regression. As the Kalman recursions only depend on the ratio Q/σ_w^2, σ_w was set to one. The Kalman fixed-point smoother recursions reaching one second into the future were used.

2.4. Postprocessing and optimization

In order to get an estimate $\hat{v}$ of the VF part (including as much frequencies as possible), the model estimate of c was up-sampled again, yielding $\hat{c}$, and subsequently subtracted from the CPR+VF mixture, i.e., $\hat{v} = y - \hat{c}$. The restored SNR, defined as

$$\text{rSNR} = 10 \cdot \log_{10} \left(\frac{\text{Var}(v)}{\text{Var}(v - \hat{v})} \right),$$

and the difference in mean frequency (MF) of v and its estimate $\Delta(\text{MF}) = \text{MF}_v - \text{MF}_{\hat{v}}$ were computed. First, the rSNR-optimal OLS model parameters $(f, \delta, l_{min}, l_{max})$ were searched by a coarse grid search. Using these values the rSNR-optimal α value for the ALR model was searched by a coarse grid search.

3. Results

For each SNR the rSNR and $\Delta(\text{MF})$ values were computed for all signals in the test data set using the rSNR-optimal model parameters, cf. Figures 3 and 4. All models underestimate the VF mean frequency by up to approx. 1.5 Hz. For low SNR corrupted signals the ALR model exceeds the OLS regression model, whereas for high SNR corrupted signals the ALR model performs comparably or slightly worse than the OLS regression model.

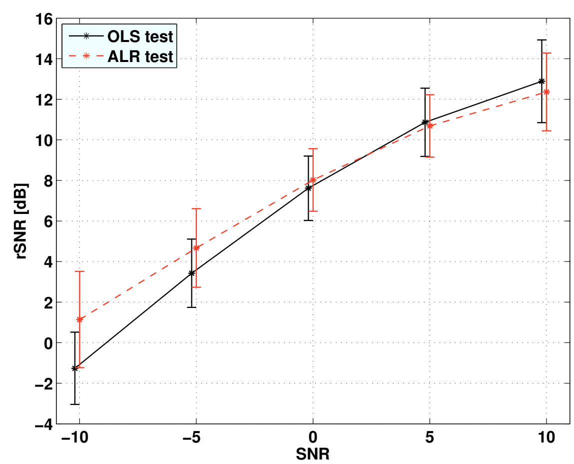

Figure 3. Evaluation results: rSNR values (mean $\pm$ std) for the two models depending on the SNR of the signal mixture.

4. Discussion and conclusions

Our approach consists in estimating the CPR-part of a corrupted signal by adaptive regression on lagged copies of a reference signal which correlate with the CPR artifact signal. It allows for stochastically changing regression coefficients.

The evaluation based on a small pool of human artifact-free VF and porcine asystole CPR data outperforms comparable previous studies with respect to rSNR [12, 9, 15]. In comparison with OLS regression the proposed algorithm shows, for low SNR corrupted signals, rSNR im-

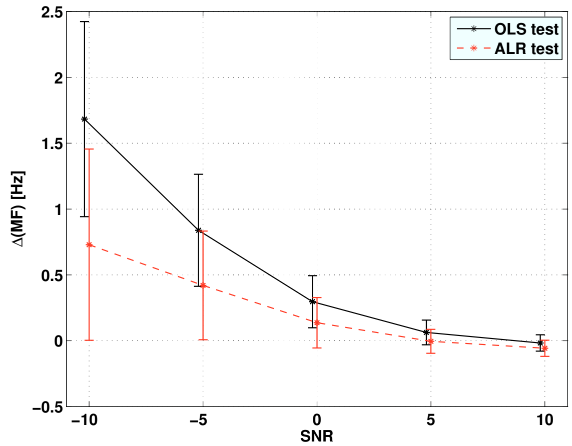

Figure 4. Evaluation results: $\Delta(\mathrm{MF})$ values (mean $\pm$ std) for the two models depending on the SNR of the signal mixture. The MF values were computed in the frequency range $[0.1\ \mathrm{Hz}, 50\ \mathrm{Hz}]$.

provements and yields better estimates of the mean frequency of the true VF ECG signal. Thus, the ALR model presents an improvement compared to the non-adaptive OLS model for the purpose of CPR artifact removal from VF ECG signals. This holds, in particular, because we optimized only one parameter (α) of the ALR model using the fixed OLS-optimal values for $(f, \delta, l_{min}, l_{max})$, which was done for computational reasons.

Besides the limited optimization procedures applied, the results are mainly limited by the small data sets. Furthermore, only VF signals and no other shockable signals were used. To investigate the feasibility of rhythm detection algorithms during CPR also non-shockable signals should be included, cf. [13]. The rSNR is a common parameter to quantify the performance of a signal separation algorithm. For the practical application of CPR removal algorithms in defibrillators, however, other objective functions such as the performance of a rhythm detection algorithm or $\Delta(\mathrm{MF})$ could be more reasonable.

References

[1] Anonymous. 2005 American Heart Association Guidelines for Cardiopulmonary Resuscitation and Emergency Cardiovascular Care. Circulation 2005;112(24 Suppl):IV1–203.

[2] Hazinski MF, Nadkarni VM, Hickey RW, O'Connor R, Becker LB, Zaritsky A. Major changes in the 2005 AHA Guidelines for CPR and ECC: reaching the tipping point for change. Circulation 2005;112(24 Suppl):IV206–11.

[3] Sato Y, Weil M, Sun S, Tang W, Xie J, Noc M, Bisera J. Adverse effects of interrupting precordial compression during cardiopulmonary resuscitation. Crit Care Med 1997; 25(5):733–6.

[4] Eftestol T, Wik L, Sunde K, Steen P. Effects of cardiopulmonary resuscitation on predictors of ventricular fibrillation defibrillation success during out-of-hospital cardiac arrest. Circulation 2004;110(1):10–5.

[5] Eftestol T, Sunde K, Steen P. Effects of interrupting precordial compressions on the calculated probability of defibrillation success during out-of-hospital cardiac arrest. Circulation 2002;105(19):2270–3.

[6] Amann A, Rheinberger K, Achleitner U. Algorithms to analyze ventricular fibrillation signals. Curr Opin Crit Care 2001;7(3):152–6.

[7] Strohmenger H, Lindner K, Brown C. Analysis of the ventricular fibrillation ECG signal amplitude and frequency parameters as predictors of countershock success in humans. Chest 1997;111(3):584–9.

[8] Amann A, Tratnig R, Unterkofler K. Reliability of old and new ventricular fibrillation detection algorithms for automated external defibrillators (AEDs). Biomedical Engineering Online 2005;Accepted for publication.

[9] Ruiz J, Aramendi E, Ruiz de Gauna S, Lazkano A, Leturiendo L, Gutierrez J. Ventricular fibrillation detection in ventricular fibrillation signals corrupted by cardiopulmoary resuscitation artifacts. Computers in Cardiology 2004;221–4.

[10] Klotz A, Amann A, Feichtinger H. Removal of CPR artifacts in ventricular fibrillation ECG by local coherent line removal. EUSIPCO (12th European Signal Processing Conference), 2004; .

[11] Langhelle A, Eftestol T, Myklebust H, Eriksen M, Holten B, Steen P. Reducing CPR artefacts in ventricular fibrillation in vitro. Resuscitation 2001;48(3):279–91.

[12] Husoy J, Eilevstjonn J, Eftestol T, Aase S, Myklebust H, Steen P. Removal of cardiopulmonary resuscitation artifacts from human ECG using an efficient matching pursuit-like algorithm. IEEE Trans Biomed Eng 2002;49(11):1287–98.

[13] Eilevstjonn J, Eftestol T, Aase S, Myklebust H, Husoy J, Steen P. Feasibility of shock advice analysis during CPR through removal of CPR artefacts from the human ECG. Resuscitation 2004;61(2):131–41.

[14] Rheinberger K, Baubin M, Unterkofler K, Amann A. Removal of Resuscitation Artefacts from Ventricular Fibrillation ECG Signals Using Kalman Methods. Proceedings of the 32nd annual international conference on Computers in Cardiology 2005;32:555–558.

[15] Rheinberger K, Steinberger T, Unterkofler K, Baubin M, Klotz A, Amann A. Removal of CPR Artifacts from the Ventricular Fibrillation ECG by Adaptive Regression on Lagged Reference Signals. IEEE Trans Biomed Eng 2006; submitted.

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