REMOVAL OF CPR ARTIFACTS IN VENTRICULAR FIBRILLATION ECG BY LOCAL COHERENT LINE REMOVAL

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ABSTRACT

We extend a method described by Sintes/Schultz (1998) for the removal of *coherent signals* in stationary broadband noise to the case of non-stationary broadband noise by applying time-frequency methods. The new method is applied to the removal of cardiopulmonary resuscitation (CPR) artifacts in the ECG of domestic pig suffering from ventricular fibrillation (VF). The excellent filtering properties and the possibility of real-time signal processing might have applications in emergency medical settings.

1. INTRODUCTION

Ventricular fibrillation (VF) claims more than 450000 lives per year in the United States [14]. Any attempt to improve resuscitation success is therefore highly welcome. Improvements may, for example, rely on more effective defibrillation waveforms, improved medication, or on a more appropriate timing of cardiopulmonary resuscitation (CPR) and defibrillation shock. ECG-based prediction of defibrillation success [10, 9, 6, 2, 3, 4] may improve timing of CPR and defibrillation shock and therefore avoid myocardial injury and give a performance feedback during cardiopulmonary resuscitation (CPR). It requires algorithms to analyze ventricular fibrillation (VF) signals, to remove artefacts and to classify patterns of parameters. To date, no entirely satisfactory methods have been found to cope with CPR artifacts. These artefacts are characterized by large spikes in the time domain of the signal, and by a tonal structure in the frequency domain. The present contribution is an attempt to develop such algorithms for CPR-artefact removal, based on one ECG-channel only. Presently, external manual resuscitation has to be stopped for ECG-analysis, which leads quickly to a deterioration of the patients' status. Developing and improving algorithms of CPR-artefact removal could therefore have an important impact on emergency medical protocols. In particular, CPR could be performed in parallel with analysis of ECG, leading to better resuscitation results. In this contribution, we adapt a technique, which has originally been developed for the analysis of data obtained from gravitational wave interferometers, to ECG analysis. Technically, this means an adaption of the original method to the time-variant case by means of STFT-methods. We demonstrate the effect of our method on a VF-dataset from an animal model. More detailed investigations on human VF-ECG are in preparation. Technically speaking we have to address the problem of removal of the *coherent signal content* from the broadband signal part, both being allowed to behave in a non-stationary way. In [12] the coherent signal part is described as

$$y(t) = \sum_{k=1}^{N} \left(\alpha_k m(t)^k + \overline{\alpha_k m(t)^k} \right) \tag{1}$$

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(the overbar denotes complex conjugation), where $m(t)$ is a nearly monochromatic signal (the *interference)*:

$$m(t) = r(t)\, e^{2\pi i f_0(t) t},$$

$r(t)$ and $f_0(t)$are assumed to be slowly varying. An estimate for $f_0(t)$ and an upper bound for the number of components N are assumed to be known. The α_k are complex constants. The signal is modelled as $s_0(t) = y_0(t) + n_0(t)$, where n_0 is the *broadband component*. The problem consists in estimating α_k and $m(t)$. A possible approach is described in [12] under stationarity assumptions on $n_0(t)$; our localized version will be explained in the next section.

Our model generalizes the coherent signal part to allow for piecewise constant coefficients $\alpha_k(t)$ by using TF-techniques. In particular we obtain the following improvements compared to the original algorithm:

- The approach in [12] is localized, allowing for more general signals to be represented and enabling online computation (an important aspect for the medical applications we have in mind).
- Robustness is added by regularization. This is particulary important in the case of vanishing (or very small) coherent signal components, where the original algorithm tends to produce artifacts due to instability.

These features allow for a medical application: the real-time removal of artifacts of cardiopulmonary resuscitation (CPR) in ECGs of Ventricular Fibrillation (VF) (see Fig.1 for an example). This is of great value in emergency medicine, allowing for shorter "hands-off" times (where no medical treatment is possible), so decreasing mortality.

2. OUTLINE OF THE ALGORITHM

2.1 Preliminaries

A basic tool in our analysis is the *Short-Time Fourier Transform* (STFT) of a signal f with respect g, given as:

$$\begin{aligned} V_g f(t,\omega) &= \int_{\mathbb{R}} f(\tau)\overline{g(\tau - t)} e^{-2\pi i \omega \tau} d\tau = \\ &= \mathscr{F}(f \cdot T_t \bar{g})(\omega) \\ &= \langle f, M_w T_t g \rangle . \end{aligned} \tag{2}$$

The *window function* g is usually non-negative and symmetric around zero, e.g. a Gaussian. $\mathscr{F}$ denotes the Fourier Transform, T_x is the translation operator: $T_x f(t) = f(t-x)$, and M_ω the modulation operator (frequency shift): $M_\omega f(t) = e^{2\pi i \omega t} f(t)$. The STFT is a linear operator; for basic properties see [7] or [5]. If g is normalized it is isometric with respect to the energy norm. As we will work in the discrete time setting (i.e. signals are assumed to be elements of a $\mathbb{R}^d$) the operators defined above have to be dicretized as

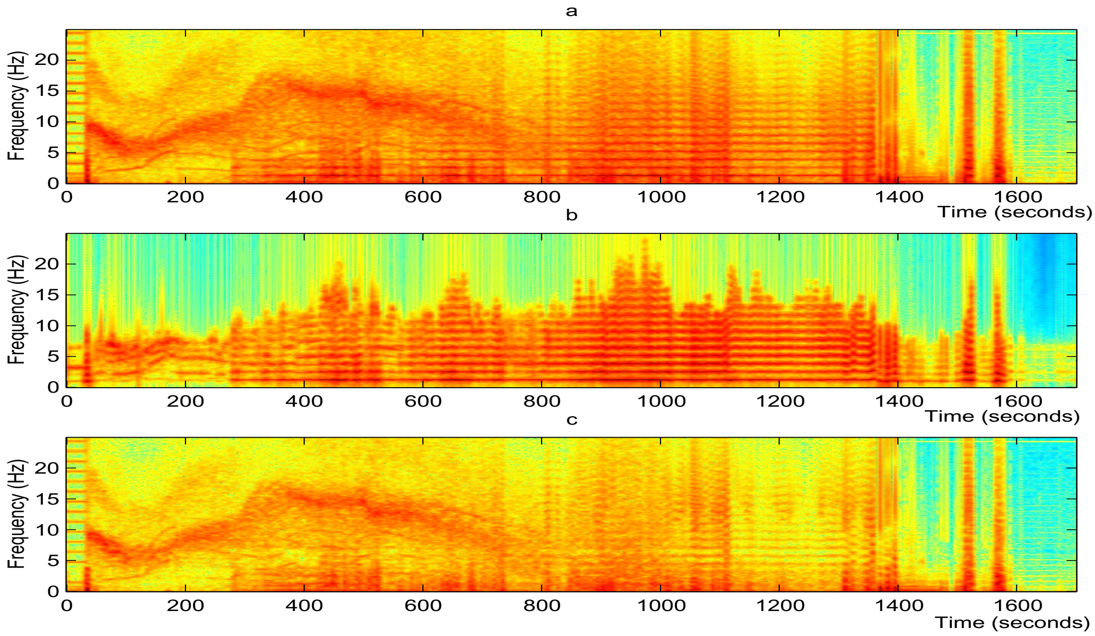

Figure 1: Example of Local CLR alg. applied to a VF ECG: Displayed are log-spectrograms of the signal (i.e. color-coded logarithm of squared STFT) (a), the estimated coherent part (b), and the estimated broadband component (c). Sampl. freq. 200 Hz, a Gaussian window, window-length 2048, $\sigma = 512$, $\Delta T = 512$ (all in samples). VF is induced after 33s, CPR starts at $t = 276$s. Estimation of coherent part (b) uses same windows, 6 freq. bins around multiples of f_0 (assumed to lie between 1.1 - 1.5 Hz 4 overtones for analysis and 20 overtones for synthesis.

well. In particular, the DFT will play the part of the Fourier Transform. Typically, the length of the DFT can be chosen to be equal to the window-length, that is $L = |\mathrm{supp}\, g|$. We will use time sampled STFT values only:

$$V_g^{\Delta T}(k,\omega) = V_g f(k\Delta T,\omega),$$

where ΔT is a fraction of the window length (in applications we will typically choose $\Delta T = L/4$ or $L/2$) and ω are the *Fourier frequencies* k/L, $k = 0,1,\ldots,L-1$.

Under these conditions (in fact under much more general ones, see [7]) and with mild conditions on g (positivity is sufficient, together with sufficient overlap between its shifted copies in combination with sufficiently dense sampling on the Fourier transform side) inversion of the STFT is possible on its range: See [11] for these and related properties of the discrete STFT.

2.2 Estimation of the interference

Our approach consists in applying the Coherent Line Removal (CLR) algorithm described in [12] to the "time slices" $V_g s_0(t,\_)$ of the given signal, and then to "glue" the local estimates together by means of the ISTFT. In the following we give a short summary of the CLR method: An estimation of $m(t)$ is constructed by "cutting off" the harmonics of the interference in the TF domain, for each of the harmonics an estimate of $m(t)$ is calculated; a preliminary version of $m(t)$ is obtained as weighted sum of these estimates, where the weights are determined by the strength of the "background noise".

As we work on single "time slices" for the most part of the estimation procedure, we set the time parameter to zero, so we will do our estimations on

$$\hat{s} = \widehat{g\cdot s_0} = \widehat{g\cdot y_0} + \widehat{g\cdot n_0} = \hat{y} + \hat{n}$$

To "cut off" the spectral content of the signal at multiples of the fundamental frequency f_0, we use a set of *smooth localizers* with disjoint supports, i.e. positive functions (e.g. smooth plateau functions) with

$$\Sigma_f h_k(f) = 1,\ h_k \geq 0$$
$$0 \in \mathrm{supp}(h_k)$$
$$\mathrm{supp}(h_k) \cap \mathrm{supp}\left(T_{f_0} h_{k+1}\right) = \emptyset$$

where the support of the localizers covers the "essential support" of $\hat{y}$; moreover the value of the localizers should be approximately constant on this set.
This produces a set of functions

$$\tilde{s}_k = \hat{s}\hat{g} \cdot T_{kf_0} h_k = \tilde{y}_k + \tilde{n}_k, \quad 1 \leq k \leq N,$$

We obtain $s_k = y_k + n_k$ by inverse Fourier transformation. With good approximation (by the conditions posed on the localizers)

$$\begin{aligned} s_k = \mathscr{F}^{-1}\tilde{s}_k &\approx \alpha_k m^k + \left(M_{kf_0}\mathscr{F}^{-1}h_k\right) * n \\ &= y_k + n_k, \end{aligned}$$

where both y_k, n_k are narrowband functions with frequency support around kf_0.
Consequently, the complex valued roots [1] B_k, defined as

$$B_k(t) = s_k^{1/k}(t) = \alpha_k^{1/k} m(t)\,\beta_k(t), \tag{3a}$$

$$\beta_k(t) = \left[1 + \frac{n_k(t)}{\alpha_k m(t)^k}\right]^{1/k}. \tag{3b}$$

all have effective frequency supports around f_0 and will be used to estimate the interference $m(t)$. Eq.(3b) has to be interpreted with caution, because its denominator can be zero, if there is no interference present at time t, or if α_k is (nearly) zero: In this case s_k

[1] some care has to be taken using the correct branch of the root, so that no "jumps" occur in $\arg B_k$

consists of the broadband component only. We read (3b) in a regularized sense: In case the quotient gets "too big" the corresponing value of $B_k(t)$ should have little influence on the estimation of the interference; so the estimates of $m(t)$ obtained from the B_k will be weighted according to the magnitude of β_k, giving less weight for large $\beta_k(t)$. See subsec.2.3 for a discussion.
The functions n_k can be interpreted as realizations of stochastic processes, so the B_k are stochastic functions as well. As the *ensemble average* $\langle n_k(t)\rangle$ is zero at any time instant t, we obtain $\langle B_k(t)\rangle = \alpha_k^{1/k} m(t)$. These functions are multiples of each other. The problem to multiply all of these functions with factors Γ_k, so that they are "most alike" is solved in [12] by introducing yet another set of functions $b_k = \Gamma_k B_k$, with $\langle b_k(t)\rangle = a \cdot g(t)\, m(t)$, and to estimate the values of the Γ_k by comparing to the first (or, more generally, any other *fixed*) harmonic:

$$\Gamma_k := \arg\min \|B_k - \Gamma_k B_1\|_2\,,\ k = 1,2,\ldots$$

what leads to

$$\Gamma_k = \langle B_1, B_k\rangle \Big/ \|B_k\|^2$$

In principle the subsequent variant of deriving the weights Γ_k should be applicable in more general situations, because it does not favour one specific B_k (here B_1): one solves the following minimization problem:

$$\min \sum\nolimits_{1\leqslant k<l\leqslant N} \|\Gamma_k B_k - \Gamma_l B_l\|_2^2 \quad s.t.\, \|\Gamma\|_2 = 1$$

which determines Γ as the eigenvector to the smallest eigenvalue of a certain matrix. This will be carried out in subsequent work. On the other hand, the choice of a fixed reference signal as proposed appears to improve stability.
The interference $m(t)$ is constructed as a function in the linear span of the b_k with the same mean and minimum variance $V(m(t))$:

$$\begin{aligned} m(t) &= \sum_{k=1}^{N} \xi_k(t)\, b_k(t), \quad \sum_{k=1}^{N} \xi_k = 1 \\ V(m(t)) &= \sum_{k=1}^{N} \xi_k^2 V(b_k(t)) = \sum_{k=1}^{N} \xi_k^2 \left|\Gamma_k^2\right| V(B_k(t)) \to \min!. \end{aligned}$$

This leads to [2]

$$\xi_k = \frac{V(\beta_k(t))^{-1}}{\sum_{l=1}^{N} V(\beta_l(t))^{-1}}. \tag{4}$$

An estimation of the variance can be obtained by a Taylor expansion of the root in Eq.(3b) to the first order:

$$\beta_k(t) \approx 1 + \frac{n_k(t)}{k\alpha_k m(t)^k} \tag{5}$$

Obviously this approximation *overestimates* the magnitude of β_k, so the expression for the variance resulting from (5),

$$V(\beta_k(t)) = \frac{\left\langle |n_k(t)|^2 \right\rangle}{k^2 \left|a_k m(t)^k\right|^2} \tag{6}$$

(the brackets denoting ensemble averages) is an overestimation either, resulting in *less weight* ξ_k for the corresponding function b_k in the estimation of $m(t)$ (Eq.(4)), making the approximative estimation *stable* against noise. - In the denominator of (6) $a_k m(t)^k$ can be approximated by $s_k(t)$, giving

$$V(\beta_k(t)) \approx \left\langle |n_k(t)|^2 \right\rangle k^{-2} |s_k(t)|^{-2} \tag{7}$$

[2] In [12] the expression for the variance in (4) does not to contain the factor Γ_k, obviously due to a typo or implicit normalization assumption.

For a *stationary* broadband component $n_k(t)$ the ensemble average $\left\langle |n_k(t)|^2 \right\rangle$ is equal to the power spectral density of n_k, which can be estimated by calculating the PSD of s in a neighbourhood of $\operatorname{supp}\hat{s}_k$ not containing $\operatorname{supp}\hat{s}_k$. This completes the estimation of $m(t)$.
The coefficients α_k are calculated by projection:

$$\alpha_k = \left\langle s, m^k \right\rangle \Big/ \left\|m^k\right\|^2 \tag{8}$$

This gives $y(t)$ as in Eq.(1). - We should state that it can make sense to use more overtones (a larger value of N in Eq. (4)) for reconstruction than for analysis. Similarily, the CLR algorithm will work if only a subset of the harmonics is used for estimation.

2.3 Regularization

The estimation procedure as described above is not stable in the cases of

(a) vanishing broadband component $n_k(t)$,
(b) vanishing interference $m(t)$,

In the "no-noise" case the variance of one or more β_k is zero, giving weight one (in the case of one vanishing β_k) to the corresponding function-value $c_k(t)$ and zero to all the others. As the estimation of the power spectral density (inherently, and by the stationarity assumption implicitely contained in its usage as noise estimate) tends to give only rough estimtes of the real noise component the corresponding weigths can be too big in the low-noise case. A regularized expression for the variance is given by

$$V_\varepsilon(\beta_k(t)) = \frac{\left\langle |n_k(t)|^2 \right\rangle + \varepsilon\, |s_k(t)|^2}{k^2 |s_k(t)|^2}$$

In fact, in our experiences the CRL algorithm is rather robust with that kind of regularization: Even the limit for $\varepsilon \to \infty$, leading effectively to fixed variances $V(\beta_k(t)) \sim k^{-2}$ gives acceptable results in many cases.

The case of vanishing $m(t)$ is more subtle: Two cases have to be distinguished:

(b1) There is no interference present, while the estimated interference $m(t)$ is non-zero (the case of non-vanishing noise)
(b2) The estimated intererence is (approximately) zero (the low-noise case)

Case (b1) happens if some broadband components are large compared to the coherent component. The approximation in the expression for the variance in (7): $s_k \approx \alpha_k m^k$, not being valid in this case, as $\left|\alpha_k m(t)^k\right| \ggg n_k(t)$, will assign an arbitrary number to the estimated variances, resulting most probably in a non-zero, but finite, estimate of $m(t)$. The components $a_k m^k(t)$ will be of the order of magnitude of the broadband signal. So this case cannot be detected by the CLR algorithm in general. Actually this is a problem of the f_0 estimation procedure and related to problems of spectral peak detection in high noise. Here statistical tests for the reliability of a detected spectral peak can be done [13]. In the medical application this case corresponds to no CPR + VF with dominant frequency around f_0 (a number that is typically lower than 1.5 Hz). - The experimental data we have got for this case shows that at least some of the broadband component at this frequency remains, so that correct classification is possible.
Case (b2) corresponds to weak broadband, weak interference signals. Here regularization methods can be applied succesfully: In the exact representation of the variance and in the approximation (6) all variance terms diverge, leading to *indefinite* values for the weigths in Eq.(4). Moreover, the magnitudes of the coefficients α_k in Eq.(8) tend to infinity for all indices k. This could result in a

large value for $|y(t)|$, contrary to the real situation $m(t) \approx 0$. - A regularized estimation of the coefficients,

$$\left\| \alpha_k^{(\delta)} \right\| = \frac{\langle s, m^k \rangle}{\|m^k\|^2 + \delta}$$

leads to the asymptotic behavior

$$\left\| \alpha_k^{(\delta)} m^k \right\| \leqslant \frac{\|s_k\|}{1 + \delta \Big/ \|m^k\|^2} \approx \frac{\|m^k\|^2 \|n_k\|}{\delta}$$

for m^k small. On the other hand, this regularization leaves an coherent signal part of the order

$$\frac{|\alpha_k \delta|}{\|m^k\|^2} |m_k(t)|$$

on the broadband signal for big values of m^k. So there is a data-dependent "trade-off" for the optimal value of δ.

2.4 Global reconstruction of the coherent signal part

The locally estimated values of $y(t)$ can now be "glued" together to give a global estimate in a way that avoids discontinuites on the ends of the estimation intervals. This can be done by standard STFT inversion procedures; an overlap-add (OLA)([1]) algorithm will allow for online processing. Inverse STFT can be realized as

$$ISTFT(u)(t) = \frac{\left(V_g^{\Delta T}\right)^* u}{\sum_{k \in \mathbf{Z}} |g(t - \Delta T k)|^2}$$

(the star denotes the adjoint operator).

3. PRACTICAL REALIZATION

We have worked out a MATLAB implementation of the discribed algorithm adapted to the case of CPR removal in VF-ECGs. This means we have some knowledge about the fundamental CPR frequency f_0, which is assumed to vary between 1 and 1.5 Hz (what is actually true). Estimation of the fundamental frequency is based on the calculating the "Harmonic spectrogram" [8]

$$W_g s(t, \omega) = \sum_{k=1}^{n} |V_g s|^2 (t, k\omega)$$

and finding the maximum of this function in the chosen frequency band for every time slice. No search for the actual existence of harmonics is performed, neither is the existence of spectral lines tested. (There are many algorithms for f_0 estimation; we chose a simple algorithm based on the STFT for computational purposes.)
Using standard equipment (800 MHz Processor) and MATLAB, the algorithm needs about $1/5$ of the time span of the ECG experiment to calculate the results. As OLA-algorithms can be easily adapted to online processing the limiting factor for real time processing is the length of the analysis window g (approx. 10s in the example of Fig.1) and the time-step ΔT (approx. 2.5s). This seems to be "compatible" to practical use (Automated external defibrillators typically need a measurement time of about 10s.)

4. AN EXAMPLE

We will illustrate the foregoing statements by the means of an example: We use data from a VF ECG, the corresponding spectrograms are displayed in Fig.1, see there for the technical data. In subfig.(a) the original data is displayed. Fibrillation (VF) starts at $t_0 = 33s$ (before that time the overtones of normal heart rhythm are visible at multiples of 5/3 Hz), the VF "band" starting at approx. 10 Hz. At $t = 276s$ CPR starts, producing spectral lines with "overtones" in the spectrogram. (The visible constancy of f_0 is a part of the experiment, which is not exploited in the estimation procedure and which has no influence on the results. Important is the *harmonic relation* of the overtones.) These lines finally overlap with the VF spectral part after $t \approx 700$s. After $t \approx 850$s there is no VF content visible, the spectrogram is dominated by CPR artifacts. Many of these artefacts seem to be removed in subfig.(c).

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