Review of filtering methods for artifacts removal in ECG signals

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Outline

Introduction

Filtering methods

Evaluation of the methods

Reproducible research

Notation

$$y = v + \alpha c \qquad (*)$$

y — measured signal $\quad$ v — desired signal

c — "noise" signal, $\|c\| = 1$ $\quad$ α — noise level

$$\text{SNR}(y, v) := 10 \log_{10} \left(\frac{\|v\|_2^2}{\|v - y\|_2^2} \right) \qquad \text{— data SNR}$$

Two players:

- Nature: chooses c, v, α, and constructs y according to $(*)$
- Estimator (we): given y and some partial knowledge of how nature chooses c, v, α, find a good estimate of v

The filtering problem

Given y, find in real-time an approximation $\widehat{v}$ of v.

$$y \longrightarrow \boxed{\text{Filter}} \longrightarrow \widehat{v}$$

Choose the filter, so that the approx. error $\|v - \widehat{v}\|$ is "small".

$$\text{SNR}(\widehat{v}, v) = 10 \log_{10} \left(\frac{\|v\|_2^2}{\|v - \widehat{v}\|_2^2} \right) \qquad \text{— restored SNR}$$

Filtering methods

Filtering is based on prior knowledge about v, c, α.

- Bandpass filtering v and c are separated in frequency and the cutoff frequency f_0 is known
- Kalman filtering $\operatorname{col}(v, c)$ is modeled as an ARMA(X) process M and that model is known
- Adaptive filtering uses an additional signal u that is well correlated with c but uncorr. with v

Biomedical context

Meaning of the signals:

- v — pure ECG signal
- c — artifact on the ECG caused by resuscitation
- u — arterial blood pressure signal
  u is “well” correlated with c and is measured

Main questions from the application point of view:

1. What is the most relevant prior knowledge about v, c, α?
   (How nature “chooses” these signals?)
2. In what norm $\|\cdot\|$ should the est. error $v - \widehat{v}$ be small?
   (In what sense we want the “best” approximation of v?)

Our approach

We study the first question empirically.

A database of separately recorded v, c, u signals allows us to

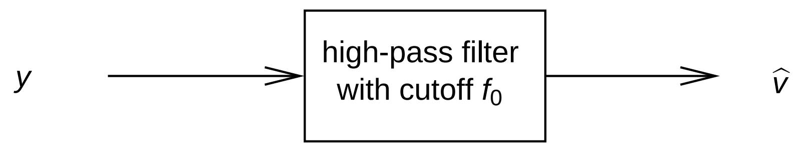
1. verify what properties v, c, u have
2. test the methods (by constructing y and checking the SNR improvement $\text{SNR}(\widehat{v})/\text{SNR}(y)$)

The second question is currently unexplored.

We use the default choice in signal processing: 2-norm

Being aware that it may not be the best one for artifacts removal.

Band-pass filtering

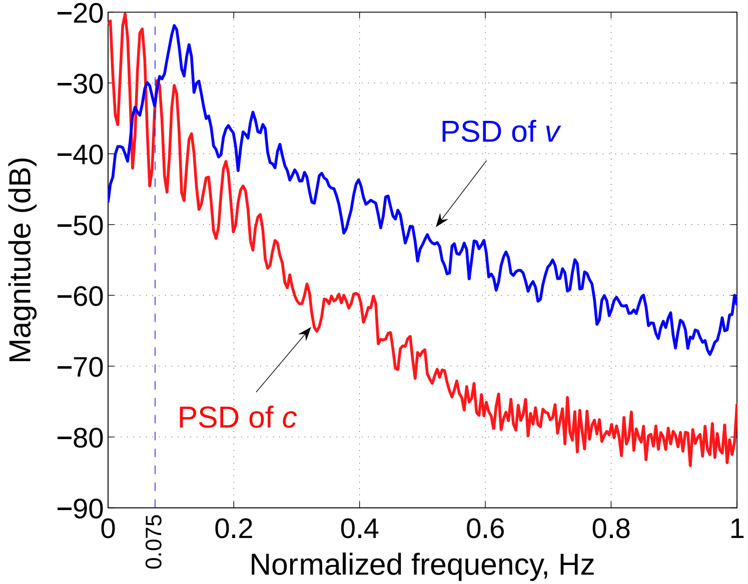


Notes:

- the arterial blood pressure signal u is not used
- the cutoff frequency f_0 is the only parameter

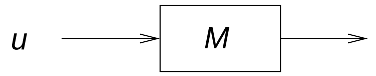
We choose f_0 empirically from the identification data. It turns out that f_0 doesn't vary much from one pair (v, c) to another.

Frequency separation of v and c $(f_0 = 0.075Hz)$

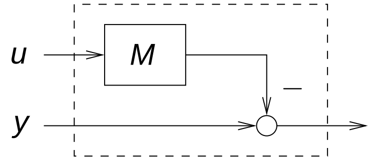


Filtering based on a model $u \mapsto c$

u is well correlated with c and is measured $\Longrightarrow \exists$ model M



such that $\hat{c}$ is a “good” approximation of c. Then $\hat{v}$ can be constructed as follows:



Filter

Actually, $\hat{c}$ is computed by a Kalman filter and not by simulation.

Filtering based on a model $u \mapsto c$

M is a prior knowledge. However, it is not given in practice!

Contrary to f_0, M differs a lot from one pair (u, c) to another

$\Longrightarrow$ computing M from one part of the data and using it on another part is not an option.

Possible solution: use adaptive filter; it identifies M in real-time from the given data (u, y).

In the simulations, we identify M from the testing data (unrealistic)

Reason: this serves as a reference method, *i.e.*,

gives an upper bound for the achievable performance.

Adaptive filters proposed in the literature

Main idea: simultaneously identify M from past data (u, y) and filter (u, y), using M.

Various implementations. Often M is assumed FIR (simplification).

Main publications:

- Husøy *et al.* (Stavanger, Norway): matching pursuit FIR adaptive filtering
- Amann *et al.* (Innsbruck, Austria): FIR adaptive filter implemented by a Kalman filter

Tested on databases, as described in this talk.

This work does not address our “main” questions:
1) relevant prior knowledge 2) relevant estimation criterion

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Simulation setup

We use a database of triplets (u_i, c_i, v_i), $i = 1, \dots, 7$ to construct

$$y_{\alpha,i,j} = v_i + \alpha c_i, \quad i,j = 1,\dots,7 \text{ and } \alpha = -10,-5,0,5,10 \quad (*)$$

and apply the considered methods on the data $(u_i, y_{\alpha,i,j})$.

Notes:

- The database is collected at the Innsbruck Medical Univ.
- These are "real" measurement (u,v) from human, c from pigs
- y is a construction, but the "real" actifacts corrupted human ECG signal is likely to be an additive mixture $(*)$

Simulation setup

This give us 49 $\mathrm{SNR}(\widehat{v}_{i,j})$ for each method and for each α.

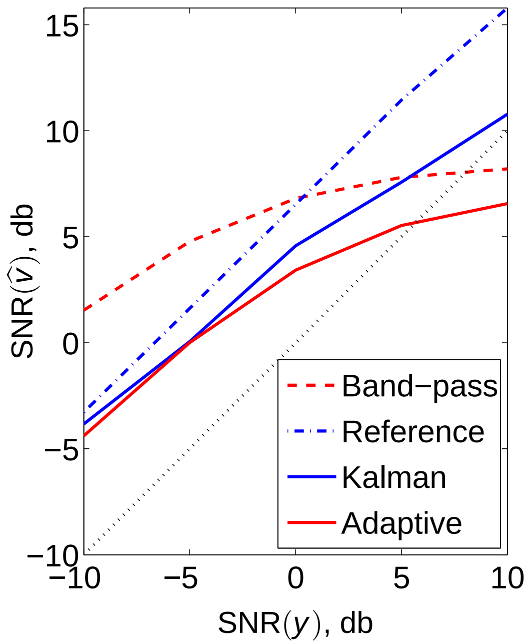
As a final result, we show

$$\boxed{\text{a plot of the average } \mathrm{SNR}(\widehat{v}) \text{ as a function of } \mathrm{SNR}(y).}$$

The plot shows the improvement of the restored signal $\widehat{v}$ as the given signal y is less corrupted by the artifacts.

A method being above the 45° line passing through (0,0) means that this method improves the given signal y.

Comparison of methods



Observations

1. For low SNR ($<$ 0db), the band-pass filter has the best performance.
2. The reference method has a steady increase of performance as the SNR increases.
3. The Kalman filter uniformly outperforms the adaptive filter.
4. The band-pass filter uniformly outperforms the adaptive filter.

All observations, except for 1 and 4 are easy to explain.

The surprisingly good performance of the band-pass filter may be due to its superior robustness.

Conclusions

- The filter robustness is crucial for ECG artifact removal.
- Reference filter: computing a "good" model for $u \mapsto c$ is challenging even when using the unknown c signal.

  The optimization methods have convergence problems.

  Typically, the best model is unstable.
- Adaptive filtering: computing a good model from (u, y) online is of course harder than offline.

  How realistic is it in view of the difficulties with designing the reference filter and of its performance at low SNR?
- The simulation results suggest that the simplest method—low-pass filtering—is overall the best one.

Reproducible research

> For a field to qualify as a science, it is important published work be reproducible by others.

Theoretical work can be reproduced, from published papers only.
Computational work, however, may use unpublished information (implementation details, software, data sets, *etc*.)

J. Buckheit and D. Donoho (Stanford Univ.) advocate:

> "When we publish articles containing figures which were generated by computer, we also publish the complete software environment which generates the figures."

They classify the state of research in wavelets as a scandal, because computational results are not reproducible.

Is biomedical signal proc. research reproducible?

> Usefulness of methods is normally and acceptably "proved" by experiments on "real" data.

However, the methods and/or data being used are rarely given.

The field will benefit from having publicly available benchmark data sets against which the methods can be tested.

Currently this is not the case for ECG artifacts removal.