Review of filtering methods for removal of resuscitation artifacts from human ECG signals

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Outline

Introduction

Filtering methods

Evaluation of the methods

Notation

$$y = v + \alpha c$$

y	—	measured signal	v	—	desired signal
c	—	"noise" signal, $\|c\| = 1$	α	—	noise level

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

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”.

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

Filtering methods

Filtering is based on prior knowledge about v and c.

- Bandpass filtering — v and c are separated in frequency and the cutoff frequency f_0 is known
- Kalman filtering — $\text{col}(v, c)$ 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 meaning of the signals

- v — pure ECG signal
- c — artifact on the ECG caused by resuscitation
- u — arterial blood pressure signal

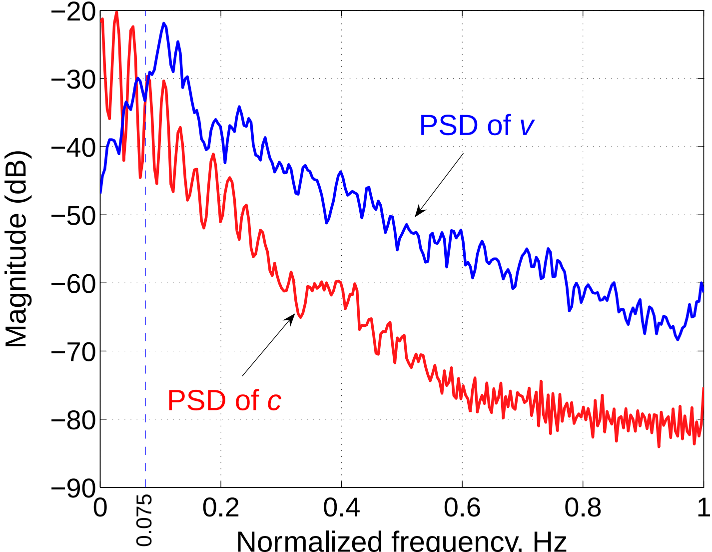
  u is "well" correlated with c and is measured

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

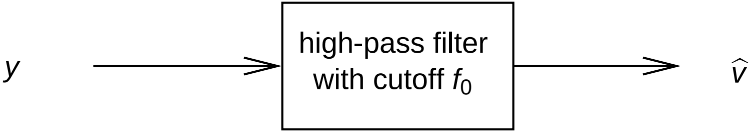
1. design the methods: choose the cutoff f_0 and the model M
2. test the methods: construct y and check the SNR improvement $\mathrm{SNR}(\widehat{v})/\mathrm{SNR}(y)$

Note: In realistic testing f_0 and M should be chosen from part of the data that is not used for testing.

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



Band-pass filter

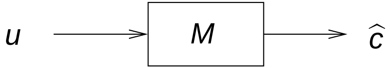


Notes:

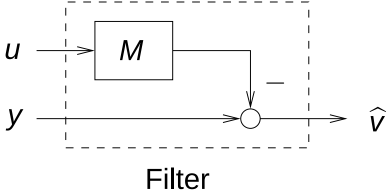
- the arterial blood pressure signal u is not used
- the cutoff frequency f_0 is the only parameter
- f_0 doesn't change much from one pair of signals to another

Filtering based on a model $u \mapsto c$

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



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



Actually, $\widehat{c}$ 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 (y, c).

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

Reason: it is a candidate for a reference method, *i.e.*,

$$\boxed{\text{gives an upper bound for the achievable performance.}}$$

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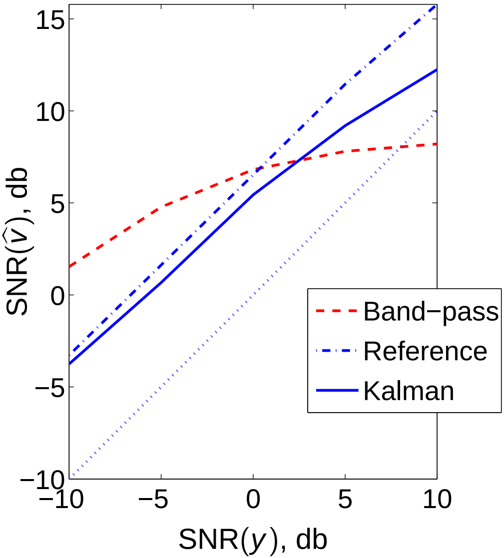
Comparison of band-pass and Kalman filters



Objectives/questions

- For SNR(y) $<$ 0db, the band-pass filter performs better than the reference filter.

  Surprising result, for which currently we have no explanation.

- Add on the same plot the results of other methods (*e.g.*, the best methods from the literature).

  The best methods are not implemented in a free software.

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?
- Our simulation results suggest that the simplest method—low-pass filtering—is overall the best one.