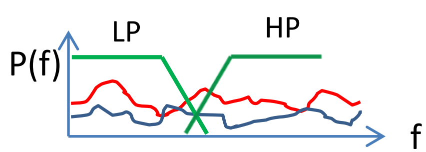
Biosignal filtering and artifact rejection, Part II

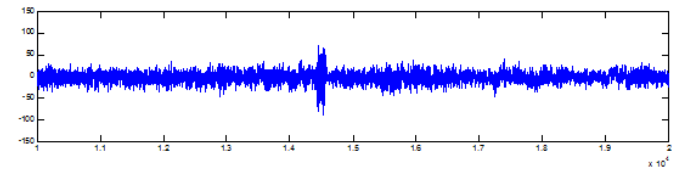
Biosignal processing, 521273S
Autumn 2019

Example: eye blinks interfere with EEG

- EEG includes ocular artifacts that originates from eye blinks
  - EEG: electroencephalography
  - EOG: electrooculography
- The artifacts interfere with the analysis of true EEG signal
- How to get rid of the interfering component, the eye blinks?
  - LP/HP/BP/BR filters defined in spectral domain?
  - No: EEG and EOG overlap in spectral domain -> we could loose both noise and signal!



Pure EEG



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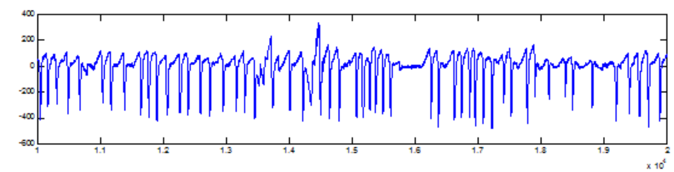
Pure EOG



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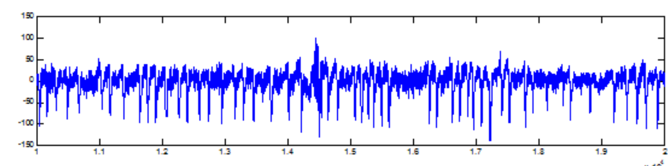
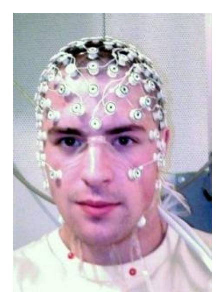
Resulting signal



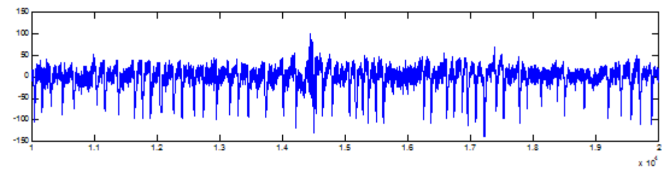


https://upload.wikimedia.org/wikipedia/commons/b/bf/EEG_cap.jpg

Example: eye blinks interfere with EEG

- Adaptive filtering can be used to remove ocular artifacts
  - Interfering signal is subtracted from EEG
- Reference signal is taken from electrodes close to the eye
- But, what if the reference signal is not exactly like the interfering signal?

Measured EEG signal



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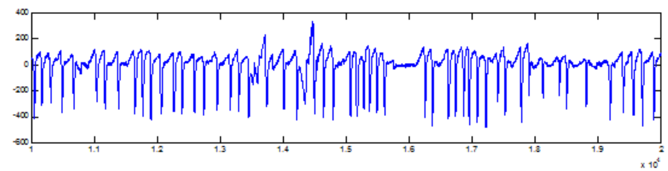
Reference EOG



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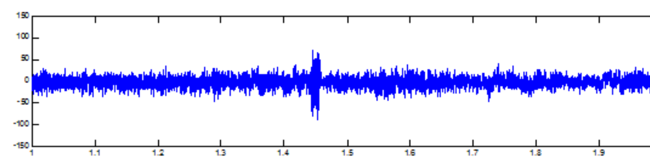
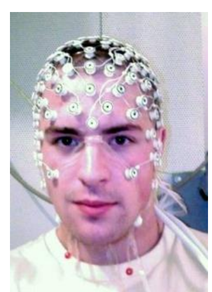
Filtered EEG

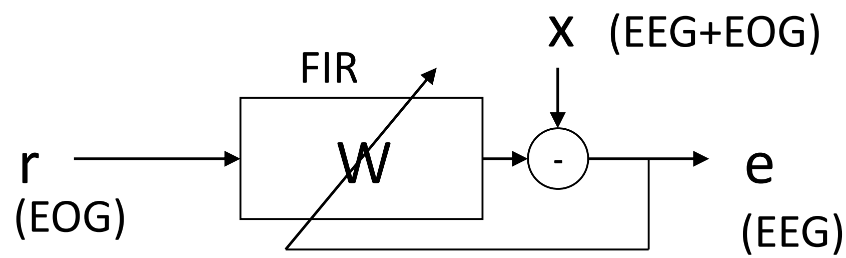




https://upload.wikimedia.org/wikipedia/commons/b/bf/EEG_cap.jpg

LMS adaptive filtering (Least Mean Square)

- Situation: an interfering signal component has been summed to the actual biosignal
- Filter aims to subtract the interfering signal from the "noisy" biosignal
- For that, a reference signal is needed that resembles the interfering signal
- The reference signal r is measured independently and simultaneously with another sensor device
- In an ideal situation, the reference signal r is identical to the interfering component in x
  - one filter coefficient (weight) is enough
- Sometimes only a correlated version of the interference can be measured. The filter adapts the correlated interference signal shape r optimally to the interference signal component that appears in the actual measured biosignal x
  - many filter coefficients (weights) are needed



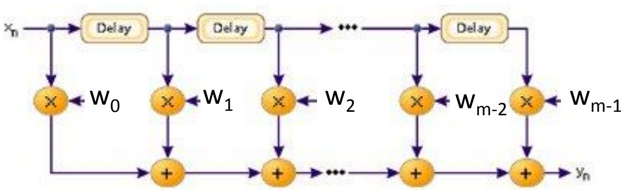
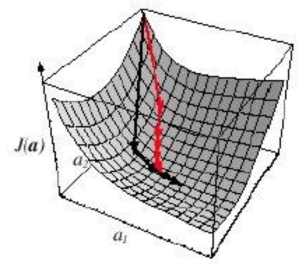


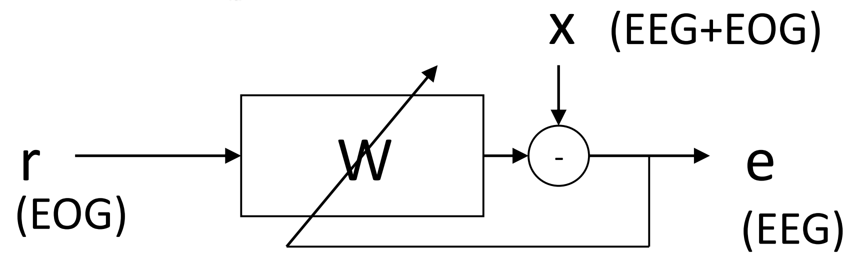
Figure 2. The logical structure of an FIR filter

(Source for FIR figure: http://www.netrino.com/Publications/Glossary/Filters.php)

LMS adaptive filtering (Least Mean Square)

- Based on steepest descent optimization algorithm, where the m filter coefficients are updated at every sample iteratively according to local gradients on error surface
  - Intends to minimize signal energy at the output e. That occurs when EOG component has been removed from x
- Learning rate parameter μ controls how much coefficients are modified by the update rule
  - $0 < \mu < 1/\lambda_{max}$
  - λ_{max} : largest eigenvalue of the correlation matrix of the reference signal within the FIR filter
  - $\mu = c/\lambda_{max} = {}^{c}\!/\!\sum_{j=0}^{m-1} r_j^{\;2}$, where 0<c<1
  - should be adaptive if data is nonstationary
- Proper initialization of filter coefficients is important
  - E.g., letting the filter adapt for a while without outputting anything (works on-line)
  - E.g., running filter backwards in time to initialize (works only off-line)
- Be careful with the possible delay between the interference signal and biosignal





$$e_{LMS,k} = x_k - \sum_{i=0}^{m-1} w_k(i) r_{k-i}$$

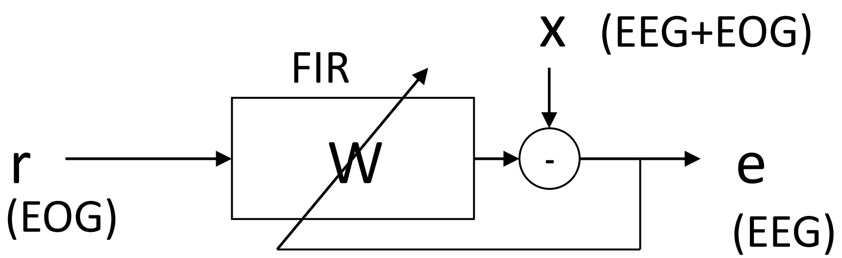
$$w_{i(k+1)} = w_{ik} + 2\mu e_{LMS,k} r_{k-i}$$

$$= w_{ik} + 2\frac{c}{\sum_{j=0}^{m-1} r^2{}_{k-j}} e_{LMS,k} r_{k-i}$$

Example case 1: reference signal is equal to interfering signal component

- Reference signal r can be directly subtracted from x
  - $w_0 = 1$
  - $w_k = 0$, k=1,...,m-1

- (Basically: One filter coefficient (w_0) should be enough)



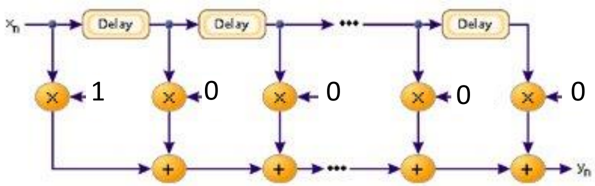
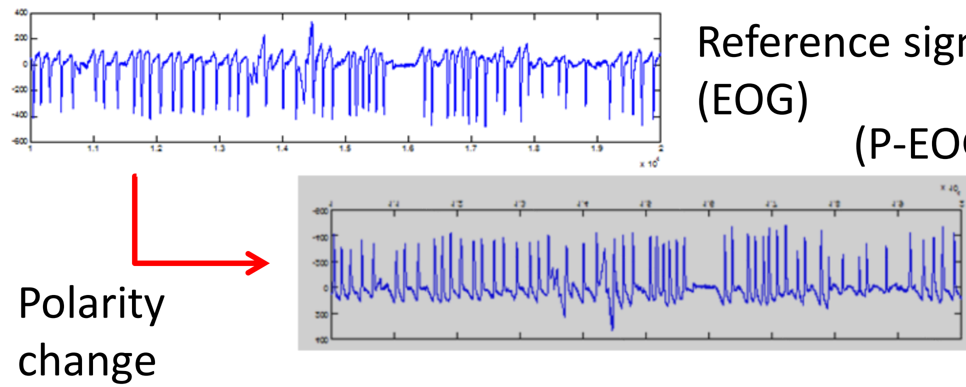


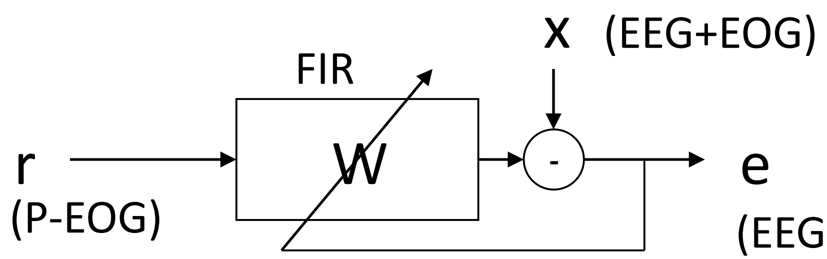
Figure 2. The logical structure of an FIR filter

Example case 2: reference signal is equal to interfering signal component but has changed polarity during measurement

- Perhaps reference electrode-pair was attached in wrong order...
- Polarity change: multiplication by -1
- Reference signal r can be subtracted from x after multiplication by -1
  - $w_0 = -1$
  - $w_k = 0, k=1,\dots,m-1$

- (Basically: One filter coefficient (w_0) should be enough)





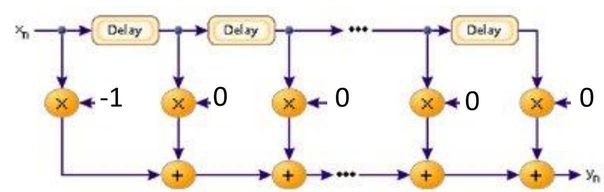
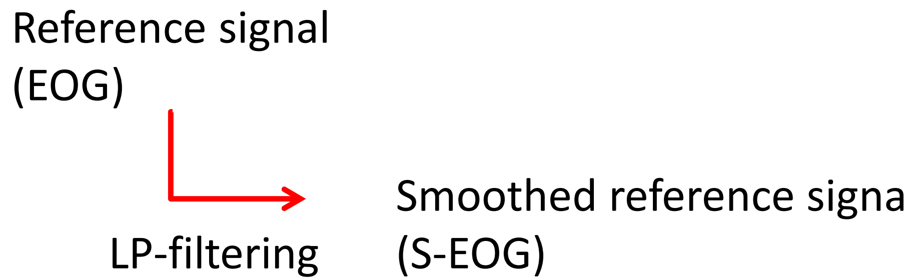
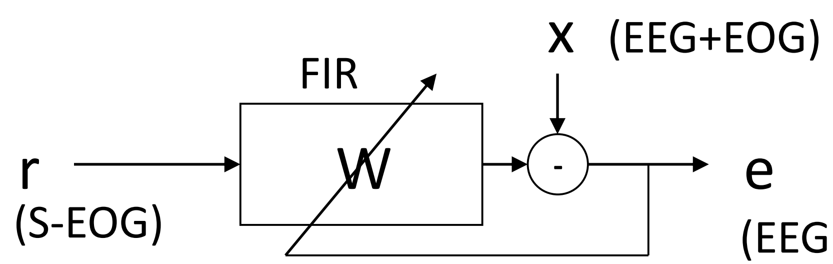


Figure 2. The logical structure of an FIR filter

Example case 3: reference signal has been LP-filtered during measurement

- Perhaps an extra analogue LP-filter was switched on in the recording device for the reference signal...
  - Low-pass filtering smoothes the signal
- The FIR filter will learn to inverse the LP-filtering
- Reference signal r can be subtracted from x after FIR-filtering
  - w_k = ?, k=0,...,m-1





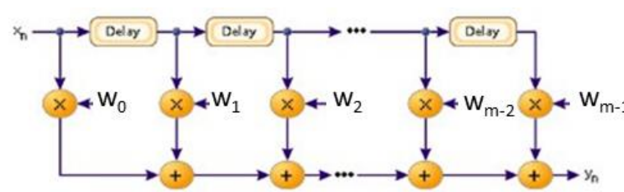


Figure 2. The logical structure of an FIR filter

Example case in the labwork: Adaptive filtering to separate maternal ECG and fetus ECG

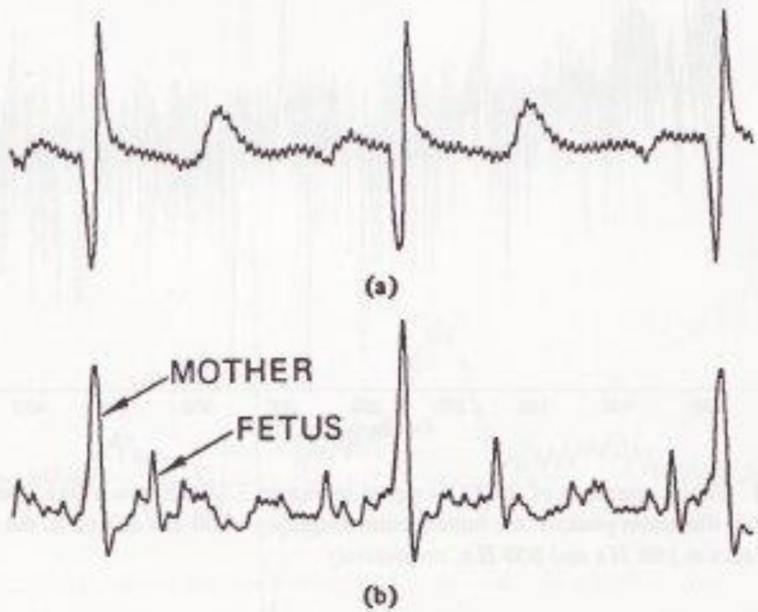


Figure 3.9 ECG signals of a pregnant woman from abdominal and chest leads: (a) chest-lead ECG, and (b) abdominal-lead ECG; the former presents the maternal ECG whereas the latter is a combination of the maternal and fetal ECG signals. (See also Figure 3.58.) Reproduced with permission from B. Widrow, J.R. Glover, Jr., J.M. McCool, J. Kaunitz, C.S. Williams, R.H. Hearn, J.R. Zeidler, E. Dong, Jr., R.C. Goodlin, Adaptive noise cancelling: Principles and applications, *Proceedings of the IEEE*, 63(12):1692–1716, 1975. ©IEEE.

Selected references

Course text book: Section 3.6 (2002) / Section 3.9 (2015), Adaptive filters for removal of interference

Case study:
Removing respiration component from heart rate signal using LMS adaptive filtering

Source: Tiinanen S, Tulppo MP, Seppänen T. Reducing the Effect of Respiration in Baroreflex Sensitivity Estimation with Adaptive Filtering.
IEEE Transactions on Biomedical Engineering 2008;55(1):51-59.

What cardiovascular variability indexes tell us?

- High cardiovascular variability is a sign of a healthy heart.
  - Heart rate variability, HRV
  - Respiratory sinus arrhythmia, RSA

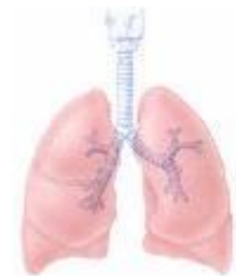
- Cardiovascular indexes are used in discriminating between patient groups (*Diagnostic tool*)

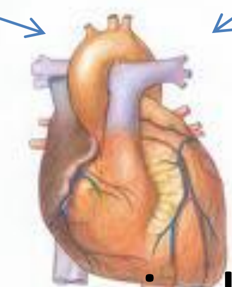
- Among people with cardiovascular disorders, cardiovascular variability may be used as a *Prognostic tool* (e.g. Sudden cardiac death risk)

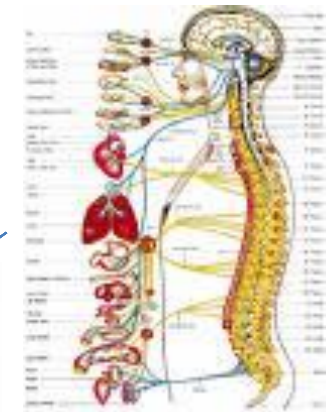
- Applications in exercise physiology (e.g. HF-index controlled training)

Respiratory sinus arrythmia (RSA)

- Oscillatory component in cardiovascular signals
- Heart rate changes synchronously with respiration:
  - mechanical effects of respiration
  - inputs from autonomic nervous system (ANS)





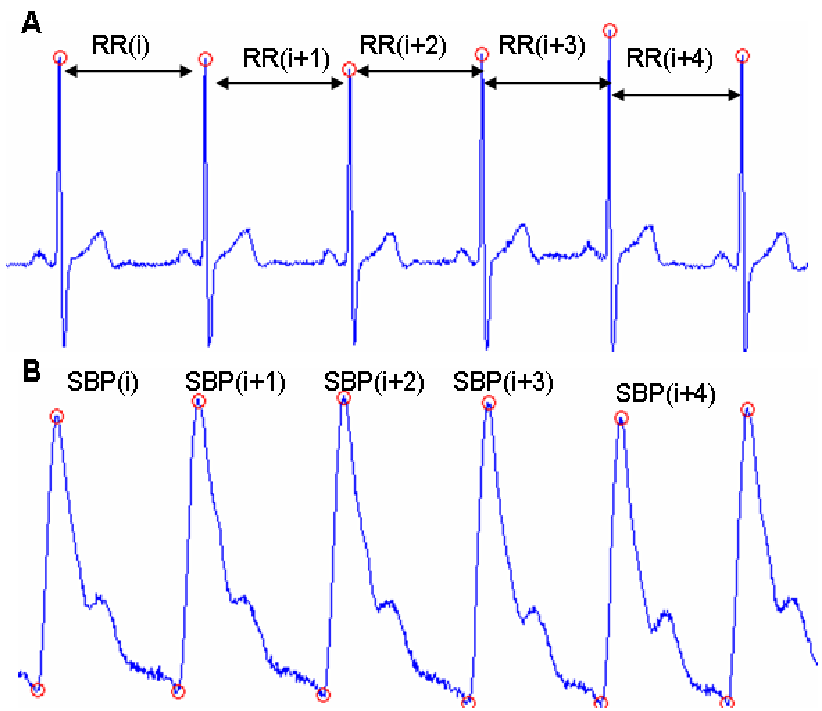


ANS

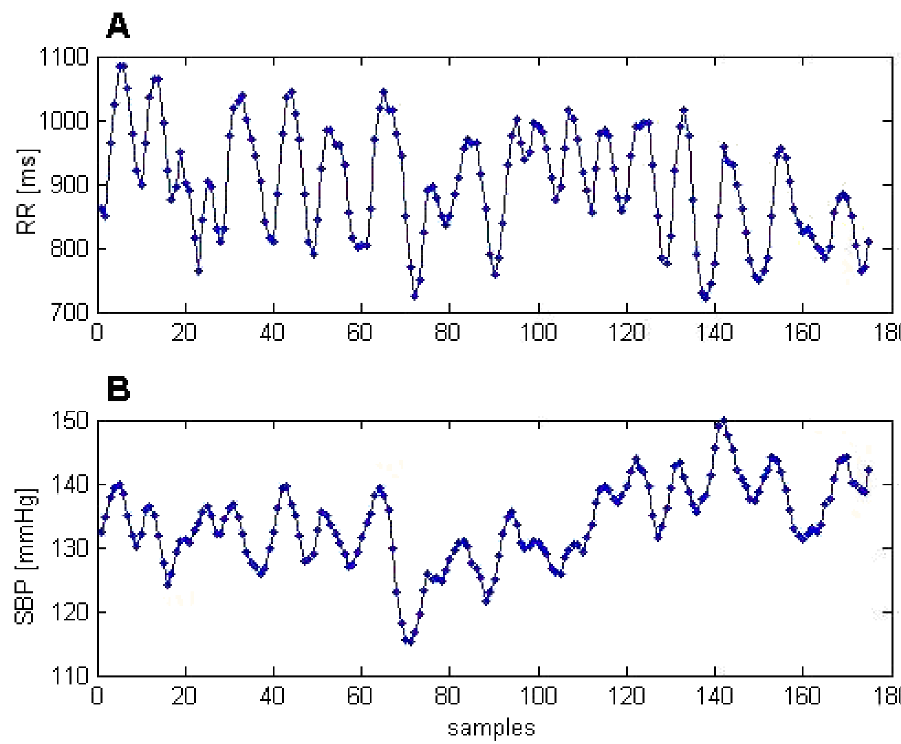
- Respiration component is also seen in blood pressure
  - mechanical intra-thoracical pressure changes

Tachogram and Systogram signals

Beat-to-beat variability of A) ECG and B) BP:



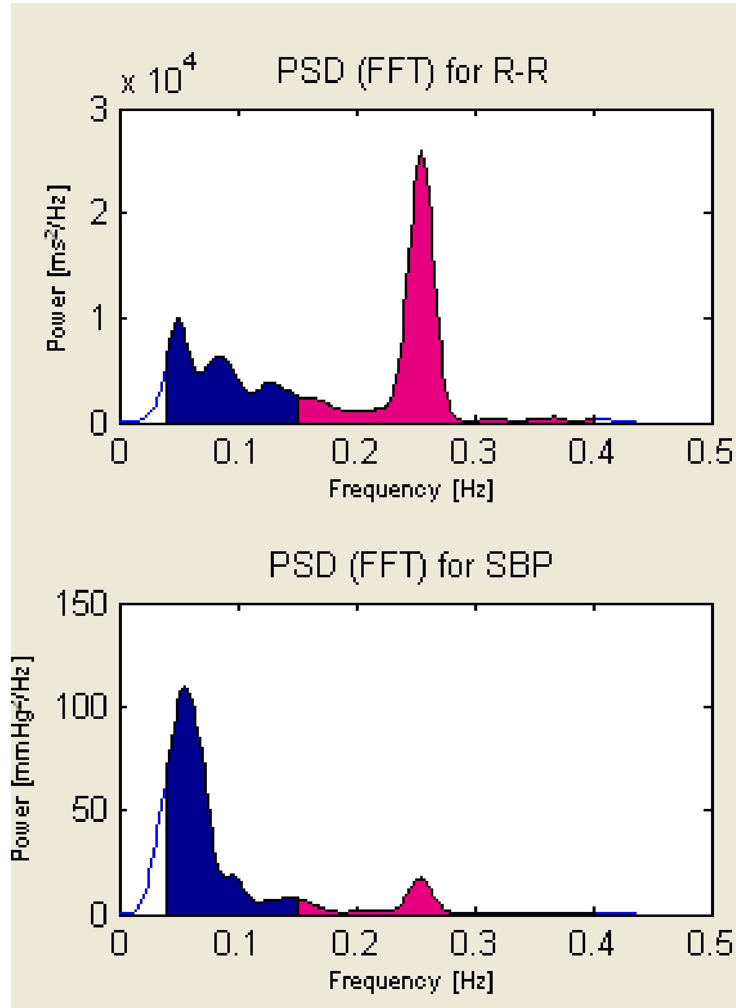
Examples of A) Tachogram and B) Systogram:



Tachogram: R-to-R interval sequence from ECG signal
Systogram: peak-to-peak amplitude sequence from blood pressure signal

Power spectrum of tachogram and systogram

- Low frequency component (LF): 0.04-0.15Hz
  - Mostly originated from the sympathetic branc of autonomic nervous system
- High frequency component (HF): 0.15-0.4Hz
  - Usually originated from respiration
- Sympathovagal balance LF/HF



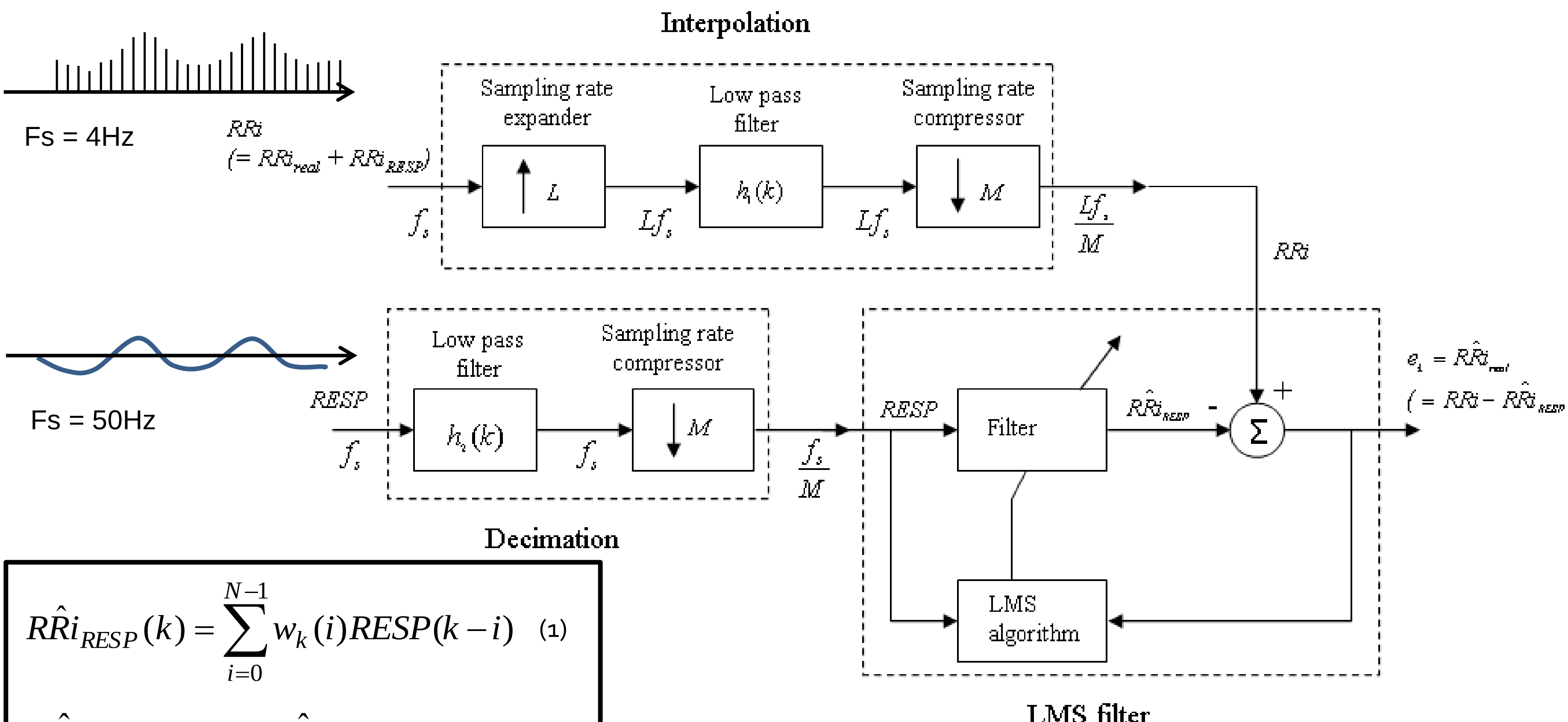
Motivation

Why RSA extraction?

- If respiration rate is *low*, RSA overlaps the low frequency (LF) range - > Biased cardiovascular indices!

- The extracted RSA component itself is also a useful index of cardiovascular system.

Block diagram of the LMS filter and signal preprocessing



$$\hat{RRi}_{RESP}(k) = \sum_{i=0}^{N-1} w_k(i) RESP(k-i) \quad (1)$$

$$\hat{RRi}_{real} = RRi - \hat{RRi}_{RESP} \quad (2)$$

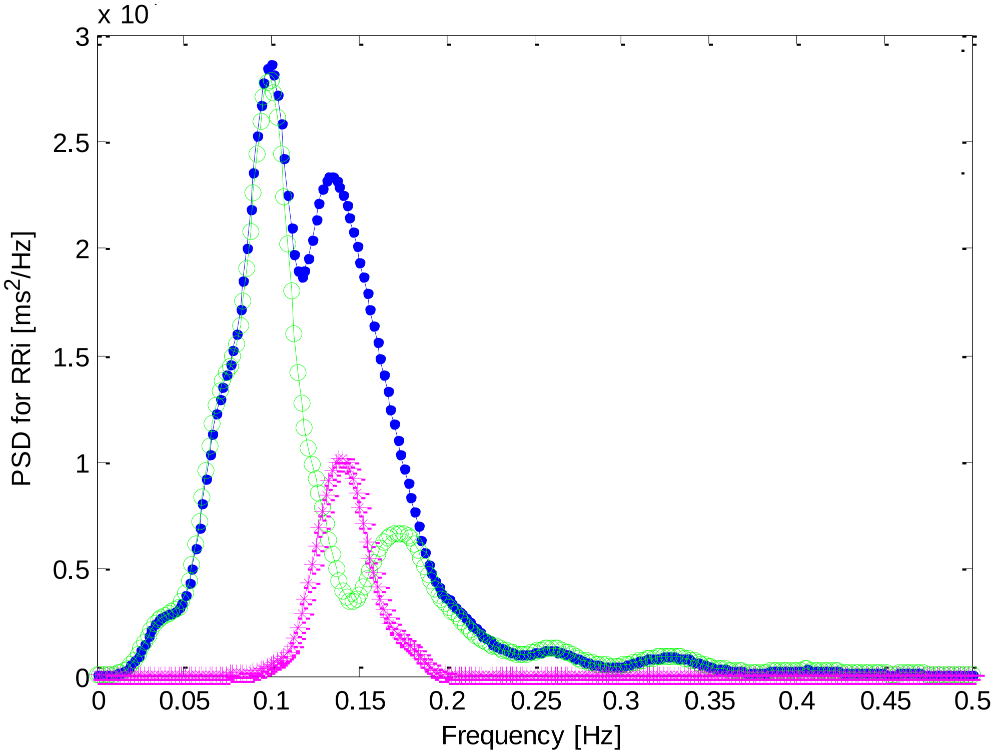
$$w(k+1) = w(k) + 2\mu e_k RESP(k) \quad (3)$$

Steps:

1) Select filter order N and convergence rate μ
2) Initialization of w(k)
3) Filtering

Example 1: Frequency domain presentation of tachogram filtering

- Original tachogram is decomposed into two parts:
  - Respiration (RSA) signal
  - The rest of signal
- The figure on right shows this in frequency domain:
  - Blue: original tachogram
  - Pink: RSA estimate
  - Green: residual



Example 2: Effect of adaptive filtering on LF power and peak index

- Adaptive filtering decreases the effect of respiration on LF power estimation