Pattern Recognition

Part 2: Noise Suppression

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Contents

- Generation and properties of speech signals
- Wiener filter
- Frequency-domain solution
- Extensions of the gain rule
- Extensions of the entire framework
Source-filter principle:

- An airflow, coming from the lungs, excites the vocal cords for voiced excitation or causes a noise-like signal (opened vocal cords).
- The mouth, nasal, and pharynx cavity are behaving like controllable resonators and only a few frequencies (called formant frequencies) are not attenuated.
Source-Filter Model for Speech Generation

![Diagram of Source-Filter Model for Speech Generation](image-url)

- **Fundamental frequency**
- **Impulse generator**
- **Noise generator**
- **Vocal tract filter**
- **Source part of the model**
- **Filter part of the model**

**Spectrum of the excitation signal**

- /a/
- /s/

**Output spectrum**

- /a/
- /s/

- **Frequency in Hz**
- **dB**
Properties of Speech Signals

Some basics:

- Speech signals can be modeled for short periods (about 10 ms to 30 ms) as weak stationary. This means that the statistical properties up to second order are invariant versus temporal shifts.
- Speech contains a lot of pauses. In these pauses the statistical properties of the background noise can be estimated.
- Speech has periodic signal components (fundamental frequency about 70 Hz [deep male voices up to 400 Hz [voices of children]]) and noise-like components (e.g. fricatives).
- Speech signals have strong correlation at small lags on the one hand and around the pitch period (and multitudes of it) on the other hand.
- In various application the short-term spectral envelope is used for determining what is said (speech recognition) and who said it (speaker recognition/verification).
**Wiener Filter – Part 1**

*Filter design by means of minimizing the squared error (according to Gauß)*


**Assumptions / design criteria:**

- Design of a filter that separates a desired signal optimally from additive noise
- Both signals are described as stationary random processes
- Knowledge about the statistical properties up to second order is necessary
Literature about the Wiener Filter

**Basics of the Wiener filter:**

- E. Hänsler: *Statistische Signale: Grundlagen und Anwendungen – Chapter 8* (Optimalfilter nach Wiener und Kolmogoroff), Springer, 2001 (in German)
- S. Haykin: *Adaptive Filter Theory – Chapter 2 (Wiener Filters)*, Prentice Hall, 2002
Wiener-Filter – Teil 2

Application example:

Model:

Speech (desired signal) $s(n)$

Noise (undesired signal) $b(n)$

The Wiener solution is often applied in a “block-based fashion”.

$y(n)$

$\hat{s}(n)$
Wiener Filter – Part 3

**Time-domain structure:**

\[
\hat{s}(n-M) = \sum_{i=0}^{N-1} h_i y(n-i)
\]

**FIR structure:**

**Optimization criterion:**

\[
E\{e^2(n-M)\} \xrightarrow{h_i=h_{i,\text{opt}}} \min
\]

*This is only one of a variety of optimization criteria (topic for a talk)!*
Assumptions:

- The desired signal $s(n)$ and the distortion $b(n)$ are uncorrelated and have zero mean, i.e. they are orthogonal:

$$\mu_s = \mu_b = 0, \quad s_{sb}(l) = \mu_s \mu_b = 0.$$

Computing the optimal filter coefficients:

$$\mathbb{E}\{e^2(n-M)\} \xrightarrow{h_i = h_{i,\text{opt}}} \min$$

$$\frac{d}{dh_i}\mathbb{E}\{e^2(n-M)\}\bigg|_{h_i = h_{i,\text{opt}}} = 0$$

$$2\mathbb{E}\{e(n-M)\frac{d}{dh_i}e(n-M)\}\bigg|_{h_i = h_{i,\text{opt}}} = 0$$
Computing the optimum filter coefficients (continued):

\[ 2E \left\{ e(n-M) \frac{d}{dh_i} e(n-M) \right\} \bigg|_{h_i=h_{i,\text{opt}}} = 0 \]

Inserting the error signal:

\[ e(n-M) = s(n-M) - \sum_{i=0}^{N-1} h_i y(n-i) \]

\[ 2E \left\{ \left( s(n-M) - \sum_{j=0}^{N-1} h_j y(n-j) \right) y(n-i) \right\} \bigg|_{h_i=h_{i,\text{opt}}} = 0 \]

\[ s_{sy}(i-M) = \sum_{j=0}^{N-1} h_{j,\text{opt}} s_{yy}(i-j) = 0 \]

Exploiting orthogonality of the input components:

\[ s_{sy}(l) = s_{ss}(l) + s_{sb}(l) = s_{ss}(l) \]

\[ s_{ss}(i-M) - \sum_{j=0}^{N-1} h_{j,\text{opt}} s_{yy}(i-j) = 0 \]

True for \( i = 0 \ldots N-1 \).
Computing the optimum filter coefficients (continued):

\[
\begin{bmatrix}
    s_{yy}(0) & s_{yy}(1) & \ldots & s_{yy}(N-1) \\
    s_{yy}(1) & s_{yy}(0) & \ldots & s_{yy}(N-2) \\
    \vdots & \vdots & \ddots & \vdots \\
    s_{yy}(N-1) & s_{yy}(N-2) & \ldots & s_{yy}(0)
\end{bmatrix}
\begin{bmatrix}
    h_{0,\text{opt}} \\
    h_{1,\text{opt}} \\
    \vdots \\
    h_{N-1,\text{opt}}
\end{bmatrix}
= 
\begin{bmatrix}
    s_{ss}(-M) \\
    s_{ss}(-M+1) \\
    \vdots \\
    s_{ss}(N-M-1)
\end{bmatrix}
\]

Problems:

- The autocorrelation of the undisturbed signal is not directly measurable.
  
  **Solution**: \( s_{ss}(l) = s_{yy}(l) - s_{bb}(l) \) and estimation of the autocorrelation of the noise during speech pauses.

- The inversion of the autocorrelation matrix might lead to stability problems (because the matrix is only non-negative definite).
  
  **Solution**: Solution in the frequency domain (see next slides).

- The solution of the equation system is computationally complex (especially for large filter orders) and has to be computed quite often (every 1 to 20 ms).
  
  **Solution**: Solution in the frequency domain (see next slides).
Solution in the time domain:

\[ s_{ss}(i - M) - \sum_{j=0}^{N-1} h_{j,\text{opt}} s_{yy}(i - j) = 0 \]

Delayless solution:

\[ s_{ss}(i) - \sum_{j=0}^{N-1} h_{j,\text{opt}} s_{yy}(i - j) = 0 \]

Removing the „FIR“ restriction:

\[ s_{ss}(i) - \sum_{j=-\infty}^{\infty} h_{j,\text{opt}} s_{yy}(i - j) = 0 \]
Solution in the time domain:

\[ s_{ss}(i) - \sum_{j=-\infty}^{\infty} h_{j,\text{opt}} s_{yy}(i-j) = 0 \]

Solution in the frequency domain:

\[ S_{ss}(\Omega) - H_{\text{opt}}(e^{j\Omega}) S_{yy}(\Omega) = 0 \]

\[ H_{\text{opt}}(e^{j\Omega}) = \frac{S_{ss}(\Omega)}{S_{yy}(\Omega)} \]

Inserting orthogonality of the input components:

\[ S_{ss}(\Omega) = S_{yy}(\Omega) - S_{bb}(\Omega) \]

\[ H_{\text{opt}}(e^{j\Omega}) = 1 - \frac{S_{bb}(\Omega)}{S_{yy}(\Omega)} \]
Solution/Approximation in the Frequency Domain – Part 3

**Solution in the frequency domain:**

\[
H_{\text{opt}}(e^{j\Omega}) = 1 - \frac{S_{bb}(\Omega)}{S_{yy}(\Omega)}
\]

**Approximation using short-term estimators:**

\[
\hat{H}_{\text{opt}}(e^{j\Omega}, n) = \max \left\{ 0, 1 - \frac{\hat{S}_{bb}(\Omega, n)}{\hat{S}_{yy}(\Omega, n)} \right\}
\]

**Typical setups:**

- Realization using a filterbank system (attenuation in the subband domain).
- The analysis windows of the analysis filterbank are usually about 15 ms to 100 ms long. The synthesis windows are often of the same length, but sometimes also shorter.
- The frame shift is often set to 1 ... 20 ms (depending on the application).
- The basic characteristic is often extended (adaptive overestimation, adaptive maximum attenuation, etc..)
**Frequency-domain structure:**

\[ y(n) \xrightarrow{\text{Analysis filterbank}} Y(e^{j\Omega_n}, n) \xrightarrow{\text{Filter characteristic}} \hat{S}(e^{j\Omega_n}, n) \xrightarrow{\text{Synthesis filterbank}} \hat{s}(n) \]

- Input PSD estimation: \( \hat{S}_{yy}(\Omega_n, n) \)
- Noise PSD estimation: \( \hat{S}_{bb}(\Omega_n, n) \)
- \( \hat{H}_{opt}(e^{j\Omega_n}, n) \)

**PSD = power spectral density**
**Noise Suppression**

Solution/Approximation in the Frequency Domain – Part 5

*Estimation of the (short-term) power spectral density of the input signal:*

\[ \hat{S}_{yy}(\Omega_{\mu}, n) = |Y(e^{\Omega_{\mu}} n)|^2 \]

*Estimation of the (short-term) power spectral density of the background noise:*

- Schemes based on speech activity/pause detection (VAD)
- Tracking of temporal minima
**Solution/Approximation in the Frequency Domain – Part 6**

**Scheme with speech activity/pause detection**

\[
\hat{S}_{bb}(\Omega_\mu, n) = \begin{cases} 
\beta \hat{S}_{bb}(\Omega_\mu, n-1) + (1 - \beta) \hat{S}_{yy}(\Omega_\mu, n), & \text{during speech pauses,} \\
\hat{S}_{bb}(\Omega_\mu, n-1), & \text{else.}
\end{cases}
\]

**Temporal minima tracking:**

\[
\overline{S}_{yy}(\Omega_\mu, n) = \beta \overline{S}_{yy}(\Omega_\mu, n-1) + (1 - \beta) \hat{S}_{yy}(\Omega_\mu, n)
\]

**Bias correction**

\[
\hat{S}_{bb}(\Omega_\mu, n) = K \begin{cases} 
\max \{ S_{\min}, \hat{S}_{bb}(\Omega_\mu, n-1) \} \Delta_{\text{inc}}, & \text{if } \overline{S}_{yy}(\Omega_\mu, n) > \hat{S}_{bb}(\Omega_\mu, n-1), \\
\max \{ S_{\min}, \hat{S}_{bb}(\Omega_\mu, n-1) \} \Delta_{\text{dec}}, & \text{else.}
\end{cases}
\]

**Bias correction**

**Constant slightly larger than 1**

**Constant slightly smaller than 1**
Solution/Approximation in the Frequency Domain – Part 7

Short-term powers at 3 kHz

Time-frequency analysis of the noise input signal

Microphone amplitude at 3 kHz
Short-term power
Estimated noise power
Problem:

- In most estimation algorithms the estimated power spectral density of noise input signal will have *more fluctuations* than the corresponding estimated power spectral density of the noise. This leads to so-called *musical noise* (explanation in the next slides).

First solution:

- By introducing a so-called fixed *overestimation*

\[ \hat{S}_{bb}(\Omega, n) \rightarrow K_{over} \hat{S}_{bb}(\Omega, n) \]

the undesired “opening” during speech pauses of the noise suppression filter can be avoided. However, this leads to a *lower signal quality during speech activity*. 
Extensions for the Wiener Characteristic – Overestimation of the Noise (Part 2)

**Second solution:**

- By replacing the fixed *overestimation* with an *adaptive* one (strong overestimation during speech pauses, no overestimation during speech activity), the drawbacks of the fixed overestimation can be avoided.

- An adaptive overestimation can be computed in a simple manner by *using the filter coefficients of the previous frame*:

\[
\tilde{S}_{bb}(\Omega_\mu, n) \rightarrow \frac{1}{\tilde{H}(e^{j\Omega_\mu}, n - 1)} \tilde{S}_{bb}(\Omega_\mu, n).
\]

- In addition the filter coefficients should be *limited* prior to their usage (otherwise the overestimation might be too strong):

\[
\tilde{H}(e^{j\Omega_\mu}, n) = \max \left\{ \frac{1}{K_{\text{over}}}, \tilde{H}_{\text{opt}}(e^{j\Omega_\mu}, n) \right\}.
\]
Extensions for the Wiener Characteristic – Overestimation of the Noise (Part 3)

„Rekursives“ Wiener-Filter:

- Analysis filterbank
  - Input PSD estimation
    - \( \hat{S}_{yy}(\Omega, n) \)
    - \( \hat{S}_{bb}(\Omega, n) \)
- Synthesis filterbank
  - Filter char.
    - \( z^{-1} \)
    - \( \hat{H}_{opt}(e^{j\Omega}, n - 1) \)
- \( \hat{S}(e^{j\Omega}, n) \)

\( PSD = power~spectral~density \)
Extensions for the Wiener Characteristic – Overestimation of the Noise (Part 4)

**Short-term powers at 3 kHz**

- Microphone amplitude at 3 kHz
- Short-term power
- Estimated noise power
- Fixed overestimated noise power
- Adaptively overestimated noise power (+1 dB)

**Attenuation coefficient at 3 kHz**

- Without overestimation
- Using 12 dB overestimation (+1 dB)
- Adaptive overestimation (+2 dB)
Problem:

- If we would try to get rid of the noise completely, we would also loose the (acoustic) information about the environment in which the person is speaking. As a result it turned out that a noise reduction is better than a complete removal.
- In addition, it’s very complicated to design a high quality noise suppression that removes all noise.

Solution – Limiting the maximum filter attenuation:

- Introducing a „desired“ noise (power spectral density)
- Inserting an attenuation limit
Extensions for the Wiener Characteristic – Maximum Attenuation (Part 2)

Specification of a „desired noise“:

- We can try to specify or design one (or more) desired background noise types.
- If we specify more than one type of noise (e.g. train noise, car noise, “party” noise, or noises of different cars to “transform“ one car into another) we have to classify first the original noise type.
- The filter coefficients can be limited according to:

\[
\hat{H}_{opt}(e^{j\Omega_{\mu}}, n) = \max \left\{ H_{\min}(e^{j\Omega_{\mu}}, n), 1 - \frac{\hat{S}_{bb}(\Omega_{\mu}, n)}{\hat{S}_{yy}(\Omega_{\mu}, n)} \right\}.
\]

- In the simplest case we chose the maximum attenuation as follows:

\[
H_{\min}(e^{j\Omega_{\mu}}, n) = \min \left\{ 1, \sqrt{\frac{S_{bb,des}(\Omega_{\mu})}{|Y(e^{j\Omega_{\mu}}, n)|^2}} \right\}.
\]

\[
\left( H_{\min}(e^{j\Omega}, n) |Y(e^{j\Omega}, n)| = \sqrt{S_{bb,des}(\Omega_{\mu})} \right)
\]
Specification of a „desired noise“ (continued):

- Problem: If we would use the procedures of the last slide, we would get a constant magnitude output spectrum (during speech pauses). Only the phase would vary from frame to frame. This sounds very unpleasant.

- Solution: If we add (or multiply) a random component to the attenuation limit, e.g. as

\[
H_{\text{min}}(e^{j\Omega}, n) = \min \left\{ 1, \sqrt{\frac{S_{bb,\text{des}}(\Omega, n)}{|Y(e^{j\Omega}, n)|^2}} + H_{\text{rand}}(n) \right\},
\]

we can avoid this effect.

- The advantage of this type of limiting the attenuation factors is to have control over the remaining background noise. If we use such an add-on in speech recognition systems (as part of a pre-processing unit), the recognition engine can reduce the amount of parameters that are used for modelling the remaining noise (only one noise type remains).
Noise Suppression

Extensions for the Wiener Characteristic – Maximum Attenuation (Part 4)

**Controlling the attenuation limit:**

- If we want *to keep the original noise type* (reduced by some decibels), we can use a fixed attenuation limit:

  \[ H_{\text{min}}(e^{j\Omega \mu}, n) = H_{\text{min}}. \]

- In addition to that we can *slowly modify the attenuation limit* (over time). This means a lower amount of (maximum) attenuation during periods containing speech activity and a larger attenuation maximum (more attenuation) during speech pauses.
Extensions for the Wiener Characteristic – Maximum Attenuation (Part 5)

**Short-term powers**

- Microphone amplitude at 3 kHz
- Short-term power
- Estimated noise power

**Attenuation factors**

- Without overestimation
- With adaptive overestimation (+1 dB)
- With adaptive overestimation and limit (+2 dB)
Example for a noise transformation – part 1:

„Cocktail party“ recording

Output using automotive noise as desired noise
Example for a noise transformation – part 2:

„Cocktail party“ recording

Output using automotive noise as desired noise
„Intermezzo“

**Partner exercise:**

- Please answer (in groups of two people) the questions that you will get during the lecture!
Extensions of Basis Noise Suppression Schemes – Reducing Reverberation (Part 1)

**Dereverberation:**

- When recording speech signal (with some distance between the microphone and the mouth of the speaker) in medium or large rooms the signals sound reverberant. This leads to reduced speech quality on the one hand and to larger word error rates of speech dialog systems on the other hand.

- However, reverberation can also contribute in a positive sense to speech quality. Early reflections (duration up to 30 to 50 ms) lead to a better sounding of speech signals. Late reflections lead to the opposite effect and degrade usually the perceived quality.

- With the same approach that was used for noise suppression also reverberation can be reduced. We can modify the power spectral density of the distortion and filter characteristic according to

\[
\hat{S}_{bb}(\Omega_\mu, n) \rightarrow \hat{S}_{bb}(\Omega_\mu, n) + \hat{S}_{rr}(\Omega_\mu, n)
\]

\[
\hat{H}_{opt}(e^{j\Omega_\mu}, n) = \max \left\{ H_{min}, 1 - \frac{K_{bb,over} \hat{S}_{bb}(\Omega_\mu, n) + K_{rr,over} \hat{S}_{rr}(\Omega_\mu, n)}{\hat{S}_{yy}(\Omega_\mu, n)} \right\}.
\]
Extensions of Basis Noise Suppression Schemes – Reducing Reverberation (Part 2)

**Estimating the power spectral density of the “reverb” components:**

- We assume that the reverb power *decays exponentially*. In addition, we assume a *fixed ratio of the direct sound and the reverberant components* and that the direct sound is large in amplitude compared to the reverberant components. This leads to the following estimation rule:

\[
\hat{S}_{rr}(\Omega, n) = |Y(e^{j\Omega}, n - D)|^2 R(e^{j\Omega}) A^D(e^{j\Omega}) + \hat{S}_{rr}(\Omega, n - 1) A(e^{j\Omega})
\]

with:

- \(D\): protection time in frames (reverberation with a delay lower than \(D\) frames is perceived as well-sounding, reverberation with a larger delay as disturbing)
- \(A(e^{j\Omega})\): attenuation parameter (reverb attenuation per frame)
- \(R(e^{j\Omega})\): direct-to-reverb ratio
Extensions of Basis Noise Suppression Schemes – Reducing Reverberation (Part 3)

**Combined reduction of noise and reverberation:**

- Analysis filterbank:
  - Input signal $y(n)$
  - Spectral representation $Y(e^{j\Omega \mu}, n)$
  - Estimation of the input PSD
- Synthesis filterbank:
  - Spectral representation after filtering $\hat{S}(e^{j\Omega \mu}, n)$
  - Estimation of the reverb PSD
  - Filter characteristic $\hat{H}_{opt}(e^{j\Omega \mu}, n)$
  - Output signal $\hat{s}(n)$

Estimation of:
- Power spectral density (PSD)
  - Input PSD
  - Noise PSD
  - Reverberation PSD

**PSD = power spectral density**
Extensions of Basis Noise Suppression Schemes – Reducing Reverberation (Part 4)

Time–frequency analysis of the input signal

Time–frequency analysis of the output signal
Partial Signal Reconstruction – Part 1

**Conventional approach:**
- Sufficient quality at medium and high SNRs

**Problems:**
- Low quality at low SNRs (high noise)
- Some spectral components will be attenuated

**Extension:**
- Transition to *model-based approaches*
- Extraction of relevant *features* out of the noisy input signal
- *Reconstruction* of the components with low SNR by using pre-trained models and extracted features (for appropriate model selection/adaption)
Noise Suppression

Partial Signal Reconstruction – Part 2

- Analysis filterbank
- Feature extraction
- Signal reconstruction
- Adaptive mixing
- Synthesis filterbank

Estimation of the input PSD
Estimation of the noise PSD
Estimation of the reverb PSD

PSD = power spectral density
Partial Signal Reconstruction – Part 3

Time-frequency analysis

Microphone signal
Recursive Wiener filter
Model-bas. approach

Noisy speech signal, measured in a car driving with 160 km/h

Analysis after EFR coding (GSM)

Source: Mohamed Krini, SVOX Deutschland, (Dissertation at TU Darmstadt)
Enhancement of EEG Signals – Background

**EEG (and MEG) signal enhancement:**
- Channel-specific enhancement (without taking source [or network] localization into account)
- Mainly for the removal of artifacts

**Artifacts can be:**
- Patient related (physiologic): eye movements, eye blinking, muscle artifacts, heart beating
- Technical: electrode popping, power supply

**Example:**

Example for a muscle artifact
Noise Suppression

Signal Enhancement with Real-Time EMD

Basic structure:

\[ x(n) = d(n) + a(n) + t(n) \]

- Empirical mode decomposition
- Weighting of the extracted components
- Synthesis of the weighted components

Steps and objectives:

- Split the signal into (overlapping) blocks.
- Find signal-specific components (they sum up to the input signal) and find appropriate weights.
- The phase relations of the desired components should not be changed.

\[ \hat{d}(n) = \sum_{k=0}^{M(n)-1} w_k(n) i_k(n) \]
Objective and details of an empirical mode decomposition:

- **Separate an arbitrary input signal** into different components called **intrinsic mode functions** (IMFs).

- An IMF satisfies the following **two conditions**:
  - The **number of extrema** and the **number of zero crossings** must either be **equal** or differ at most by one.
  - At any point, the **mean value** of the envelopes defined by the local maxima and the envelopes defined by the local minima **is zero**.

- The **first IMF** will contain the signal components with the **highest frequency**. The next IMF will contain lower frequencies.
Noise Suppression

Empirical Mode Decomposition – An Example (Part 1)
Noise Suppression

Empirical Mode Decomposition – The Principle

Overview of the sifting process:

Stopping criteria for sifting process:

1. The IMF of the current iteration doesn’t differ much from the previous iteration:

   \[
   \frac{\sum_n (i_{k,m}(n) - i_{k,m-1}(n))^2}{\sum_n i_{k,m-1}^2(n)} < T.
   \]

2. The maximum number of iterations is reached (for „real-time“ reasons).
Empirical Mode Decomposition – An Example (Part 2)
Empirical Mode Decomposition – An Example (Part 3)
Assumption:

Nearly all noise components are in the higher frequency range.

Approximation for SNR:

\[
r_k(n) = 10 \log_{10} \left( \frac{\int_{\Omega=0}^{\Omega_c} \hat{S}_{i_ki_k}(\Omega, n) d\Omega}{\int_{\Omega=\Omega_c}^{\Omega_c} \hat{S}_{i_ki_k}(\Omega, n) d\Omega} \right)
\]

IMF are dominated by noise, if

\[
r_k(n) < T_{\text{noise}}
\]

\[
w_k(n) = \begin{cases} 1, & \text{if } r_k(n) \geq T_{\text{noise}}, \\ 10^{\frac{r_k(n) - T_{\text{noise}}}{10}}, & \text{else.} \end{cases}
\]
Empirical Mode Decomposition – Detrending

**Assumption:**

The local trend is mostly represented by the residual.

**Observation:**

A comparison of the energy levels in the residual with the local trends has shown a proportional relationship.

**Energy coefficient:**

\[
 r_{\text{res}}(n) = \frac{\sum_{\ell} i_M(n-1)(n-\ell)}{\sum_{\ell} x^2(n-\ell)} \quad \Rightarrow \quad w_{M-1}(n) = 1 - r_{\text{res}}(n)
\]
Noise Suppression

Empirical Mode Decomposition – Data Sets Processed

- **Semi-simulated data:**
  
  Real EEG signals from the central and frontal lobes were contaminated with simulated muscle artifacts.
  
  - Length of the signals: 60 s.
  - Original sampling frequency: 5 kHz.
  - Input sampling frequency: 44.1 kHz.
  - Process sampling frequency: \( 1.378 \text{ kHz} = \frac{44.1 \text{ kHz}}{32} \)

- **Real EEG signals:**
  
  Real data from an epilepsy patients with inherent muscle artifacts were processed.
  
  - Length of the signals: 60 s.
  - Number of channels: 30 channels.
  - Sampling frequencies: Same as for the simulated case
Noise Suppression

Empirical Mode Decomposition – Real-time Demo
Real EEG Signals: Denoising

(a) Original signal
Enhanced signal

(b) Original signal
Enhanced signal
**Noise Suppression**

**Literature – Part 2**

**Noise suppression:**
- E. Hänsler, G. Schmidt: *Acoustic Echo and Noise Control – Chap. 5 (Wiener Filter)*, Wiley, 2004

**Dereverberation:**

**Signal reconstruction:**

**Empirical mode decomposition:**
**Summary:**
- Generation and properties of speech signals
- Wiener filter
- Implementation in the frequency domain
- Extension of the basic gain characteristic
- Extension of noise suppression schemes

**Next week:**
- Beamforming and postfiltering