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Noise Reduction for Hearing Aids:
Enabling Communication in Adverse Conditions

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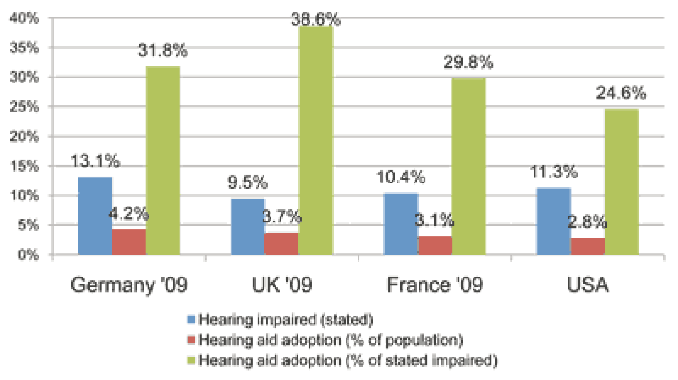
Communication in Adverse Acoustic Conditions

Source: http://cdsweb.cern.ch, accessed on Oct 28, 2012

Hearing Loss Prevalence Data

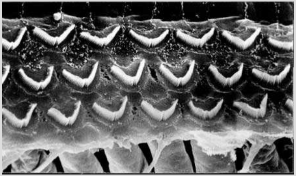
Hearing loss prevalence and hearing aid adoption rates, based on stated hearing loss on the screening survey.



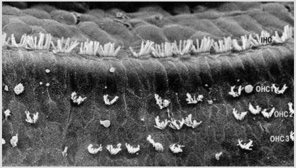
Source: http://www.hearingreview.com/issues/articles/2011-02-01.asp

Hearing Loss and its Consequences I

healthy outer hair cells



damaged outer hair cells



Source: http://dontlosethemusic.co.nz, accessed on Sept 16, 2013

- Increase of the threshold of hearing
  - soft sounds are not heard anymore
  - speech intelligibility (even without additional noise) is insufficient
  - compensation via strong amplification (up to 70 dB) without exceeding the loudness discomfort level (LDL)
  - target amplification is derived from fitting rules.

Hearing Loss and its Consequences II

- Reduction of spectral and/or temporal resolution in the inner ear
  - speech sounds are loud enough but not intelligible
  - speech communication in noisy environments is severely degraded
  - direct compensation of these effects is not possible

- Speech enhancement / noise reduction pre-processing is very important for successful rehabilitation!

Hearing Aids

Sources: Siemens Audiologische Technik, Oticon, varibel

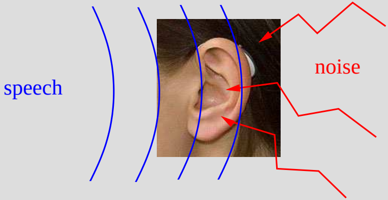
Open-Fit Hearing Aids

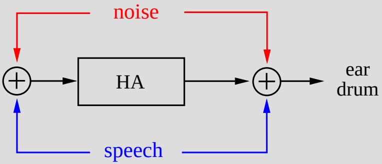
- Open-fit devices
  - are best for mild to moderate hearing loss with good residual hearing at low frequencies,
  - are comfortable to wear,
  - improve own voice reproduction,
  - require powerful feedback cancellation.

Source: www.lloydhearingaid.com

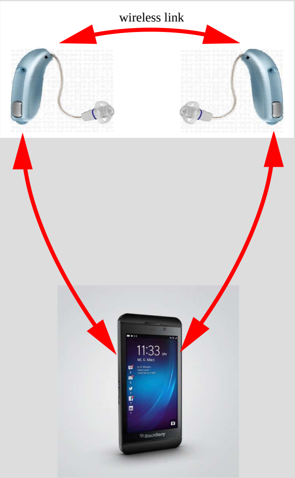
Open-Fit Signal Model

- Open-fit devices
  - require very short processing latency,
  - may be less effective in high levels of ambient noise
  - a case for active noise control?
    see [Dalga and Doclo 2013].





Wireless Connectivity



- Binaural link for the exchange of settings and parameters
- Full audio bandwidth is desired
- Audio streaming via wireless relay
- Streaming directly from a smartphone to hearing aids
- Full bi-directional signal transmission using sensors and computational power of the smartphone

Challenges

Sources: Blackberry, Nokia, Siemens, 2010

- Users expect effortless communication in complex acoustic environments
  - many spatially distributed sources
  - non-stationary, non-Gaussian signals
  - ambient noise and reverberation
  - time-varying signal paths
  - very long impulse responses
- This requires optimization of both intelligibility and quality.
- Hardware restrictions
  - very small size of device
  - very low latency < 10 ms
  - very low power < 1 mW

Outline

Spectral Analysis and Synthesis

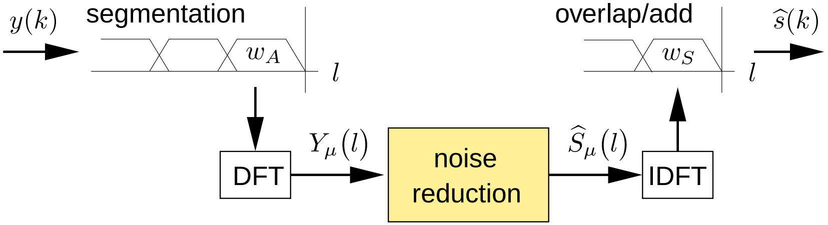
Requirements of noise reduction:

- High energy compaction of target signal
  - High spectral resolution of harmonics for voiced speech
    $\Rightarrow$ good separation of speech and noise
  - High temporal resolution for transient sounds
    $\Rightarrow$ accurate reproduction of transient speech sounds
- High stop-band attenuation
- Perfect reconstruction
- Low algorithmic delay
- High computational efficiency

Spectral Analysis / Synthesis

- DFT and uniform filter banks, e.g. [Griffin and Lim 1984]
  - high-resolution
  - perfect reconstruction
  - highly efficient
- Non-uniform filter banks, e.g. [Hohmann 2002]
  - resolution according to perceptual model
  - near-perfect reconstruction
- Low-delay filter-bank equalizer,
  e.g. [Löllmann and Vary 2005], [Vary 2006], [Löllmann and Vary 2008]
- Eigenvalue / eigenvector decomposition,
  e.g. [Ephraim and van Trees 1995]
  - signal adaptive / optimal
  - computationally expensive

Overlap-Add Analysis and Synthesis

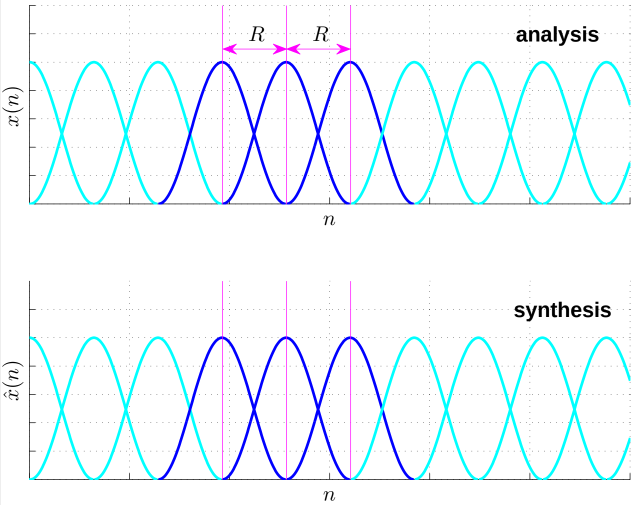


To achieve *perfect reconstruction* the product of these window functions must satisfy the *constant-overlap-add* constraint

$$\sum_{k=-\infty}^{\infty} w_A(n-R)w_S(n-R) = 1$$

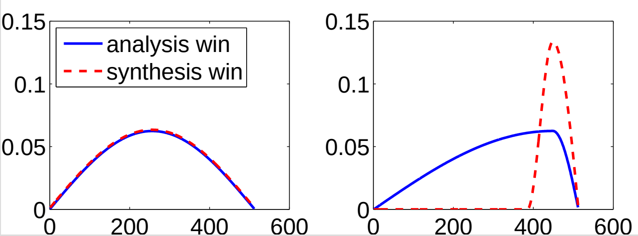
where R is the block shift of the windows.

Overlap-Add with Symmetric Windows



Low Latency Spectral Analysis / Synthesis

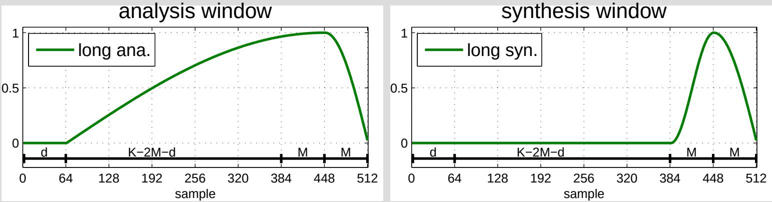
- Latency is identical to the length of the synthesis window
- Use non-symmetric analysis window and short window for synthesis
- Family of non-symmetric windows
  - right-hand side of all analysis and all synthesis windows is identical
  - left-hand side is variable
  - use different windows for different speech sounds



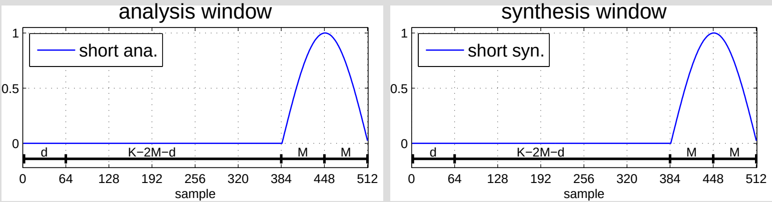
DFT: [Mauler and Martin 2007, 2009, 2010], CQT: [Nagathil and Martin, 2012]

Low Latency Spectral Analysis / Synthesis with Adaptive Resolution

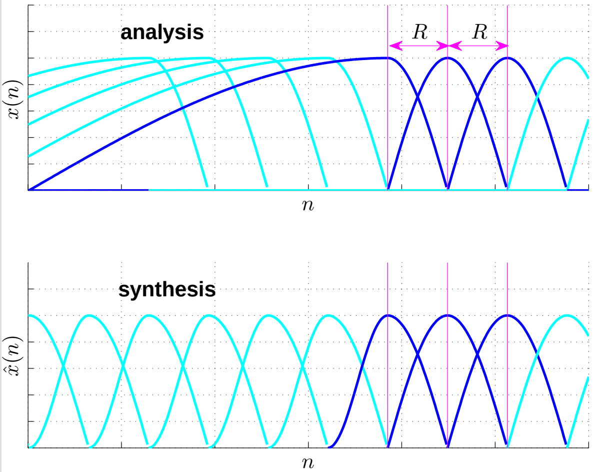
- High spectral resolution required:



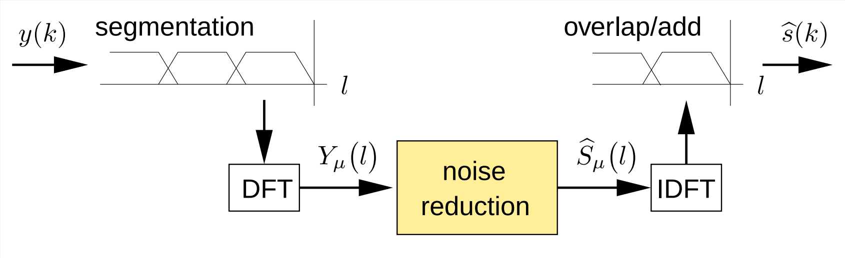
- High temporal resolution required:



Adaptive Window Switching



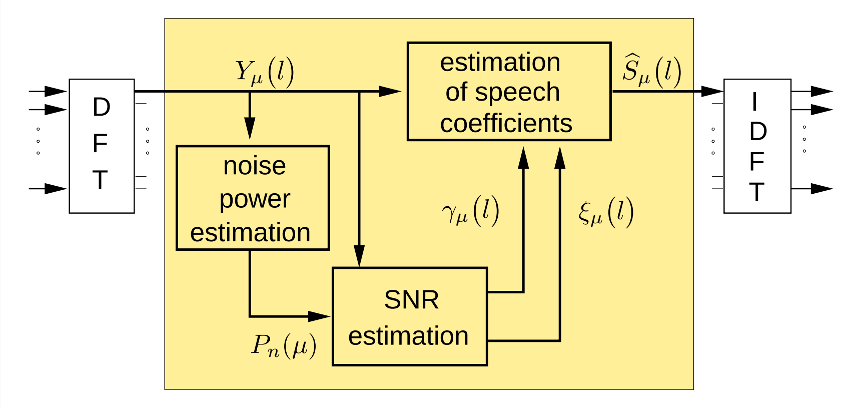
Single-channel Noise Reduction



In the DFT domain we have:

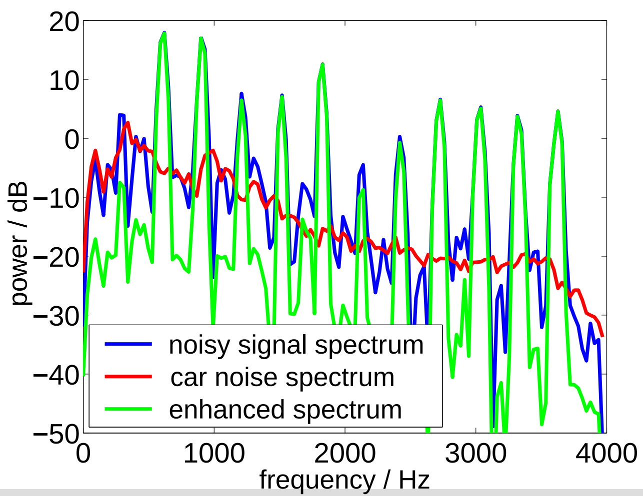
- Noisy speech: $Y_\mu(l) = S_\mu(l) + N_\mu(l)$
  - frequency index μ
  - time index l
- Estimated speech coefficient: $\widehat{S}_\mu(l) = f(Y_\mu(l))$

Noise Reduction: Basic Tasks



$P_n(\mu)$: noise power $\gamma_\mu(l)$: *a posteriori* SNR $\xi_\mu(l)$: *a priori* SNR

Principle of Single Channel Noise Reduction



Postprocessing in the Cepstrum Domain for the Reduction of Musical Noise

Definition of the **real-valued cepstrum**:

$$c_y(q) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \ln\left(\left|Y(e^{j\Omega})\right|\right) e^{j\Omega q} \mathrm{d}\Omega$$

where $Y(e^{j\Omega})$ is the spectrum of time domain signal $y(i)$.

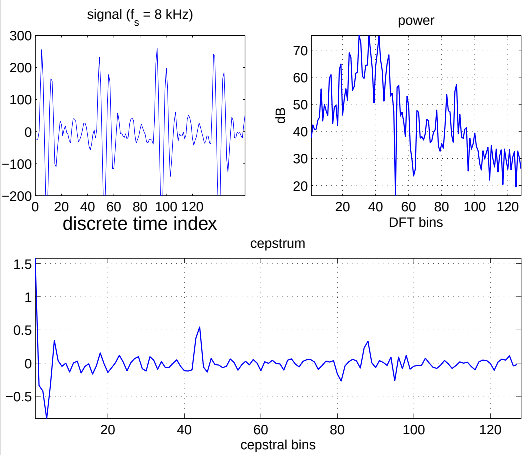
Some (strange) terminology: cepstrum, quefrency, rahmonic, ...

[B.P. Bogert, M.J.R. Healy and J.W. Tukey, 1963]

The cepstrum is very well suited to group speech components:

- coarse spectral features (envelope),
- harmonic structure, and
- fine structure of spectrum.

Cepstrum of a Voiced Speech Sound



Temporal Cepstrum Smoothing

Principle [Breithaupt, Gerkmann, Martin, IEEE Signal Proc. Lett. 2007] :

- separation of coarse and fine spectral features
- relatively strong smoothing of spectral fine structure
- relatively little smoothing of coarse spectral structures.

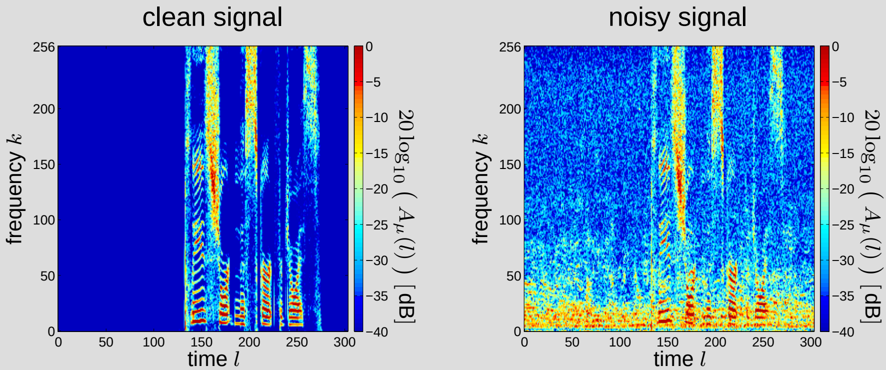
Advantages with respect to other smoothing methods:

- reduction of variance of residual noise
- negligible impact on speech signal
- preservation of harmonic spectral structure of voiced speech.

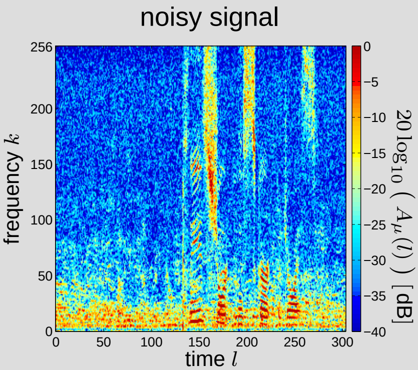
Applications:

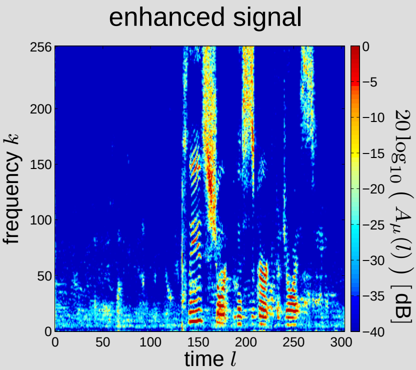
- single channel noise red. [Breithaupt, Gerkmann, Martin 2008]
- blind source separation [Madhu, Breithaupt and Martin 2008]
- automatic speech recognition [Breithaupt and Martin 2006, 2008]
- binaural dereverberation [Gerkmann 2011]

NR Example: Speech in Babble Noise



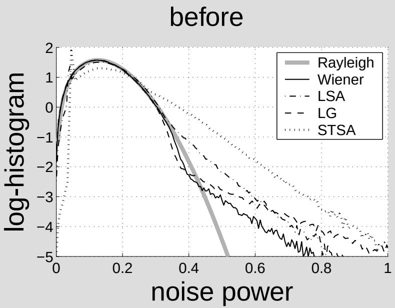
NR Example: Speech in Babble Noise





Analysis of Spectral Outliers

Log-histogram of residual noise before and after noise reduction for various estimators and white Gaussian noise:

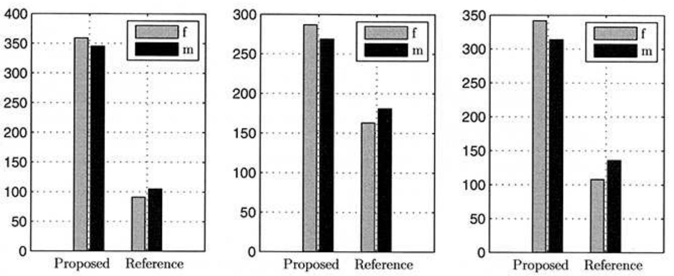


- Heavy tails result in unnatural fluctuations!
- Smoothing in the cepstro-temporal domain results in a significant reduction

Evaluation: Preference Test

- Proposed algorithm with adaptive window switching, temporal cepstrum smoothing, amplification of transient sounds
- Reference algorithm with standard components.
- Male and female speakers, 3 noise types, 3 SNRs (5, 10, 15 dB)
- 27 normally-hearing listeners

speech quality noise quality overall quality



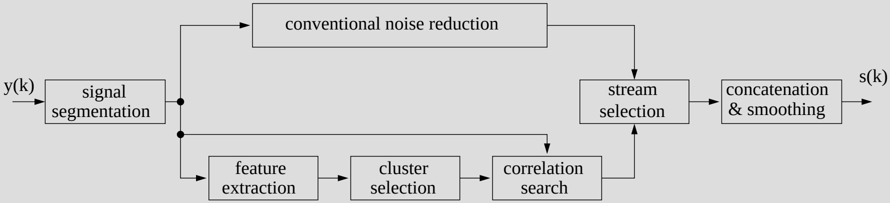
[Mauler 2010]

Performance of Single Channel NR

- Many studies, e.g. [Dahlquist et al., 2005] and [Luts et al. 2010], have shown that generic single channel methods
  - show SNR improvements in of 2-12 dB,
  - improve subjective quality,
  - reduce listener fatigue,
  - **but do not** improve intelligibility
- Improvements of about 1-2 dB are reported for CI users.
- Improvements of intelligibility are reported for the **ideal and estimated binary masks** [Hu and Wang, 2001, [Kim et al. 2008], [Healy et al., 2013].
- Alternative approach: synthesis using corpus of clean signal segments.

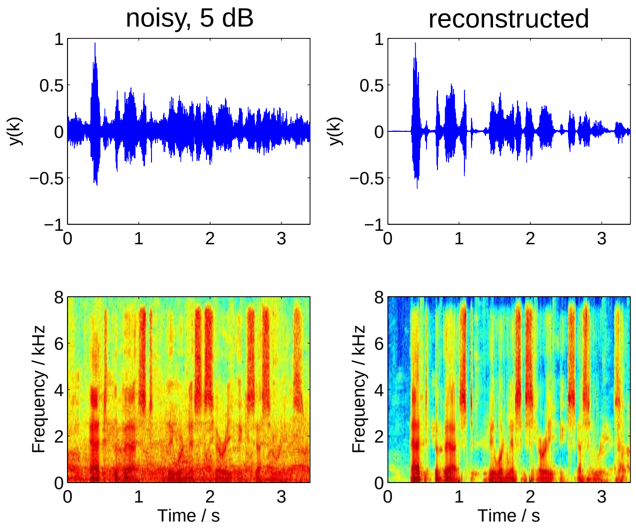
Corpus-based Speech Enhancement

- Conventional noise reduction systems suffer from
  - insufficient noise attenuation and/or
  - target signal distortions
- Idea: Resynthesize speech from clean speech segments
  [Xiao and Nickel, 2010]



[Nickel et al., 2013], also with audio-visual front-end processing: [Kolossa et al., 2012]

Example: Speech + Babble noise

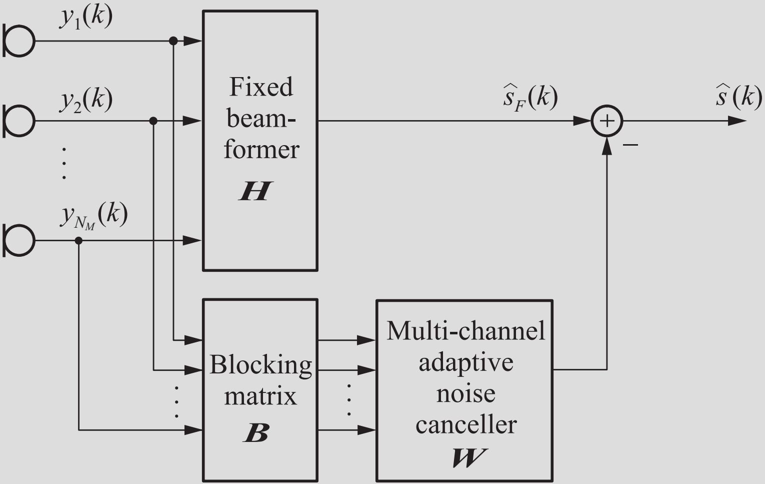


From Single- to Multi-channel Processing

- Performance of single-channel algorithms is limited because only temporal and spectral information can be used.
- Multichannel systems allow to exploit spatial information such as location of sources and spatial sound field statistics.
- Sensors can be distributed in space for improved signal pick-up.
- Many successful multichannel approaches:
  - (Adaptive) differential microphones, e.g. [Elko and Pong, 1997]
  - MVDR beamforming, e.g. [Cox et al. 1986]
  - Generalized sidelobe canceler, e.g. [Griffiths and Lim, 1982] , [Gannot et al., 2001]
  - Blind source separation, e.g. [Araki, Makino et al. 2003, ...], [Buchner, Aichner, Kellermann 2003, ...]
  - Speech distortion weighted multi-channel Wiener filter, e.g. [Doclo et al. 2005], [van den Bogaert et al. 2009]

Adaptive Beamformer

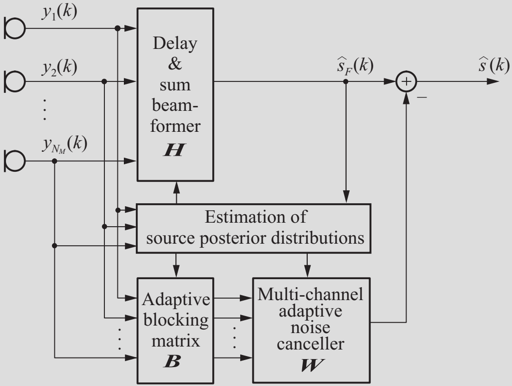
Basic *Generalized Sidelobe Canceler* (GSC) [Griffiths and Jim, 1982]:



Parsimonious Excitation-based Generalized Sidelobe Canceller (PEG)

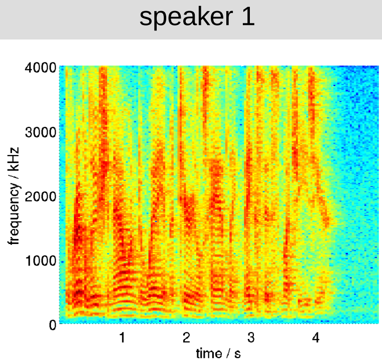
Extraction of source signal q using PEG:

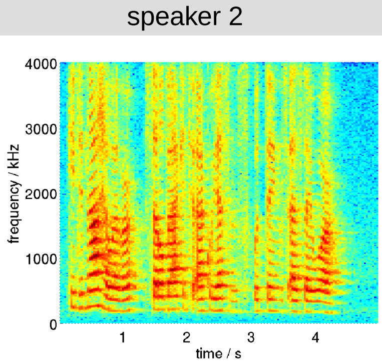
$$\hat{S}_{\mu}^{\langle q \rangle}(l) = (\boldsymbol{H}_{\mu}^{\langle q \rangle}(l))^{H} \boldsymbol{Y}_{\mu}(l) - (\boldsymbol{W}_{\mu}^{\langle q \rangle}(l))^{H} \boldsymbol{B}_{\mu}^{\langle q \rangle}(l) \boldsymbol{Y}_{\mu}(l)$$



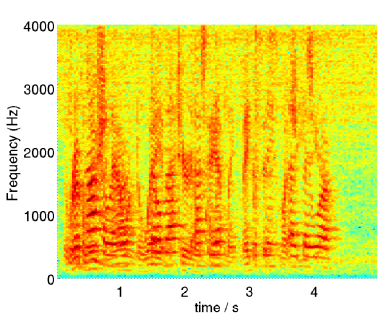
[Madhu and Martin, 2011]

Spectrograms of Speaker 1 and 2





Mixed Signal with Ambient Noise

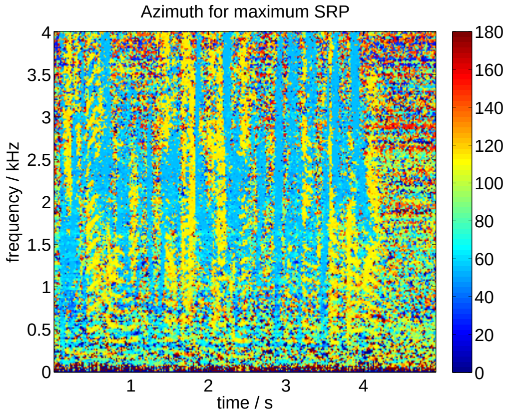


- Signal separation in two steps:
  - Source localization via steered response power (SRP-PHAT) [DiBiase et al. 2001]
  - Target signal extraction using parsimonious excitation-based GSC [Madhu and Martin 2011]

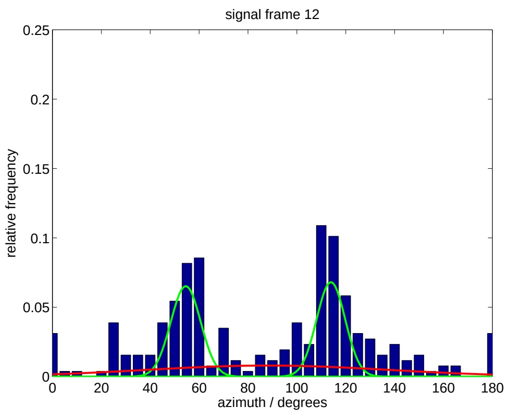
Optimal Azimuth per TF-Bin

- Optimize SRP-PHAT cost function in each time-frequency (TF) bin:

$$\widehat{\theta}_\mu(l) = \underset{\theta}{\operatorname{argmax}} J_\mu(l,\theta)$$

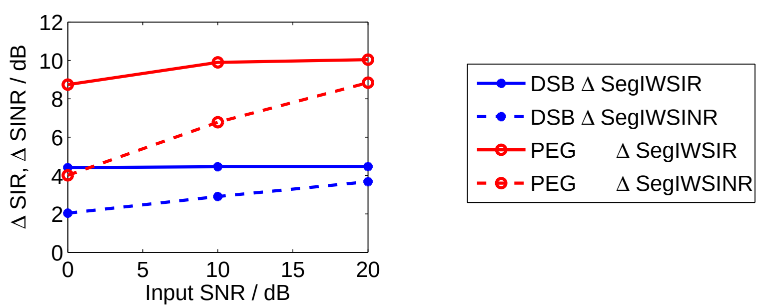


Azimuth Histogram for Single Frame



- Estimation of source posterior distributions via the *expectation-maximization* algorithm

SegIWSIR and SegIWSINR vs. Input SNR



ΔSegIWSIR: Segmental Intelligibility Weighted Signal to Interference Ratio improvement

ΔSegIWSINR: Segmental Intelligibility Weighted Signal to Interference plus Noise Ratio improvement

Summary

- Modern hearing systems are highly complex signal processing devices
- Signal enhancement is at the core of speech processing tasks in hearing aids
  - single- and multi-channel noise reduction
  - microphone array processing and source separation
- The challenge continues ...
  - enable effortless speech communication for normal-hearing people and people with a hearing loss,
  - find low complexity / low power / low latency implementations.
- New solutions and opportunities arise from
  - including more *a priori* knowledge about speech and hearing
  - the availability of sensor networks and
  - inclusion of top-down cognitive processes.

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The Future of Hearing Aids?

Source: www.bioaid.org.uk, accessed on Sept 20, 2013

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