

Hearing devices using wireless acoustic sensor networks

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Outline

- Use of multiple microphones in hearing devices
 o Monaural → Binaural → external microphones
- Binaural signal processing
 - o Objective: noise reduction and binaural cue preservation
 - o Algorithms: binaural beamforming, time-frequency masking, Multi-channel Wiener filter
 - o Experimental results
 - o Bandwidth reduction: iterative distributed MWF
- Wireless acoustic sensor networks
 - o Algorithms: extension of distributed MWF
 - o Effect of bitrate on performance
- Conclusions and future work

Hearing aids

Introduction

- Binaural processing
- Acoustic sensor networks
- Conclusion

- Problems: background noise, directional hearing
 - o signal processing to selectively enhance useful speech signal and improve speech intelligibility
 - o signal processing to preserve directional hearing (binaural auditory cues) and spatial awareness
- Digital hearing instruments allow for advanced acoustical signal pre-processing
 - o multiple microphones available \rightarrow spectral + spatial processing
 - o noise reduction (beamforming), computational auditory scene analysis (source localisation, environment classification, ...)



Monaural (2-3)

Binaural

External microphones

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Acoustic sensor networks

- Signal acquisition in adverse acoustic environments:
 - o Microphones at large distance from speaker \rightarrow background noise and reverberation

Acoustic sensor networks:

- o Network of a large number of spatially distributed nodes (each with one or multiple microphones)
- o Wireless data transmission
- o More information about spatial noise field (microphones with higher SNR, direct-to-reverberant ratio)
- Objectives:
 - o speech enhancement
 - o source localisation
 - o CASA



Subset of sensors closer to target signal

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Acoustic sensor networks

• Challenges:

- o *Dynamic array configuration*: large number of microphones at unknown positions, dynamic subset selection
- o *Distributed and collaborative algorithms:* power and complexity constraints, effect of limited bandwidth
- o Calibration and synchronisation issues: same time basis

• Prototype applications:

- o Hearing aids using extra microphones (room, other HA, ...)
- o Video-conferencing using all microphones on laptops / room
- o Surveillance







Binaural processing

Bilateral vs. Binaural

Bilateral system Hearing aid user $Y_{1,0}(\omega)\cdots Y_{1,M_1-1}(\omega)$ $Y_{0,0}(\omega)\cdots Y_{0,M_0-1}(\omega)$ $\mathbf{W}_0(\omega)$ $W_1(\omega)$ $Z_0(\omega)$ $Z_1(\omega)$

Binaural system



 Independent left/right processing: Preservation of binaural cues (ILD/ITD) for localisation ?

- Hore microphones:
 - \rightarrow better performance ?
 - \rightarrow preservation of binaural cues ?



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Bilateral vs. Binaural

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• Bilateral system

- o Independent processing of left and right hearing aid
- o Negative effect on localisation cues and intelligibility through binaural hearing advantage [Van den Bogaert et al., 2006]

• Binaural system

- o Cooperation between left and right hearing aid (e.g. wireless link) \rightarrow **centralised** vs. **distributed** processing
- o Bandwidth constraint and latency of wireless link

Objectives/requirements for binaural algorithm:

- 1. SNR improvement: noise reduction, limit speech distortion
- 2. Preservation of binaural cues (all sources) to exploit binaural hearing advantage
- 3. No assumption about position of speech source and microphones

Binaural noise reduction techniques

- Introduction
- Binaural processing
 -Algorithms
- -Experiments -Distributed MWF
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• Configuration: microphone array with *M* microphones at left and right hearing aid, communication between hearing aids

$$X_{0,m}(\omega) = X_{0,m}(\omega) + V_{0,m}(\omega), \quad m = 0...M_0 - 1$$

speech noise

• Use all microphone signals to compute output signal at both ears

$$Z_0(\omega) = \mathbf{W}_0^H(\omega)\mathbf{Y}(\omega), \quad Z_1(\omega) = \mathbf{W}_1^H(\omega)\mathbf{Y}(\omega)$$



Introduction

 Binaural processing -Algorithms

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- Time-frequency post-processing/masking:
 - Computation and application of **real-valued** binaural mask based on binaural and temporal/spectral cues
 - o Can be merged with MVDR-beamformer or ICA-based processing
 - Good preservation of binaural cues for **all** sources
 - Single-microphone spectral enhancement" artefacts at low SNRs





Beamformer: $\mathbf{W}_{b} = \frac{\Gamma^{-1}\mathbf{d}}{\mathbf{d}^{H}\Gamma^{-1}\mathbf{d}} \Rightarrow Y' = \mathbf{W}_{b}^{H}\mathbf{Y}$ Post-Filter: $H_{p} = \frac{\left(|d_{0}|^{2} + |d_{1}|^{2}\right)|Y'|^{2}}{|Y_{0}|^{2} + |Y_{1}|^{2}} \Rightarrow Z = H_{p}\begin{bmatrix}Y_{0}\\Y_{1}\end{bmatrix}$

[Rohdenburg 2009, Reindl 2010, Saruwatari 2010] 10

Binaural noise reduction techniques

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[S. Doclo, S. Gannot, M. Moonen, A. Spriet, Handbook on Array Processing and Sensor Networks, Wiley, 2010.]

[B. Cornelis, S. Doclo, T. Van den Bogaert, J. Wouters, M. Moonen, IEEE Trans. Audio, Speech and Language Processing, Feb. 2010.]

[S. Doclo, T.J. Klasen, M. Moonen, T. Van den Bogaert, J. Wouters, R.P. Derleth, S. Korl, US2010002886.] Binaural multi-channel Wiener filter: estimate of speech component in microphone signal at both ears (usually front mic) + trade-off between noise reduction and speech distortion

$$J(\mathbf{W}) = E \left\{ \begin{bmatrix} X_{0,r_0} & \mathbf{W}_0^H \mathbf{X} \\ X_{1,r_1} & \mathbf{W}_1^H \mathbf{X} \end{bmatrix}^2 + \mu \begin{bmatrix} \mathbf{W}_0^H \mathbf{V} \\ \mathbf{W}_1^H \mathbf{V} \end{bmatrix}^2 \right\} \implies \mathbf{W}_{SDW} = \mathbf{R}^{-1} \mathbf{r}$$

speech component
in from presention noise reduction
$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_x + \mu \mathbf{R}_v & \mathbf{0}_M \\ \mathbf{0}_M & \mathbf{R}_x + \mu \mathbf{R}_v \end{bmatrix}, \quad \mathbf{r} = \begin{bmatrix} \mathbf{r}_{x0} \\ \mathbf{r}_{x1} \end{bmatrix}, \quad \mathbf{R}_x = \mathbf{R}_y - \mathbf{R}_y$$

- o Estimate \mathbf{R}_{y} during speech-dominated time-frequency segments, estimate \mathbf{R}_{v} during noise-dominated segments, requiring robust voice activity detection (VAD) mechanism
- o No assumptions about positions of microphones and sources
- o Different implementations:
 - Batch (off-line) vs. adaptive (update correlation matrices)
 - Using spatial prediction (SP) between speech components [Chen 2008]

Binaural noise reduction techniques

- Binaural multi-channel Wiener filter:
 - o Preservation of binaural cues (ITD-ILD)
 - Speech cues are preserved, no a-priori assumptions
 - Noise cues are distorted
 - o **Extensions** in order to preserve binaural cues of both speech and noise sources, without substantially compromising noise reduction
 - Partial noise estimation (MWFv)
 - Extension with Interaural Transfer Function (MWF-ITF)



$$J_{SDW\eta}(\mathbf{W}) = E\left\{ \left\| \begin{bmatrix} X_L - \mathbf{W}_L^H \mathbf{X} \\ X_R - \mathbf{W}_R^H \mathbf{X} \end{bmatrix} \right\|^2 + \mu \left\| \begin{bmatrix} \eta V_L - \mathbf{W}_L^H \mathbf{V} \\ \eta V_R - \mathbf{W}_R^H \mathbf{V} \end{bmatrix} \right\|^2 \right\}, \quad 0 \le \eta \le 1$$

 $J_{ITF}(\mathbf{W}) = J_{SDW}(\mathbf{W}) + \alpha E \left\{ \left| \mathbf{W}_{L}^{H} \mathbf{X} - ITF_{in}^{x} \mathbf{W}_{R}^{H} \mathbf{X} \right|^{2} \right\} + \beta E \left\{ \left| \mathbf{W}_{L}^{H} \mathbf{V} - ITF_{in}^{y} \mathbf{W}_{R}^{H} \mathbf{V} \right|^{2} \right\}$

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Experimental results

Acoustic environment



- Cafeteria with recorded babble noise and simulated speaker at position B
- Binaural hearing aid with 3 microphones
- German sentences taken from OLSA speech material
- Speech in continuous babble noise
 - f_s: 16 kHz, WOLA, FFT-size: 256 samples, Overlap: 75%

http://medi.uni-oldenburg.de/hrir/ [Kayser et al. 2009]

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Experimental results

Objective Evaluation

- o Intelligibility weighted SNR improvement
- o Perceptual Similarity Measure (PSM)



SNR	Orig.	MWF	SP	BF + Postfilt
0 dB				

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Subjective Evaluation

- o Improvement of Speech Reception Threshold (SRT)
- o Oldenburg Sentence Test (10 NH subjects)
- o Binaural presentation using headphones



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- Binaural MWF
 - o **all** microphone signals are transmitted over wireless link
- Reduce bandwidth requirement of wireless link by transmitting one signal from contralateral ear
 - o Raw microphone signal (e.g. front)
 - o Output of fixed (e.g. superdirective) beamformer
 - o MWF-estimate using only contralateral microphone signals
 - o Iterative distributed binaural MWF scheme (DB-MWF)



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[S. Doclo, T. Van den Bogaert, M. Moonen, J. Wouters, IEEE Trans. Audio, Speech and Language Processing, Jan. 2009.]

• Iterative procedure

Binaural processing
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o In each iteration \mathbf{F}_{10} is equal to \mathbf{W}_{00} from previous iteration, and \mathbf{F}_{01} is equal to \mathbf{W}_{11} from previous iteration



Single speech source

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o MWF cost function decreases in each step of iteration

$$J\left(\left[\begin{array}{c}\mathbf{W}_{0}^{i+1}\\\mathbf{W}_{1}^{i+1}\end{array}\right]\right) \leq J\left(\left[\begin{array}{c}\mathbf{W}_{0}^{i}\\\mathbf{W}_{1}^{i}\end{array}\right]\right)$$

o Remarkably: convergence to B-MWF solution (!)

$$\mathbf{W}_0^\infty = \mathbf{W}_0^m, \quad \mathbf{W}_1^\infty = \mathbf{W}_1^m$$

- General case where **R**_x is not a rank-1 matrix
 - o MWF cost function does not necessarily decrease in each iteration
 - o usually no convergence to optimal B-MWF solution
 - o Although $J_0(\mathbf{W}_0^{\infty}) \ge J_0(\mathbf{W}_0^m)$, $J_1(\mathbf{W}_1^{\infty}) \ge J_1(\mathbf{W}_1^m)$, DB-MWF procedure can be used in practice and approaches binaural MWF performance



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Acoustic sensor networks

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Acoustic sensor networks

- Now consider more than 2 sensor nodes...
- Recently has become quite a **hot research topic**
 - o Distributed MWF: extension to multiple sensor arrays and multiple desired sources (DANSE) [Bertrand 2010]
 - o Distributed MVDR/LCMV-beamformer [Golan 2010, Bertrand 2011]
 - Performance analysis of a randomly spaced wireless microphone array [Golan 2011]
 - Dynamic signal combining (no synchronisation required)
 [Matheja 2011, Srinivasan 2011, Stenger 2011]





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Investigate effect of capacity of wireless link → encode signal(s) at finite bit-rate *R* before transmission



- **Rate-distortion:** $R(\lambda) = \frac{1}{4\pi} \int_{-\infty}^{\infty} \max\left(0, \log_2 \frac{\Phi_Y^{01}(\omega)}{\lambda}\right) d\omega$ $D(\lambda) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \min\left(\lambda, \Phi_Y^{01}(\omega)\right) d\omega,$ PSD of transmitted signal
- Upper bound on achievable performance can be calculated using forward channel representation



$$B = \max\left(0, \frac{\Phi_Y^{01} - \lambda}{\Phi_Y^{01}}\right)$$

$$\Phi_W = \max\left(0, \lambda \frac{\Phi_Y^{01} - \lambda}{\Phi_Y^{01}}\right)$$

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- Investigate effect of rate constraints on performance of centralized MWF and distributed MWF (DANSE)
- Setup and performance measures:
 - Acoustic scenario: 3 nodes,
 2 microphones per node (d=1cm)
 - o single speech source, single interference, spatially uncorrelated noise on each microphone

$$\Phi_y = \Phi_s \mathbf{A}_s \mathbf{A}_s^H + \Phi_i \mathbf{A}_i \mathbf{A}_i^H + \Phi_u \mathbf{I}_{2M}$$

 Involved PSDs are assumed to be flat, SIR=0 dB, SNR=20 dB



- ATFs modelled using spherical head shadow model, no reverberation
- **Performance measure**: ratio between MSE at rate 0 and MSE at rate *R*, *i.e.* effect of availability of wireless link

$$G(R) = 10\log_{10}\frac{\xi(0)}{\xi(R)}$$

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Effect on performance of distributed MWF (DANSE) o Case 1: total capacity *R* evenly distributed between iterations



- For infinite rate, DANSE converges to centralized MWF
- At low rates highest performance gain is achieved by transmitting just a single microphone signal (i = 1).
- > More iterations only improve performance at high rates

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Effect on performance of distributed MWF (DANSE)o Case 2: spread iterations over subsequent frames (stationarity)



DANSE scheme converges after i=2 iterations, moreover achieving highest performance gain

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Acoustic sensor networks

• Future work/challenges:

- o Speech enhancement algorithms:
 - Dynamic subset selection for time-varying situations
 - Theoretical performance analysis (statistical room acoustics) \rightarrow optimal microphone configuration
- o Computational auditory scene analysis:
 - E.g. multi-source localisation by merging energy- and correlationbased techniques
- o Calibration and synchronisation techniques:
 - With and without reference signals
- o (Perceptual) coding of transmitted signals





Conclusions

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- Speech enhancement algorithms in hearing instruments
 - o More and more microphones: monaural \rightarrow binaural \rightarrow acoustic sensor networks
 - o Algorithms: beamforming, post-processing, MWF
- Bandwidth reduction by transmitting filtered combination of microphone signals
 - o D-MWF: iterative procedure, converging to centralized MWF
- Effect of bit-rate on performance using rate-distortion theory
 - o D-MWF achieves highest performance gain, when iterations can be spread over subsequent frames
- Remaining challenges in acoustic sensor networks:
 - o **Algorithms**: robustness, dynamic subset selection, distributed algorithms, optimal microphone configuration
 - o (Perceptual) coding of transmitted signal
 - o Technical issues of wireless link: latency, synchronisation

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Questions ?



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