

Speech Separation for Recognition and Enhancement

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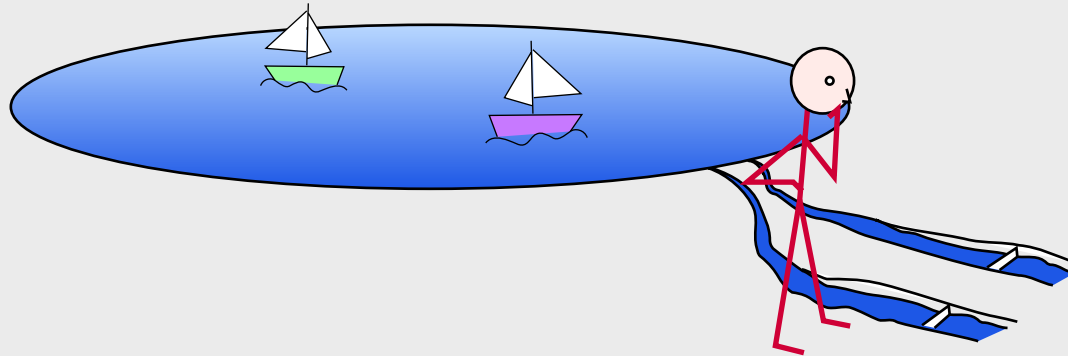
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1. Speech in the Wild
2. Separation by Space
3. Separation by Pitch
4. Separation by Model



I. Speech in the Wild



- The world is **cluttered**
sound is **transparent**
 - **mixtures** are inevitable
- Useful information is structured by ‘**sources**’
 - specific definition of a ‘source’:
intentional independence

Speech in the Wild: Examples

- Multi-party discussions



- Ambient recordings

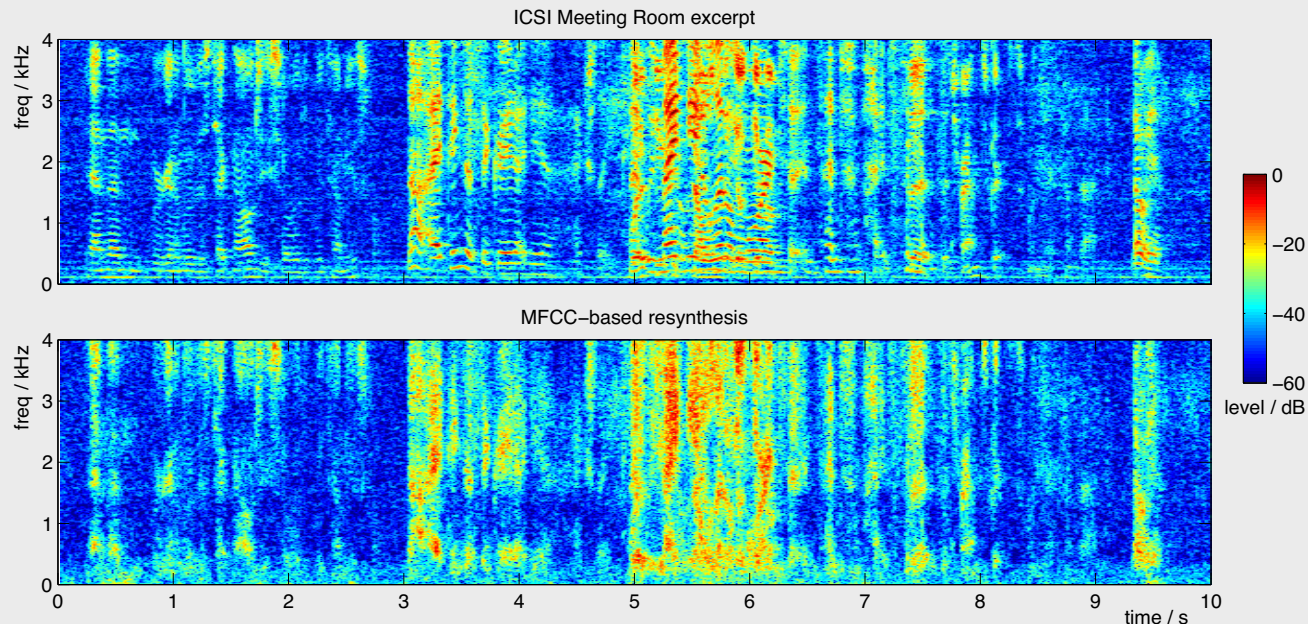


- Applications:

- communications
- robots
- lifelogging/archives

Recognizing Speech in the Wild

- Current ASR relies on **low-D** representations
 - e.g. 13 dimensional **MFCC** features every 10ms



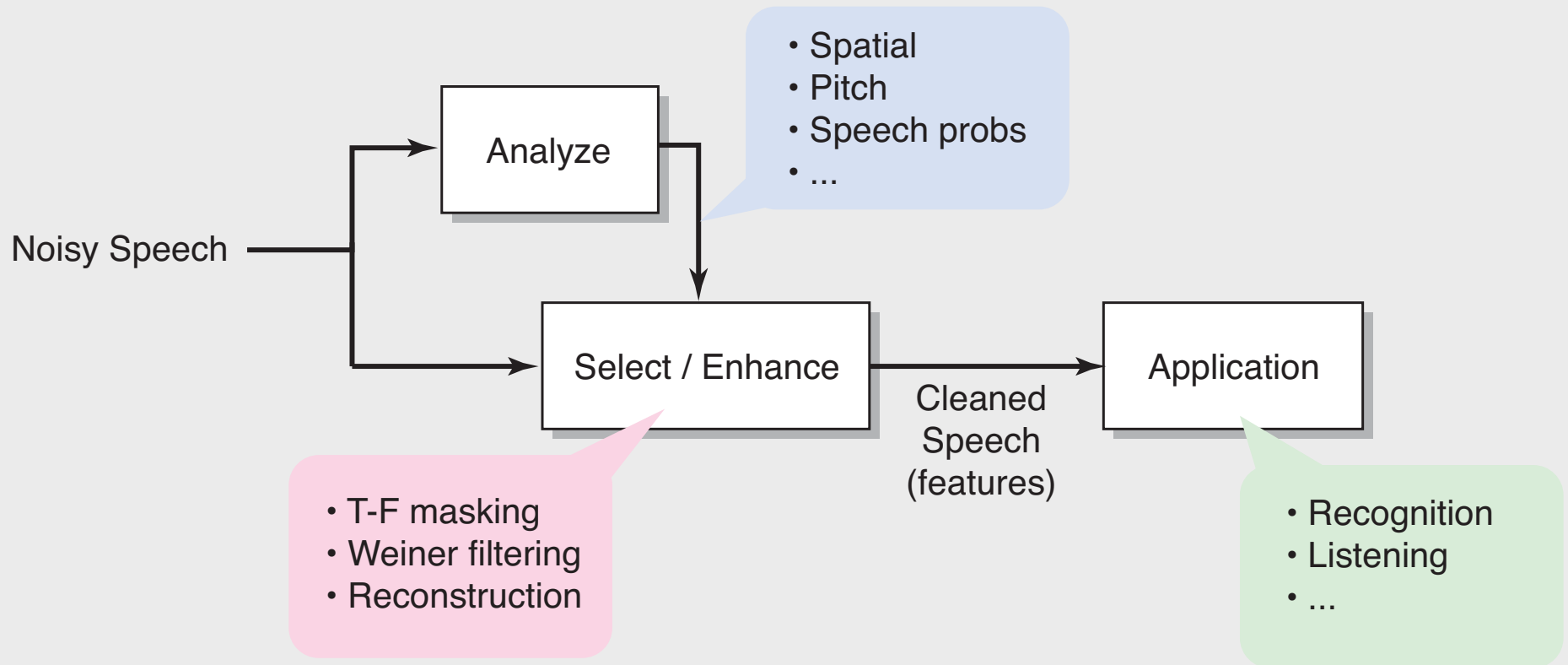
- very successful for **clean speech!**
- inadequate for **mixtures**



- We need **separation!**

2. Speech Separation

- How can we separate speech information?

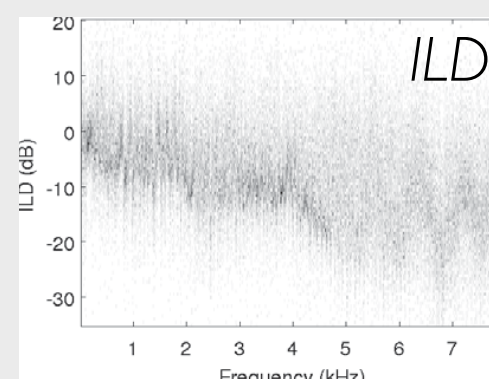
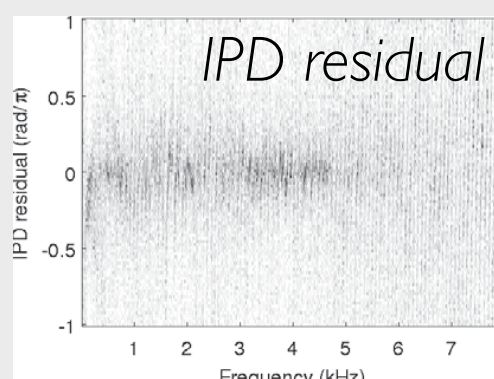
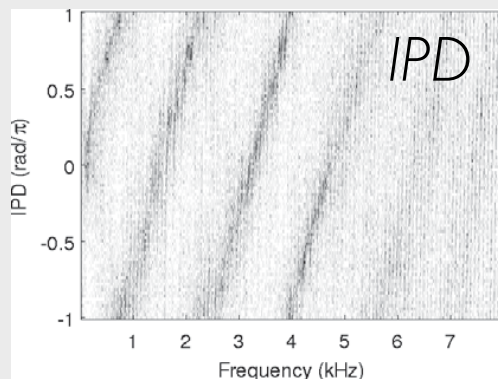


Separation by Spatial Info

- Given **multiple microphones**, sound carries **spatial information** about source
- E.g. model **interaural spectrum** of each source as stationary **level** and **time** differences:

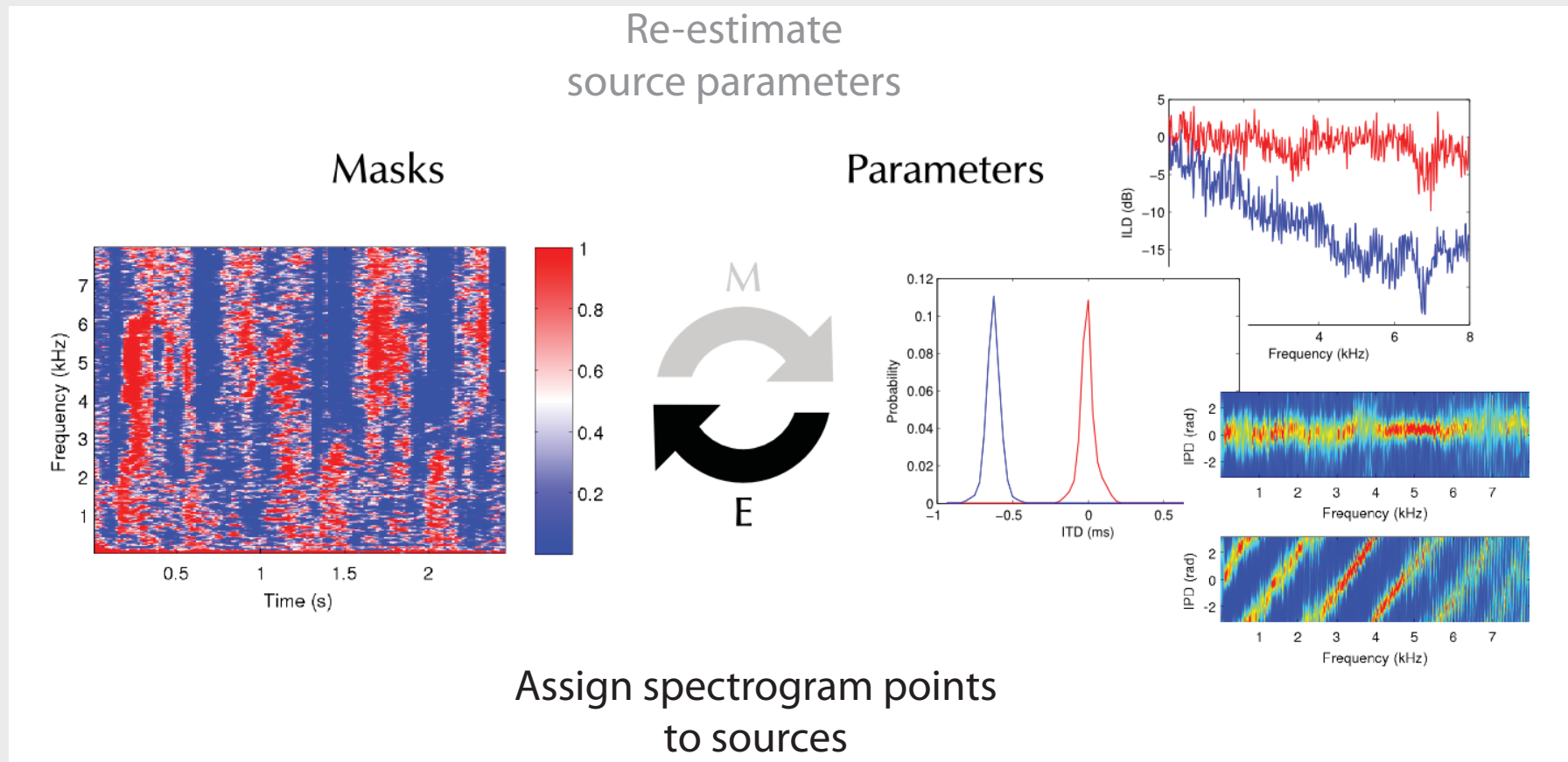
$$\frac{L(\omega, t)}{R(\omega, t)} = a(\omega) e^{j\omega\tau} N(\omega, t)$$

- e.g. at 75° , in reverb:



Model-Based EM Source Separation and Localization (MESSL)

Mandel et al. '10

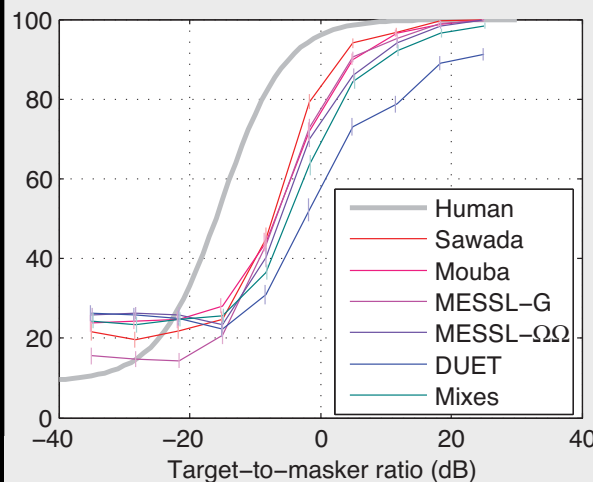
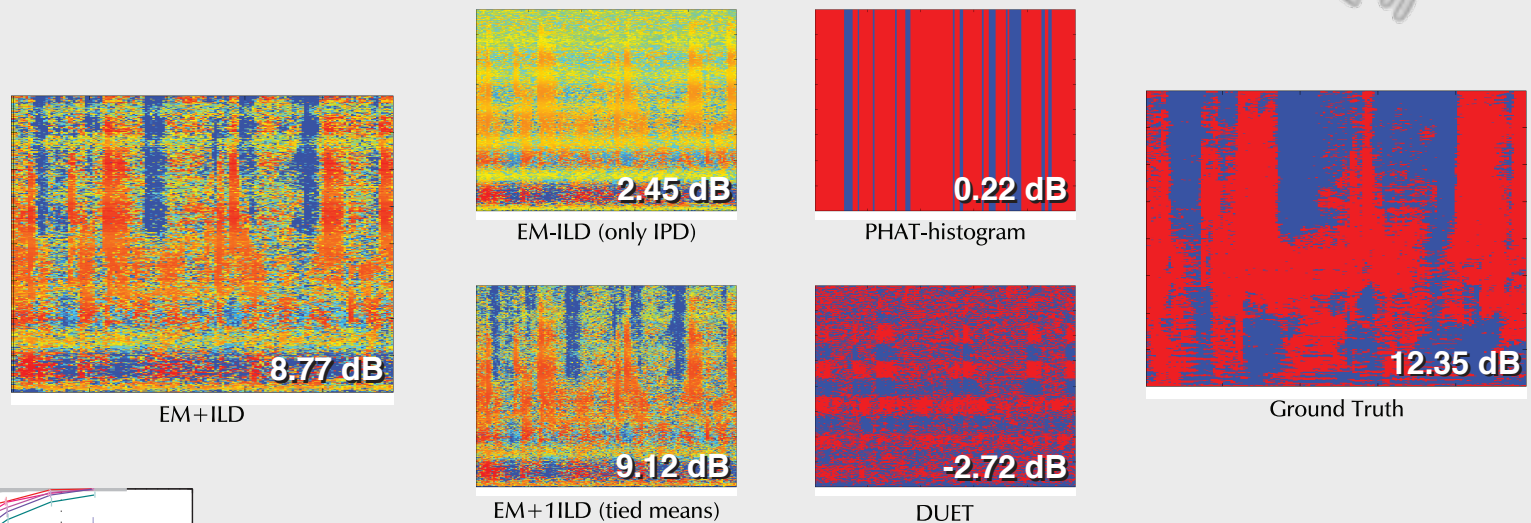


- can model more sources than sensors

MESSL Results



- **Modeling uncertainty** improves results
 - tradeoff between constraints & **noisiness**



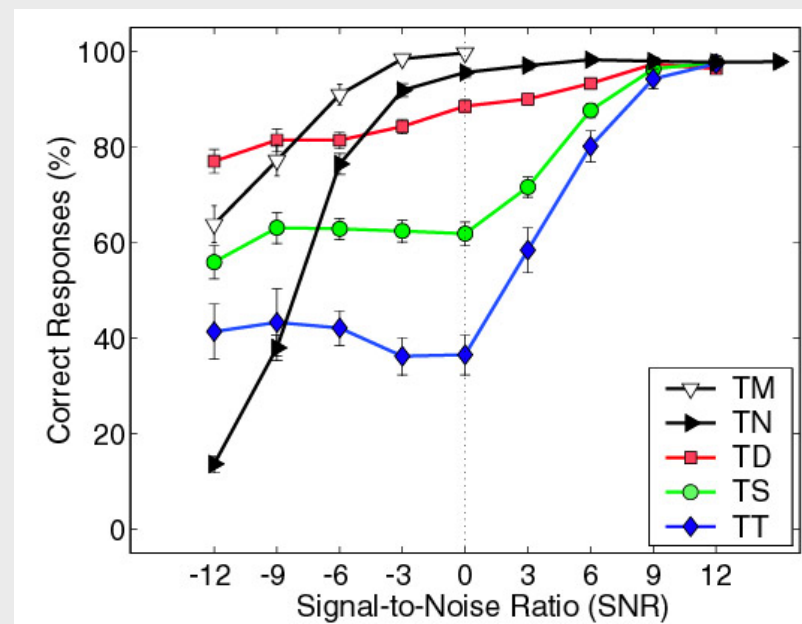
- **Helps with recognition**
 - digits accuracy

3. Separation by Pitch

- Voiced syllables have near-periodic “pitch”

- perceptually **salient**

- **lost** in MFCCs



Brungart et al.'01

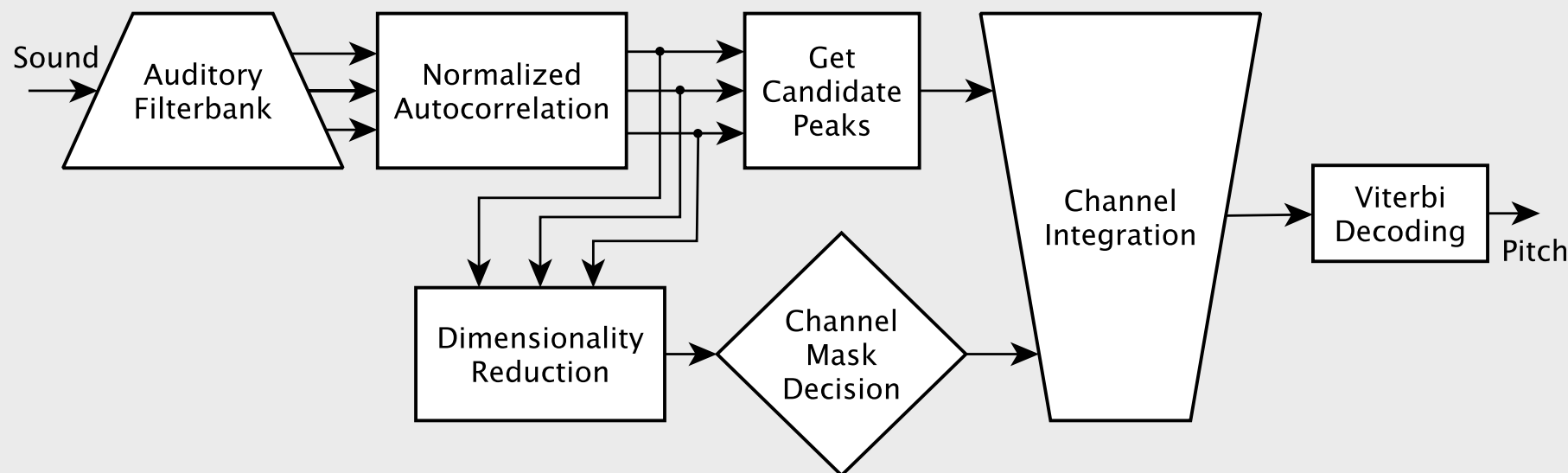
- Can we **track pitch** & use it for **separation**?

- ... and other speech tasks?

Noise-Robust Pitch Tracking

BS Lee & Ellis '12

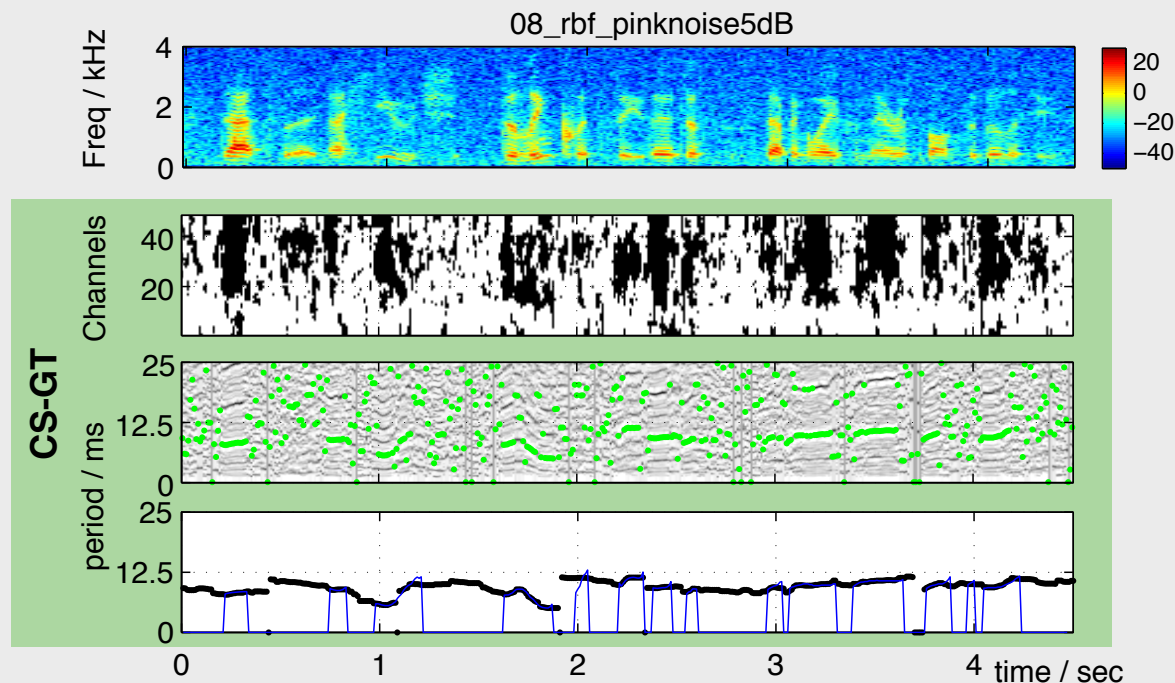
- Important for voice detection & separation
- Based on **channel selection** *Wu, Wang & Brown '03*
 - pitch from **summary autocorrelation** over “good” bands



- **trained classifier** decides which channels to include

Noise-Robust Pitch Tracking

- Channel-based classifiers
 - learn domain channel/noise characteristics
 - then *separate*, or derive features for *recognition*

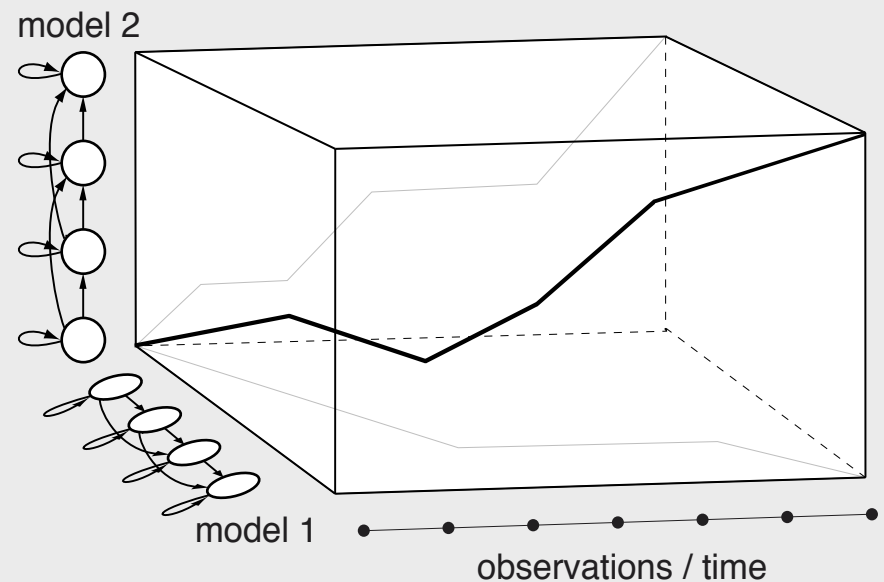
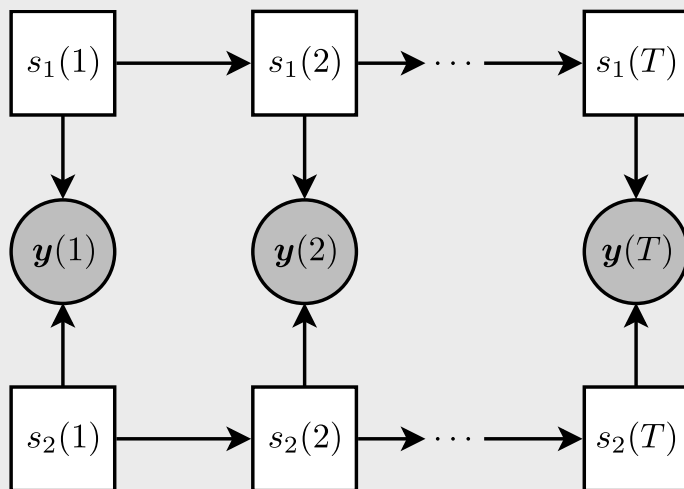


- Only works for *pitched* sounds
 - need a *broader description* of the speech source...

4. Separation by Models

Varga & Moore, '90
Hershey et al., '10

- If ASR is finding **best-fit** parameters
 $\operatorname{argmax} P(W | X) \dots$
- Recognize mixtures with **Factorial HMM**
 - model + state sequence for each voice/source
 - exploit sequence constraints, **speaker differences**



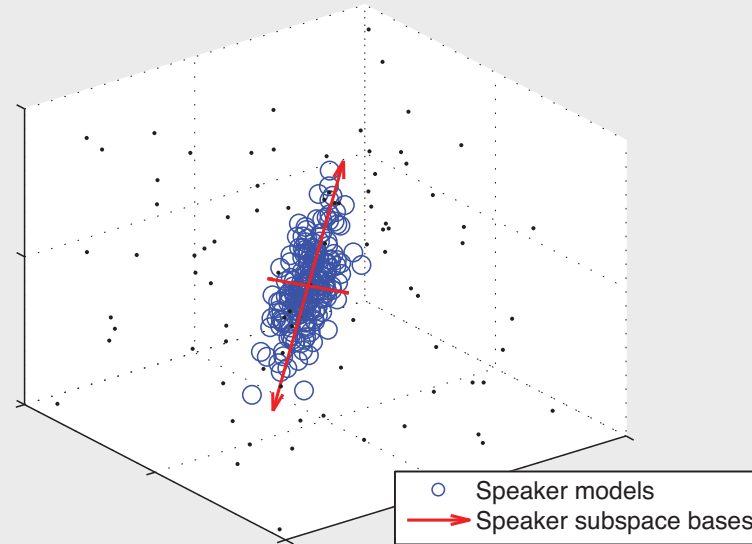
- separation relies on **detailed speaker model**

Eigenvoices

Kuhn et al. '98, '00
Weiss & Ellis '10

- Idea: Find **speaker model parameter space**

- generalize without losing **detail?**

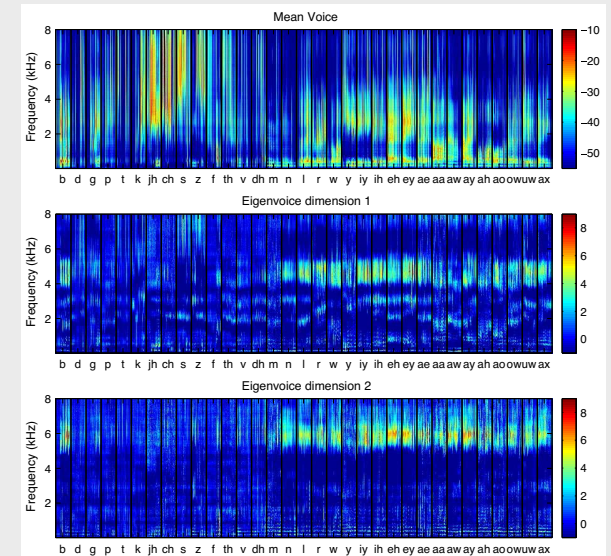


- **Eigenvoice** model:

$$\mu = \bar{\mu} + U w + B h$$

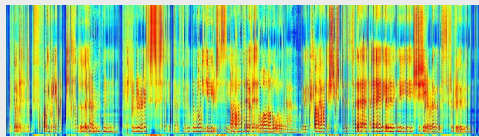
adapted model	mean voice	eigenvoice bases	weights	channel bases	channel weights
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- 89,600 dimensional space

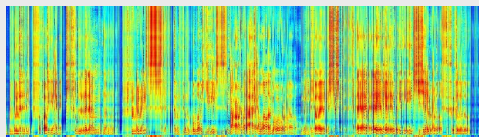


Eigenvoice Speech Separation

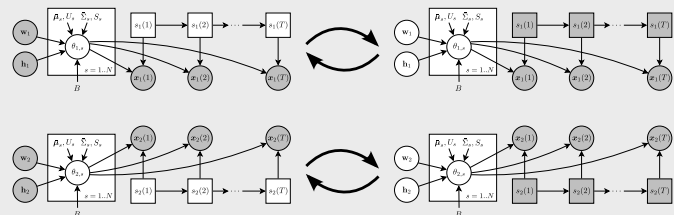
$$\mu_1 = U\mathbf{w}_1 + \bar{\mu}$$



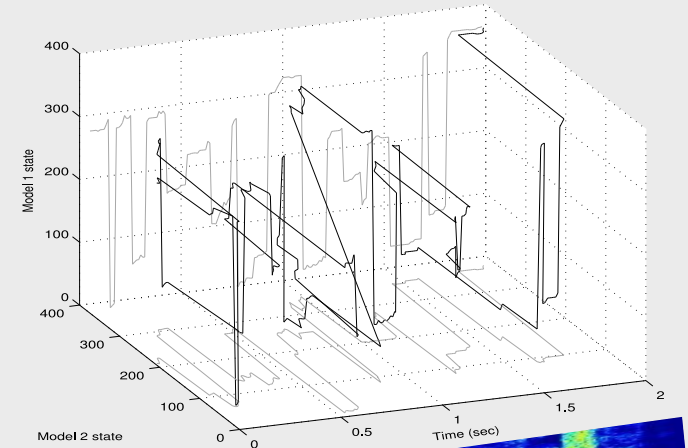
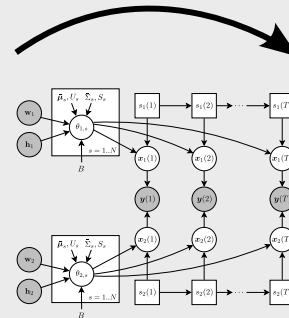
$$\mu_2 = U\mathbf{w}_2 + \bar{\mu}$$



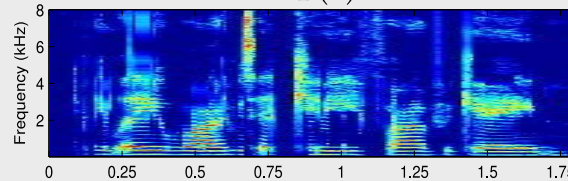
Update model parameters using EM algorithm from Kuhn et al., (2000)



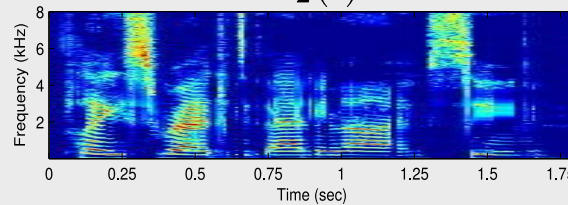
Find Viterbi path



$$\hat{x}_1(t)$$

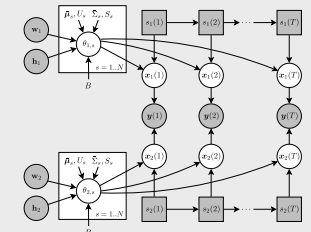


$$\hat{x}_2(t)$$



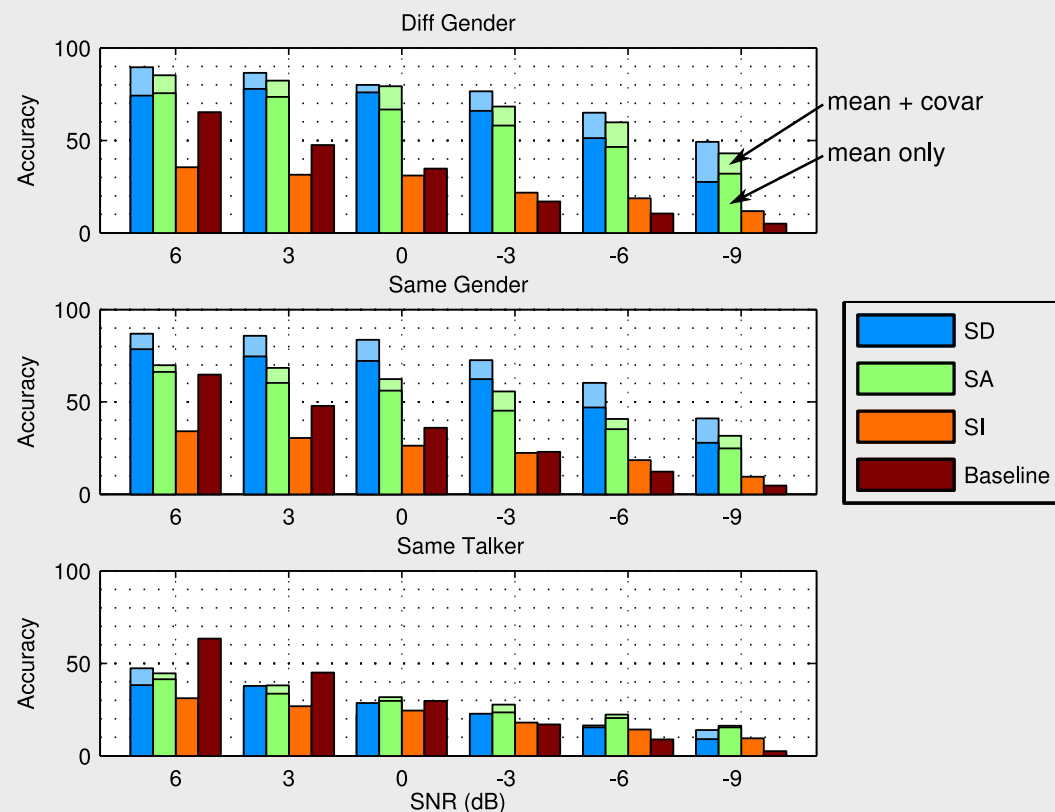
$$y(t)$$

Estimate source signals



Eigenvoice Speech Separation

- Eigenvoices for Speech Separation task
 - speaker adapted (SA) performs midway between speaker-dependent (SD) & speaker-indep (SI)



Mix



SI



SA



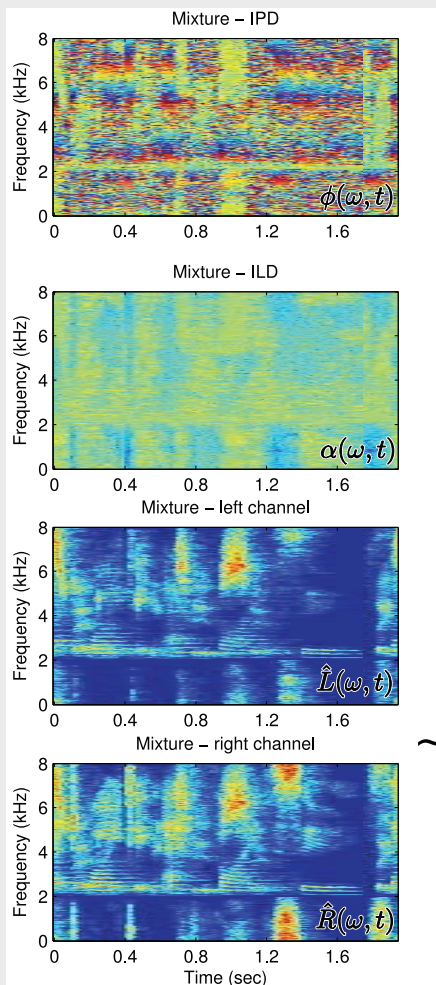
SD

Spatial + Model Separation

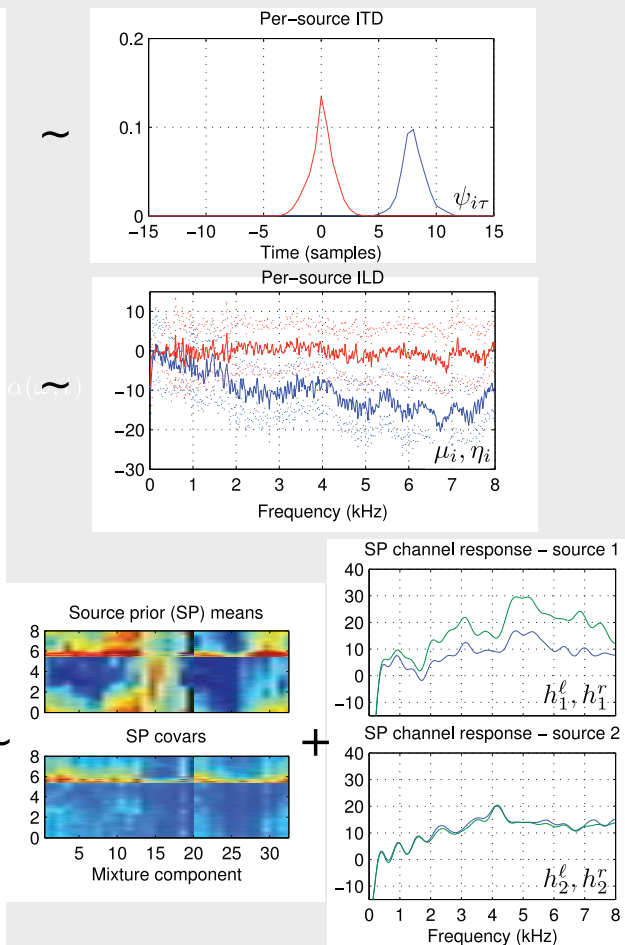
Weiss, Mandel & Ellis '11

- **MESSL** + **Eigenvoice** “priors”

Observations



Parameters



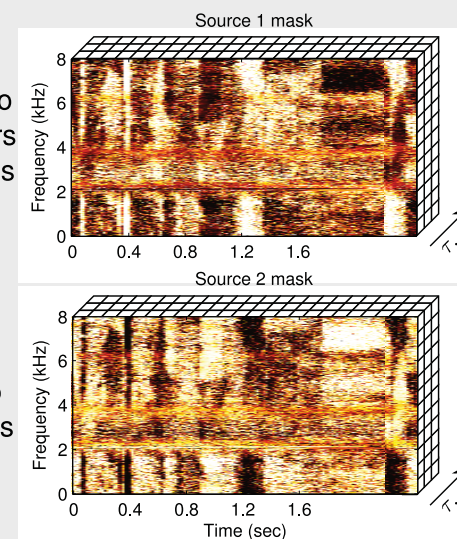
Posteriors

Each point in spectrogram is explained by a source, delay, and mixture component

E-step
Use parameters to compute posteriors of hidden variables

↻

M-step
Use posteriors to update parameters



Separate sources by multiplying mixture by different masks

Summary

- **Speech in the Wild**
 - ... real, challenging problem
 - ... applications in communications, lifelogs ...
- **Speech Separation**
 - ... by generic properties (location, pitch)
 - ... via statistical models
- **Recognition and Enhancement**
 - ... separate-then-X, or integrated solution?

References

- John Hershey, Steve Rennie, Pedr Olsen, Trausti Kristjansson, “Super-human multi-talker speech recognition: A graphical modeling approach,” *Computer Speech & Lang.* 24 (1), 45-66, 2010.
- Jon Barker, Martin Cooke, Dan Ellis, “Decoding Speech in the Presence of Other Sources,” *Speech Communication* 45(1): 5-25, 2005.
- R. Kuhn, J. Junqua, P. Nguyen, N. Niedzielski, “Rapid speaker adaptation in eigenvoice space,” . *IEEE Tr. Speech & Audio Proc.* 8(6): 695–707, Nov 2000.
- Byung-Suk Lee & Dan Ellis, “Noise-robust pitch tracking by trained channel selection,” submitted to *ICASSP*, 2012.
- Michael Mandel, Ron Weiss, Dan Ellis, “Model-Based Expectation-Maximization Source Separation and Localization,” *IEEE Tr. Audio, Speech, Lang. Proc.* 18(2): 382-394, Feb 2010.
- A. Varga and R. Moore, “Hidden markov model decomposition of speech and noise,” *ICASSP-90*, 845–848, 1990.
- Ron Weiss & Dan Ellis, “Speech separation using speaker-adapted Eigenvoice speech models,” *Computer Speech & Lang.* 24(1): 16-29, 2010.
- Ron Weiss, Michael Mandel, Dan Ellis, “Combining localization cues and source model constraints for binaural source separation,” *Speech Communication* 53(5): 606-621, May 2011.
- Mingyang Wu, DeLiang Wang, Guy Brown, “A multipitch tracking algorithm for noisy speech,” *IEEE Tr. Speech & Audio Proc.* 11(3): 229–241, May 2003.