Speech Separation in Humans and Machines

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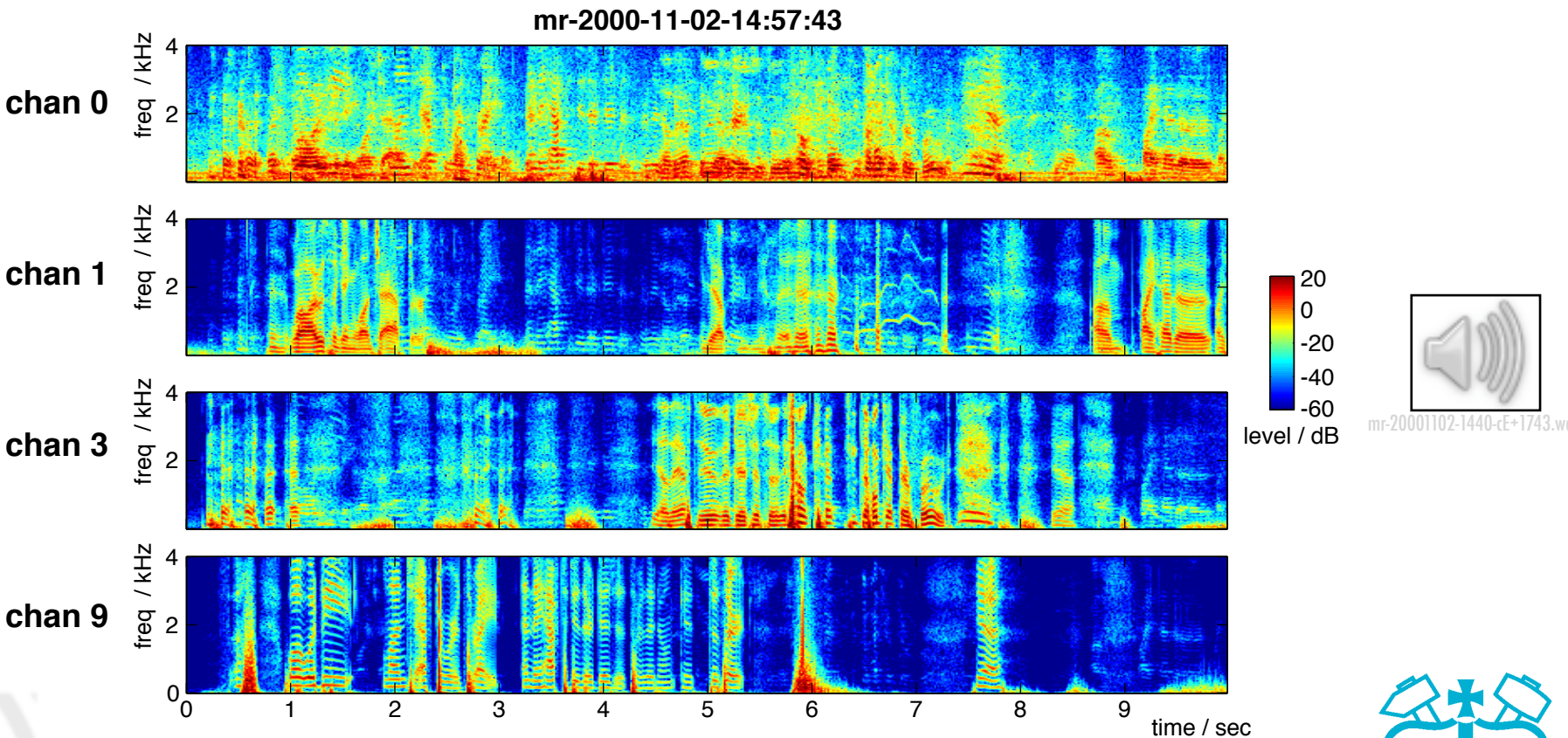
1. The Speech Separation Problem
2. Human Performance
3. Source Separation
4. Source Inference
5. Concluding Remarks

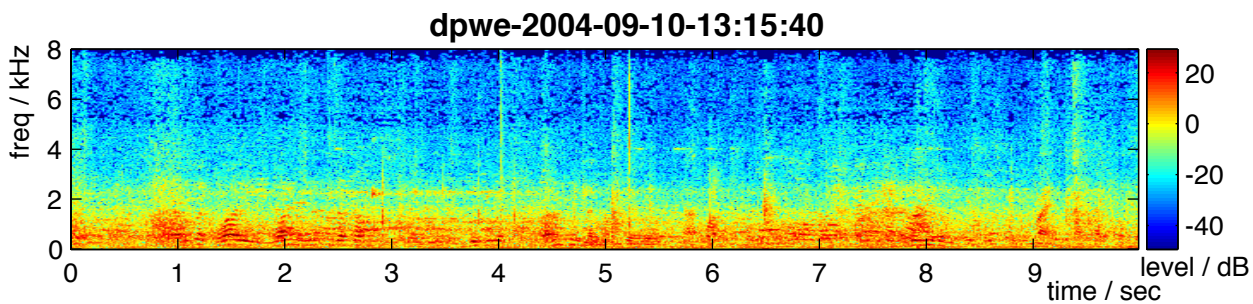
1. Speech Separation

- Speech rarely occurs in isolation
  - .. but recognizing mixed speech is a problem
  - .. for humans and machines



Speech Separation Scenarios

- **Interactive voice systems**
  - human-level understanding is expected
- **Speech prostheses**
  - crowds: #1 complaint of hearing aid users
- **Archive analysis**
  - identifying and isolating speech



- **Surveillance...**

How Can We Separate?

- By between-sensor differences (spatial cues)
  - 'steer a null' onto a compact interfering source
- By finding a 'separable representation'
  - spectral? but speech is broadband
  - periodicity? maybe – for voiced speech
  - something more signal-specific...
- By inference (based on knowledge/models)
  - speech is redundant

    → use part to guess the remainder

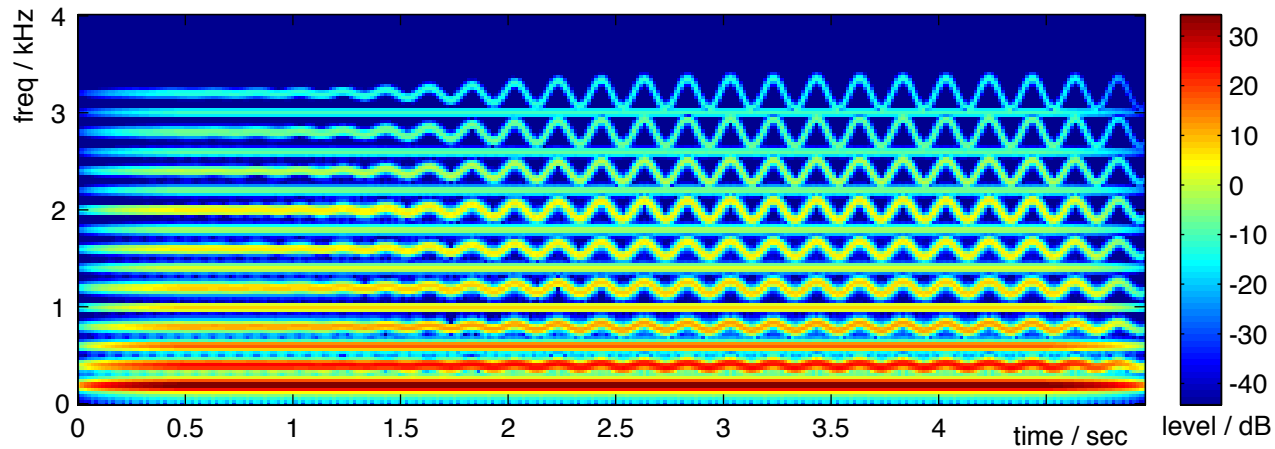
Outline

1. The Speech Separation problem
2. Human Performance
   - scene analysis
   - speech separation by location
   - speech separation by voice characteristics
3. Source Separation
4. Source Inference
5. Concluding Remarks

Auditory Scene Analysis

Bregman'90
Darwin & Carlyon'95

- Listeners organize sound mixtures into discrete perceived sources based on within-signal cues (audio + ...)
  - common onset + continuity
  - harmonicity
  - spatial, modulation, ...
  - learned "schema"



Reynolds-McAdams oboe

reynolds-mcadams-dpwe.wav

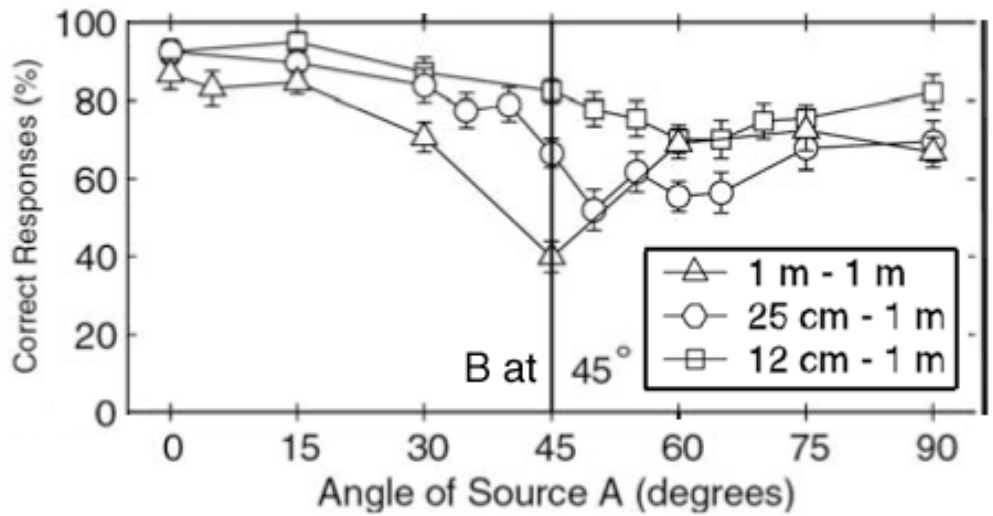
Speech Mixtures: Spatial Separation

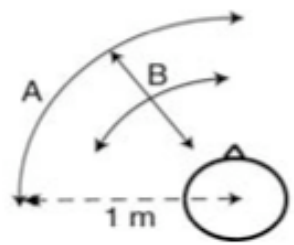
Brungart et al.'02

- **Task: Coordinate Response Measure**
  - "Ready Baron go to green eight now"
  - 256 variants, 16 speakers
  - correct = color and number for "Baron"


crm-11737+16515.wav

- **Accuracy as a function of spatial separation:**



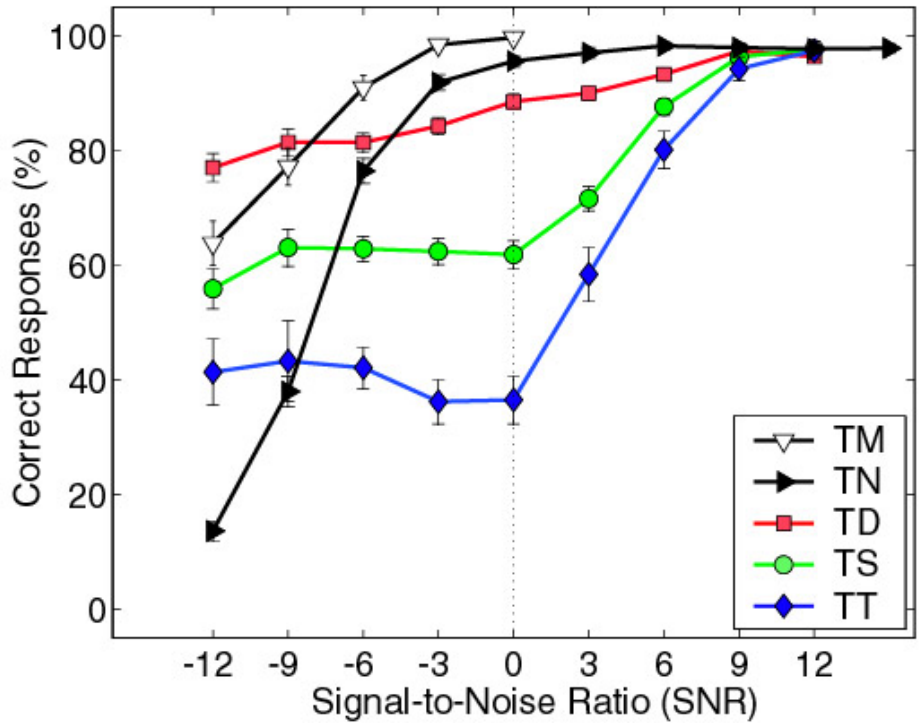


  - A, B same speaker

Separation by Vocal Differences

Brungart et al.'01

- **CRM varying the level and voice character**
  - (same spatial location)

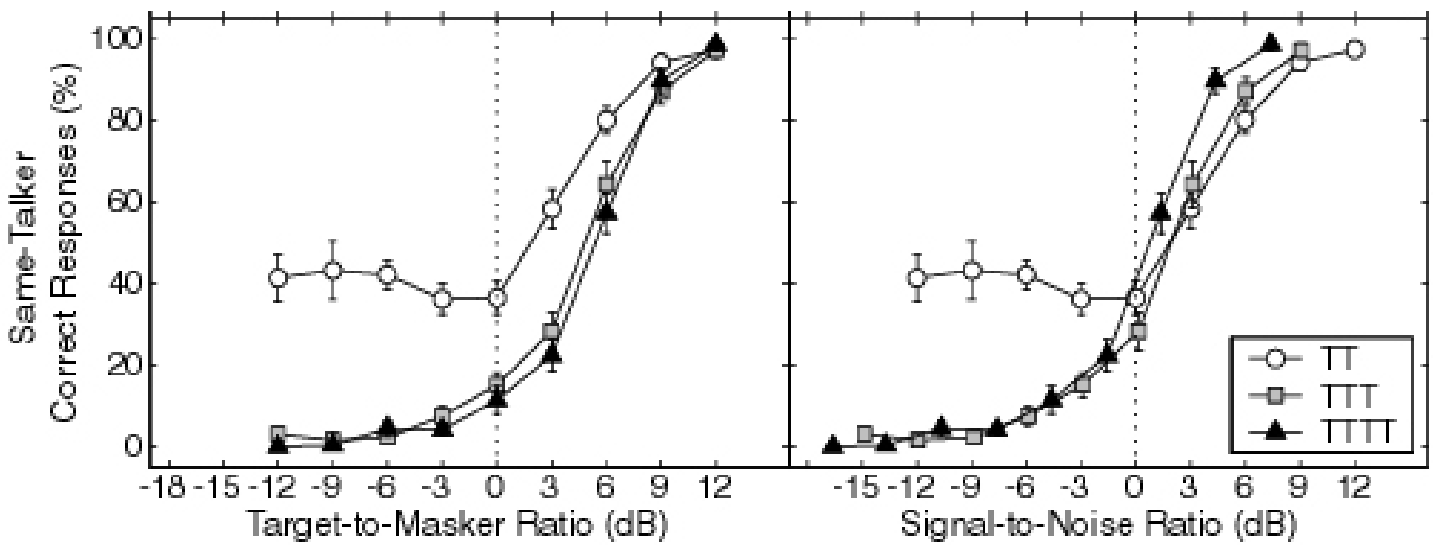


  - energetic vs. informational masking

Varying the Number of Voices

Brungart et al.'01

- Two voices OK;
  More than two voices harder
  - (same spatial origin)



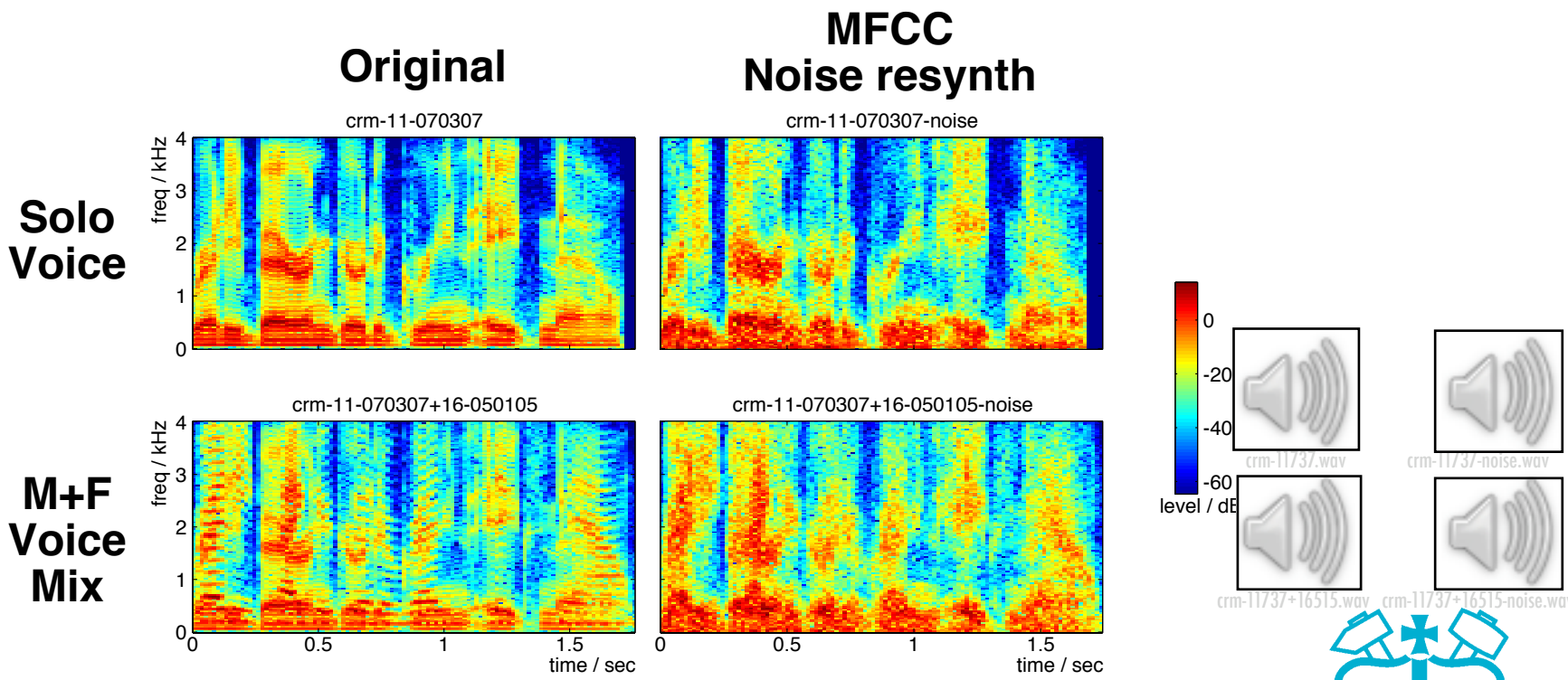
  - mix of *N* voices tends to speech-shaped noise...

Outline

1. The Speech Separation problem
2. Human Performance
3. **Source Separation**
   - Independent Component Analysis
   - Computational Auditory Scene Analysis
4. Source Inference
5. Concluding Remarks

Machine Separation

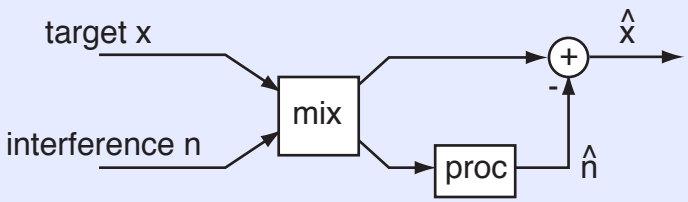
- Problem: Features of combinations are not combinations of features
  - voice is easy to characterize when in isolation
  - redundancy needed for real-world communication



Separation Approaches

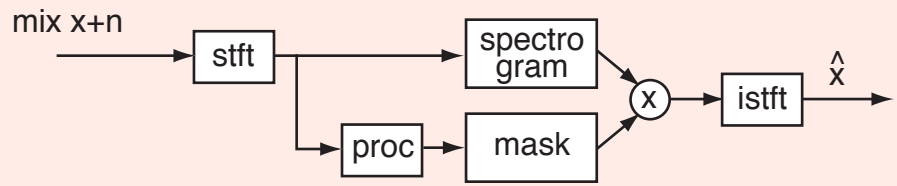
ICA

- Multi-channel
- Fixed filtering
- Perfect separation – maybe!



CASA / Model-based

- Single-channel
- Time-varying filtering
- Approximate Separation

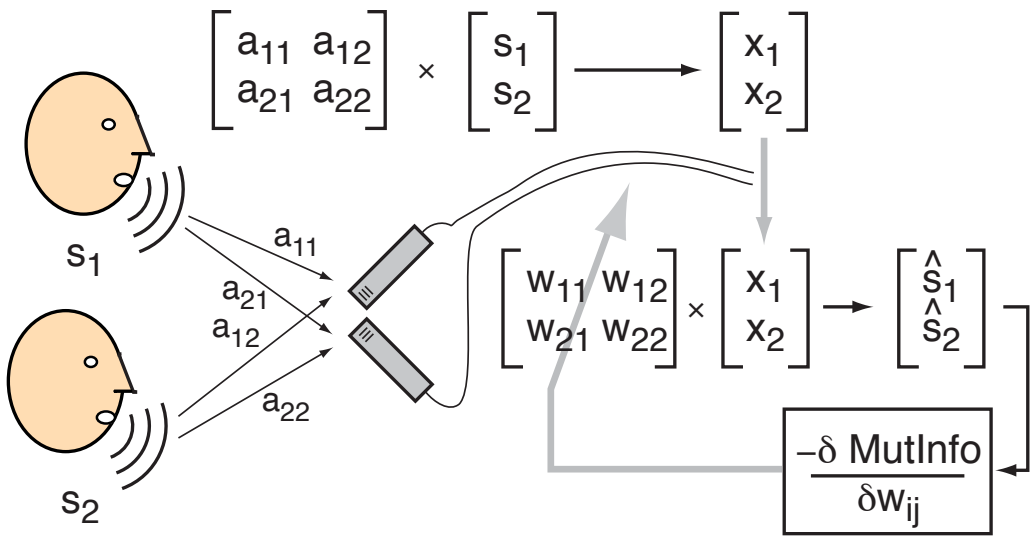


- Very different approaches!

Independent Component Analysis

Bell & Sejnowski'95
Smaragdis'98
...

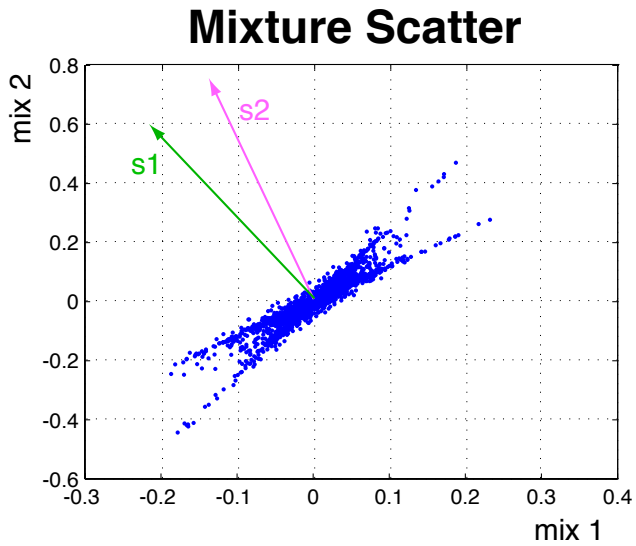
- Central idea:
  Search unmixing space
  to maximize independence of outputs

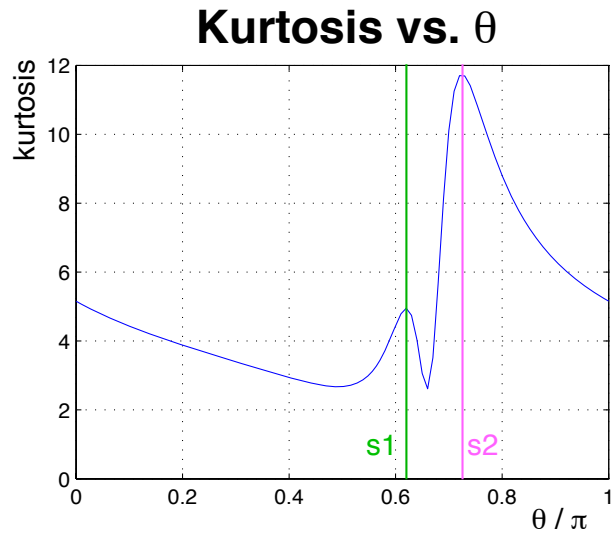


- simple mixing
  → a good solution (usually) exists

ICA Limitations

- Cancellation is very finicky
  - hard to get more than ~ 10 dB rejection





from Parra & Spence'00


lee_ss_in_1.wav

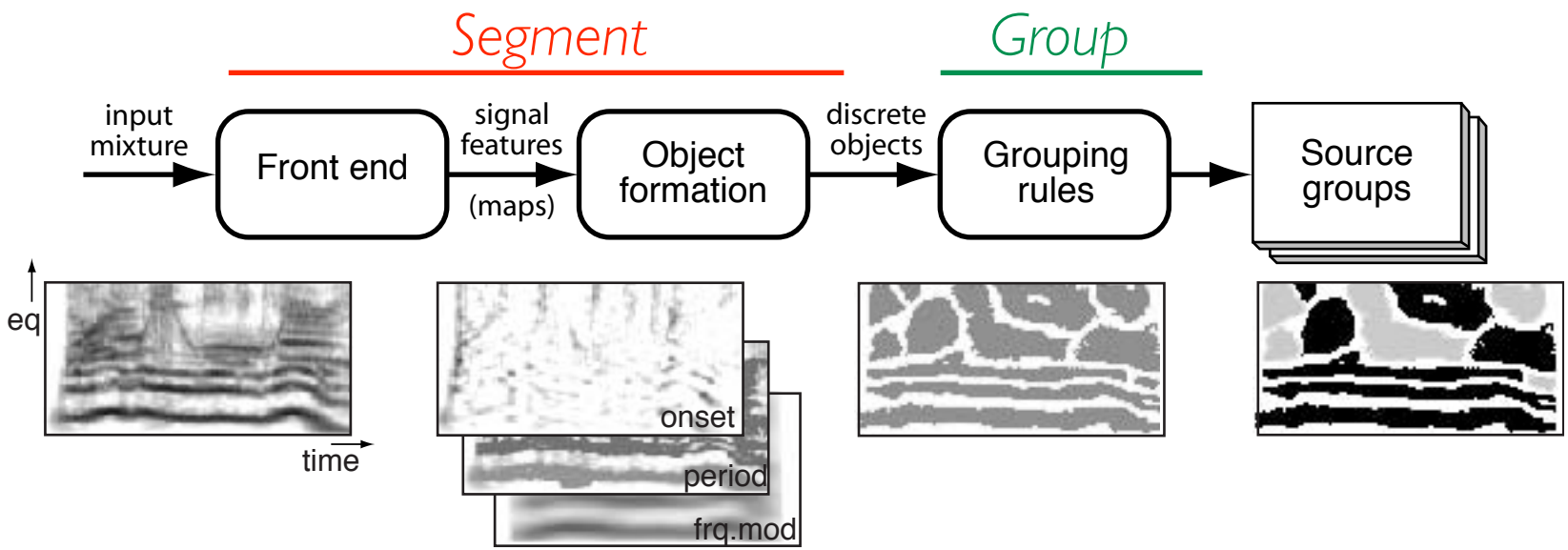

lee_ss_para_1.wav

- The world is not instantaneous, fixed, linear
  - subband models for reverberation
  - continuous adaptation
- Needs spatially-compact interfering sources

Computational Auditory Scene Analysis

Brown & Cooke'94
Okuno et al.'99
Hu & Wang'04 ...

- Central idea:
  Segment time-frequency into sources based on perceptual grouping cues

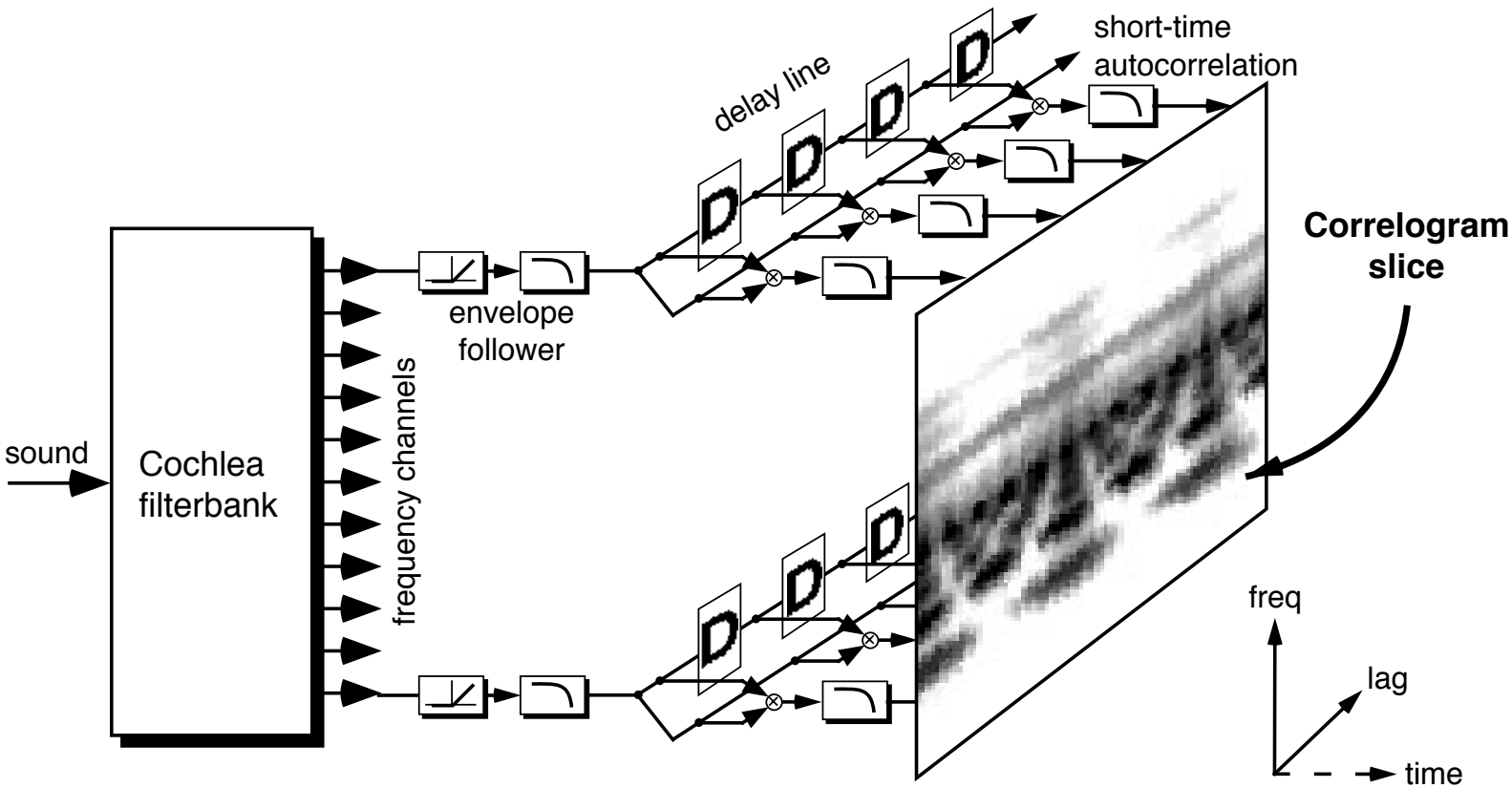


- ... principal cue is harmonicity

CASA Preprocessing

Slaney & Lyon '90

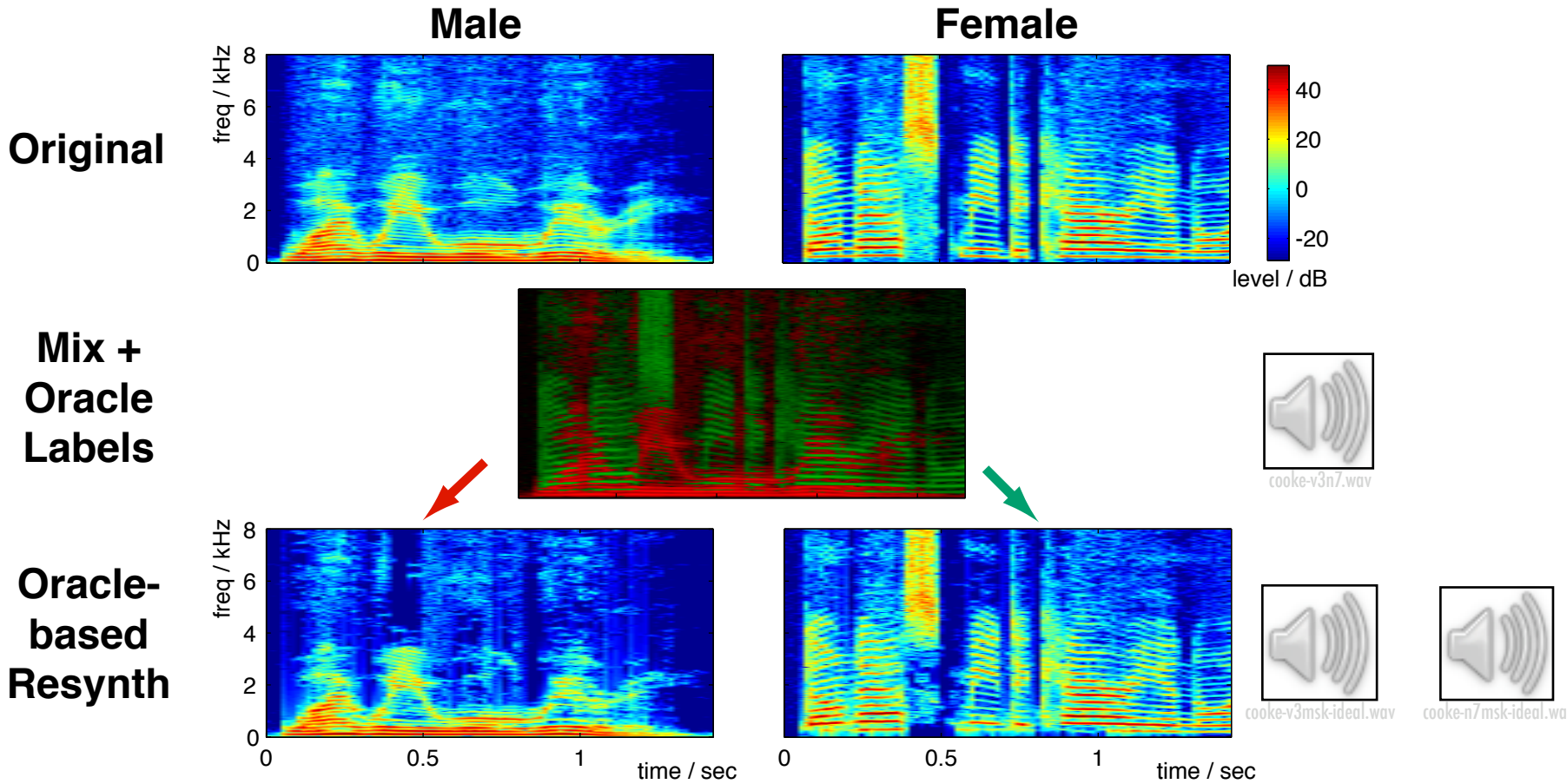
- **Correlogram**: a 3rd "periodicity" axis
  - envelope of wideband channels follows pitch



  - c/w Modulation Filtering *[Schimmel & Atlas '05]*

Time-Frequency (T-F) Masking

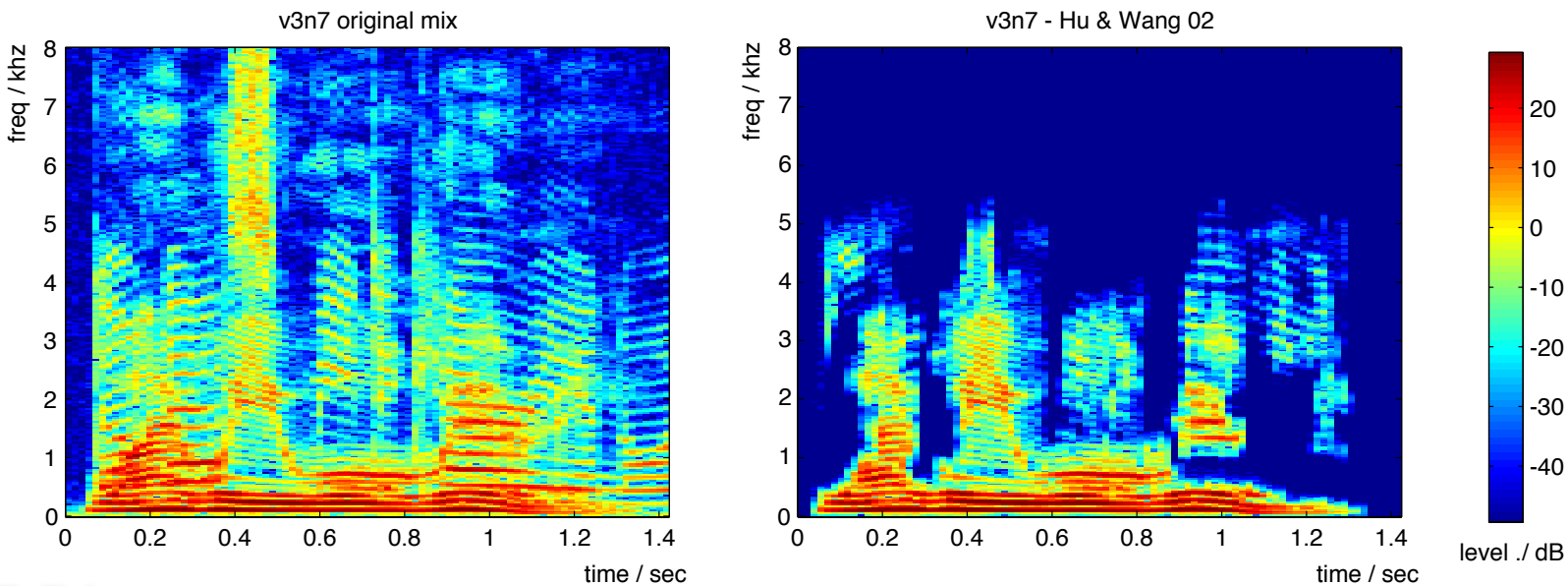
- "Local Dominance" assumption



- oracle masks are remarkably effective!
- $|mix - \max(male, female)| < 3\text{dB}$ for ~80% of cells

CASA limitations

- Driven by local features
  - problems with aperiodic sources...
- Limitations of T-F masking
  - need to identify single-source regions
  - cannot undo overlaps – leaves gaps



from Hu & Wang '04

huwang-v3n7.wav

Combining Spatial + T-F Masking

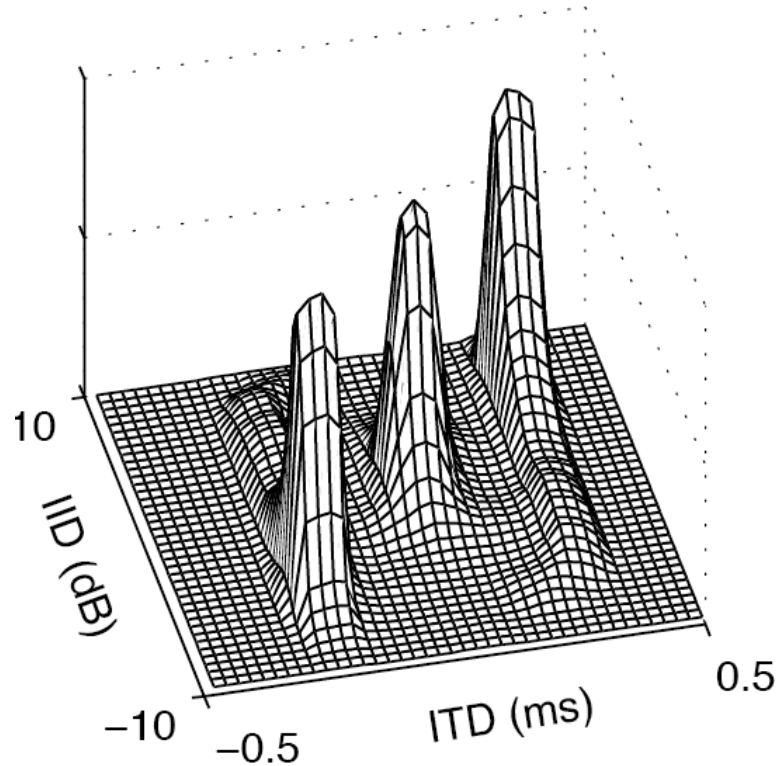
- T-F masks based on inter-channel properties

  [Roman et al. '02], [Yilmaz & Rickard '04]

  
  lee_ss_in_1.wav

  
  lee_ss_duet_1.wav

  - multiple channels make CASA-like masks better



- T-F masking after ICA

  [Blin et al. '04]

  - cancellation can remove energy within T-F cells

Outline

1. The Speech Separation problem
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4. **Source Inference**
   - Separation vs. inference
   - Model-based separation
   - Speech Fragment Decoding
5. Concluding Remarks

Separation vs. Inference

Ellis'96

- **Ideal separation is rarely possible**
  - i.e. no projection can completely remove overlaps
- **Overlaps ⇒ Ambiguity**
  - scene analysis = find "most reasonable" explanation
- **Ambiguity can be expressed probabilistically**
  - i.e. posteriors of sources $\{S_i\}$ given observations X:

$$P(\{S_i\}|\, X) \propto P(X\,|\{S_i\})\; P(\{S_i\})$$

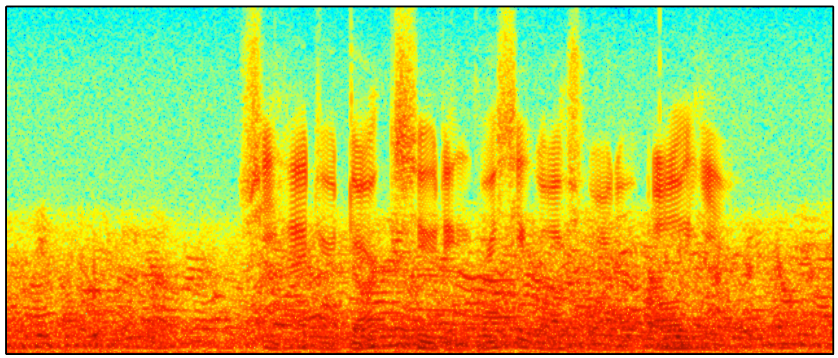
combination physics *source models*

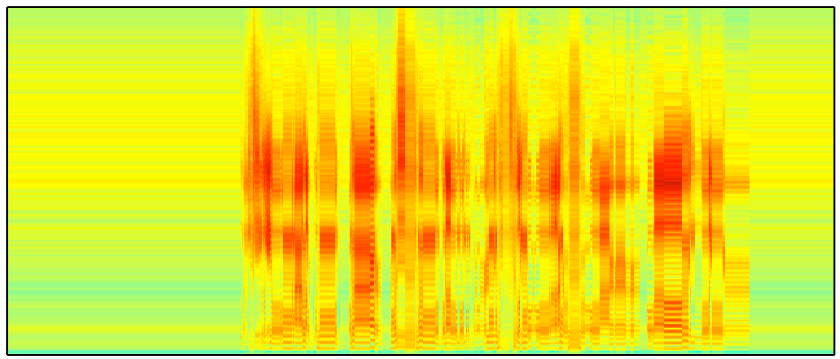
- **Better source models → better inference**
  - .. learn from examples?

Model-Based Separation

Varga & Moore'90
Roweis'03...

- Central idea:
  Employ strong learned constraints
  to disambiguate possible sources
  - $\{S_i\} = \text{argmax}_{Si}\ P(X \mid \{S_i\})$
- e.g. fit speech-trained Vector-Quantizer
  to mixed spectrum:



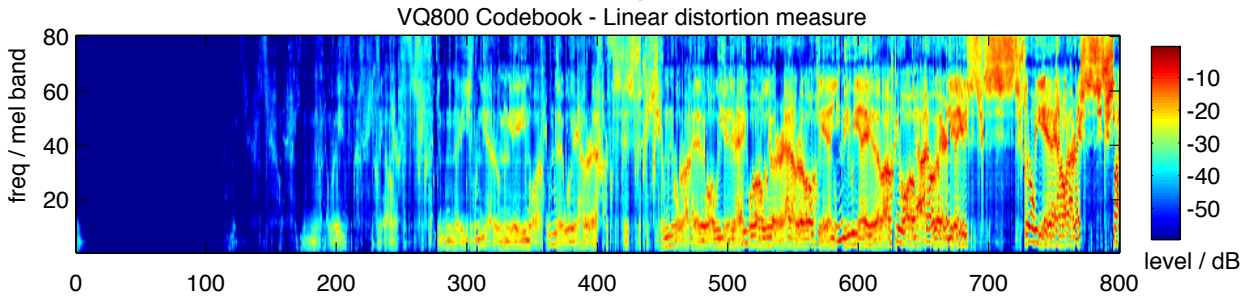


from Roweis'03

  - separate via T-F mask (again)

Can Models Do CASA?

- Source models can learn harmonicity, onset
  - ... to subsume rules/representations of CASA

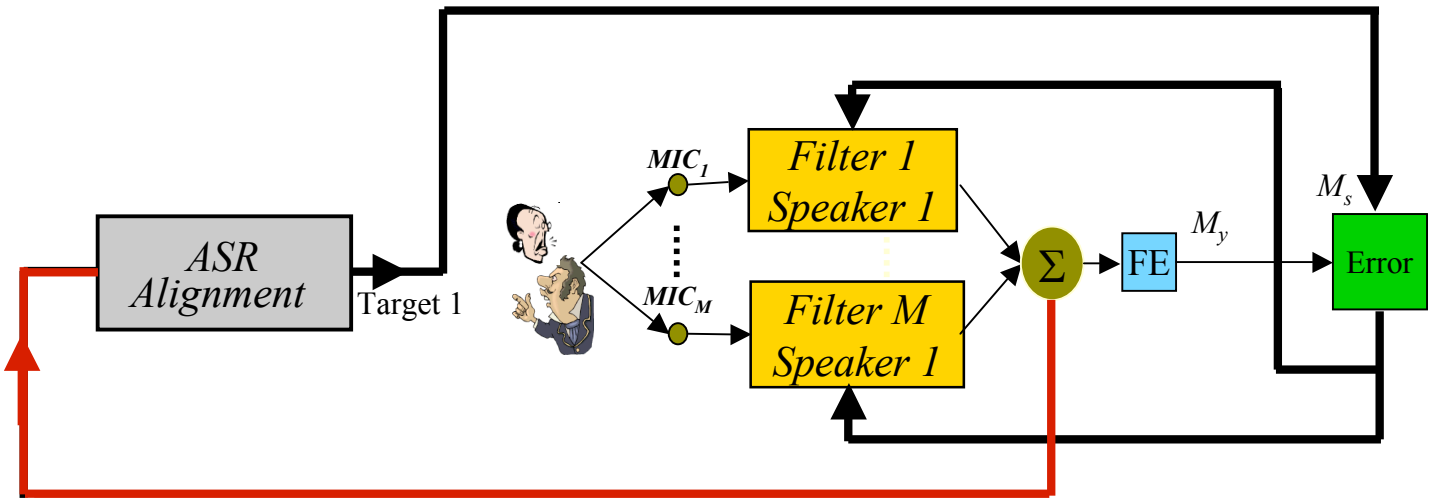


  - can capture spatial info too *[Pearlmutter & Zador'04]*
- Can also capture sequential structure
  - e.g. consonants follow vowels
  - ... like people do?
- But: need source-specific models
  ... for every possible source
  - use model adaptation? *[Ozerov et al. 2005]*

Separation with ASR Models

Seltzer et al. '02
Reyes et al. '03

- Drive separation engine to match outputs to existing speech models

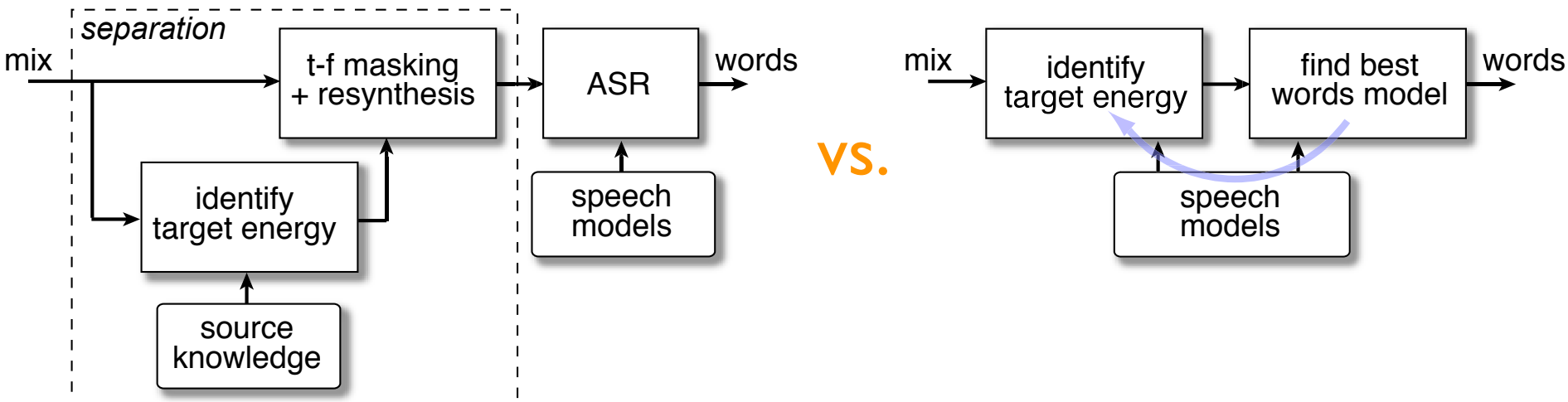


from Manuel Reyes's WASPAA 2003 presentation

  - ASR includes a very detailed source model

Separation or Description?

- Are isolated waveforms required?
  - clearly sufficient, but may not be necessary
  - not part of perceptual source separation!
- Integrate separation with application?
  - e.g. speech recognition

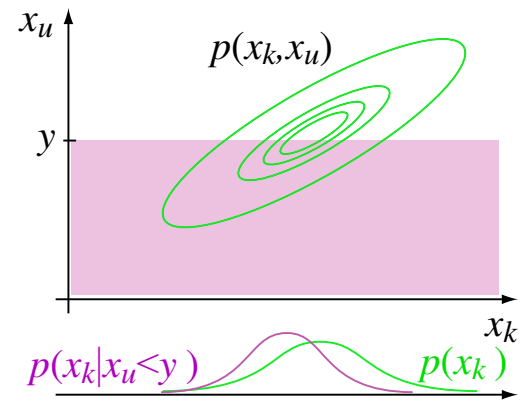


  - words output = abstract description of signal

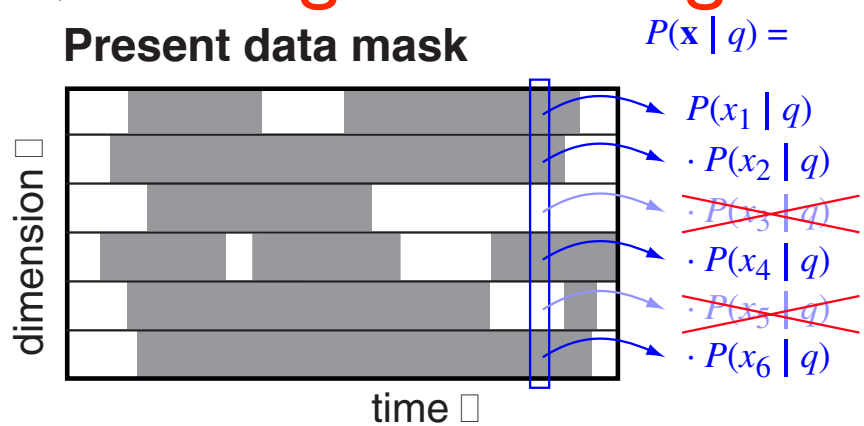
Missing Data Recognition

Cooke et al. '01

- Speech models $p(x|M)$ are multidimensional...
  - need values for all dimensions to evaluate $p(\bullet)$
- But: can make inferences given just a subset of dimensions x_k
  - $p(x_k|M) = \int p(x_k, x_u|M)dx_u$



- Hence, missing data recognition:

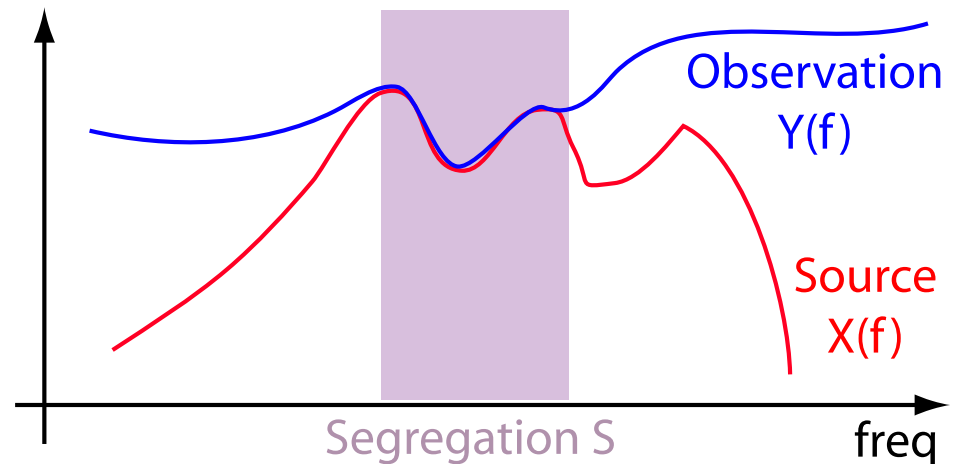


  - hard part is finding the mask (segregation)

The Speech Fragment Decoder

Barker et al. '05

- Match 'uncorrupt' spectrum to ASR models using missing data



- Joint search for model M and segregation S to maximize:

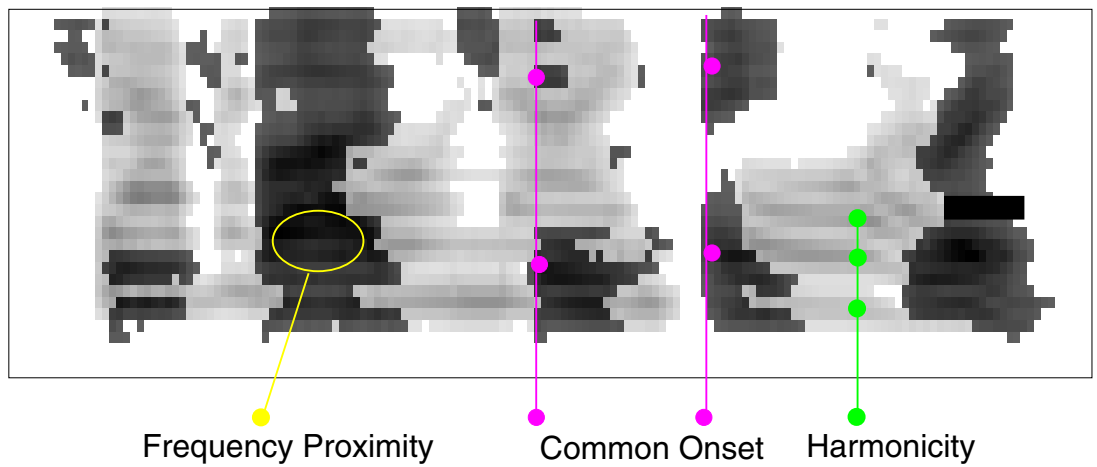
$$P(M,S|Y) = P(M)\int P(X|M)\cdot\frac{P(X|Y,S)}{P(X)}dX\cdot P(S|Y)$$

Isolated Source Model *Segregation Model*

Using CASA cues

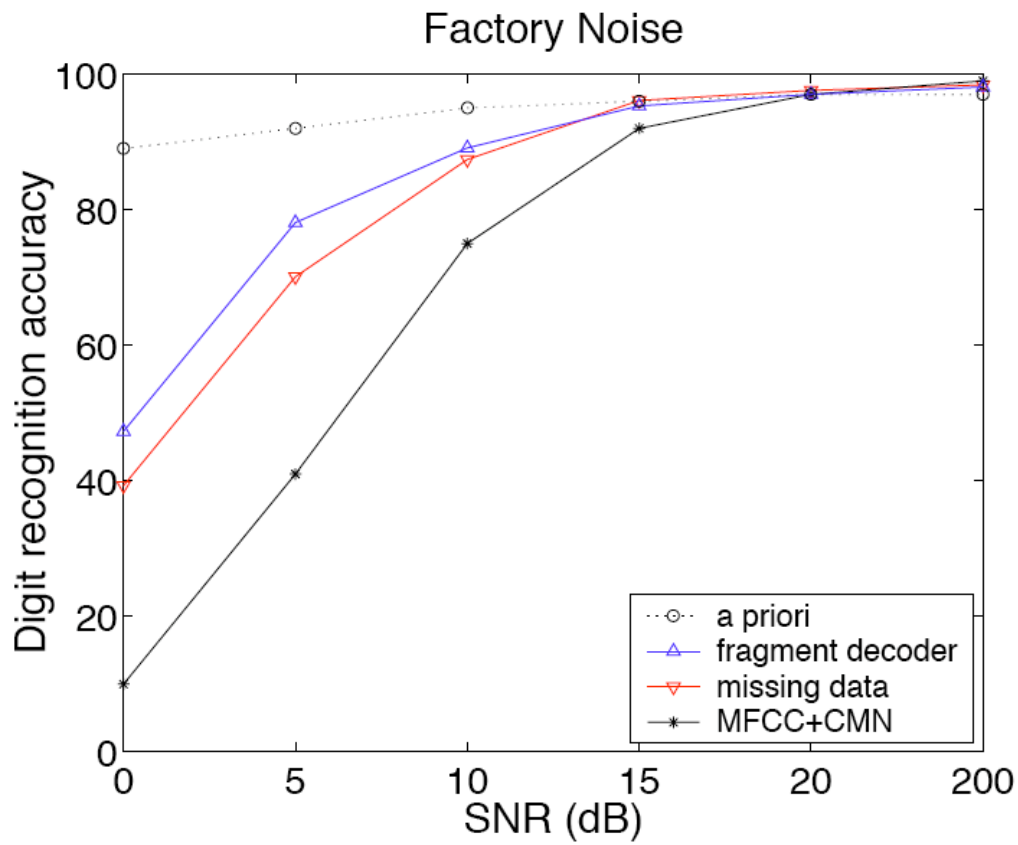
$$P(M,S|Y) = P(M)\int P(X|M)\cdot\frac{P(X|Y,S)}{P(X)}dX\cdot P(S|Y)$$

- CASA can help search
  - consider only segregations made from CASA chunks
- CASA can rate segregation
  - construct $P(S|Y)$ to reward CASA qualities:



Speech-Fragment Recognition

- CASA-based fragments give extra gain over missing-data recognition



from Barker et al. '05

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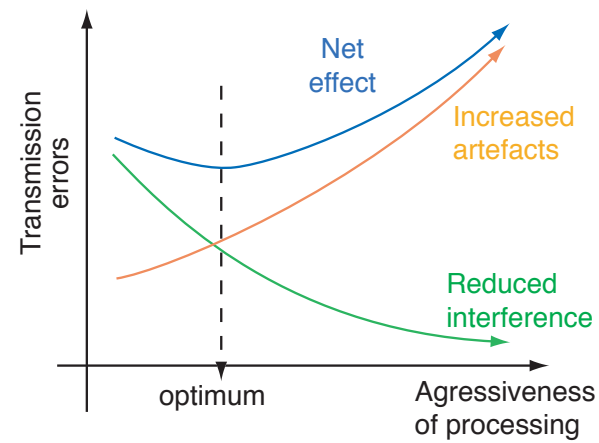
5. **Concluding Remarks**
   - Evaluation
   - Connecting to Perception

Evaluation

- How to measure separation performance?
  - depends what you are trying to do
- SNR?
  - energy (and distortions) are not created equal
  - different nonlinear components *[Vincent et al. '06]*
- Intelligibility?
  - rare for nonlinear processing to improve intelligibility
  - listening tests expensive
- ASR performance?
  - separate-then-recognize too simplistic; ASR needs to accommodate separation



"Speech Separation Challenge"

- Mixed and Noisy Speech ASR task defined by Martin Cooke and Te-Won Lee
  - short, grammatically-constrained utterances:

<command:4><color:4><preposition:4><letter:25><number:10><adverb:4>

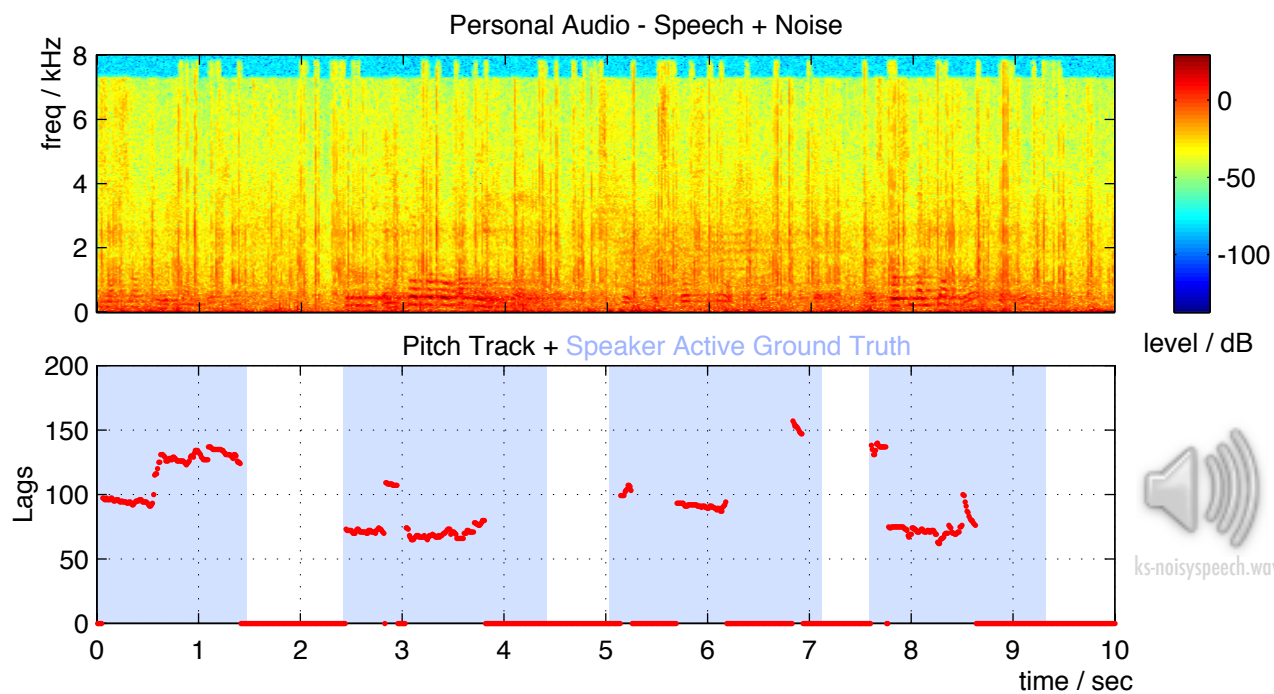
e.g. "bin white at M 5 soon"

t5_bwam5s_m5_bbilzp_6p1.wav

- Results to be presented at Interspeech'06
  - http://www.dcs.shef.ac.uk/~martin/SpeechSeparationChallenge.htm
- See also "Statistical And Perceptual Audition" workshop
  - http://www.sapa2006.org/

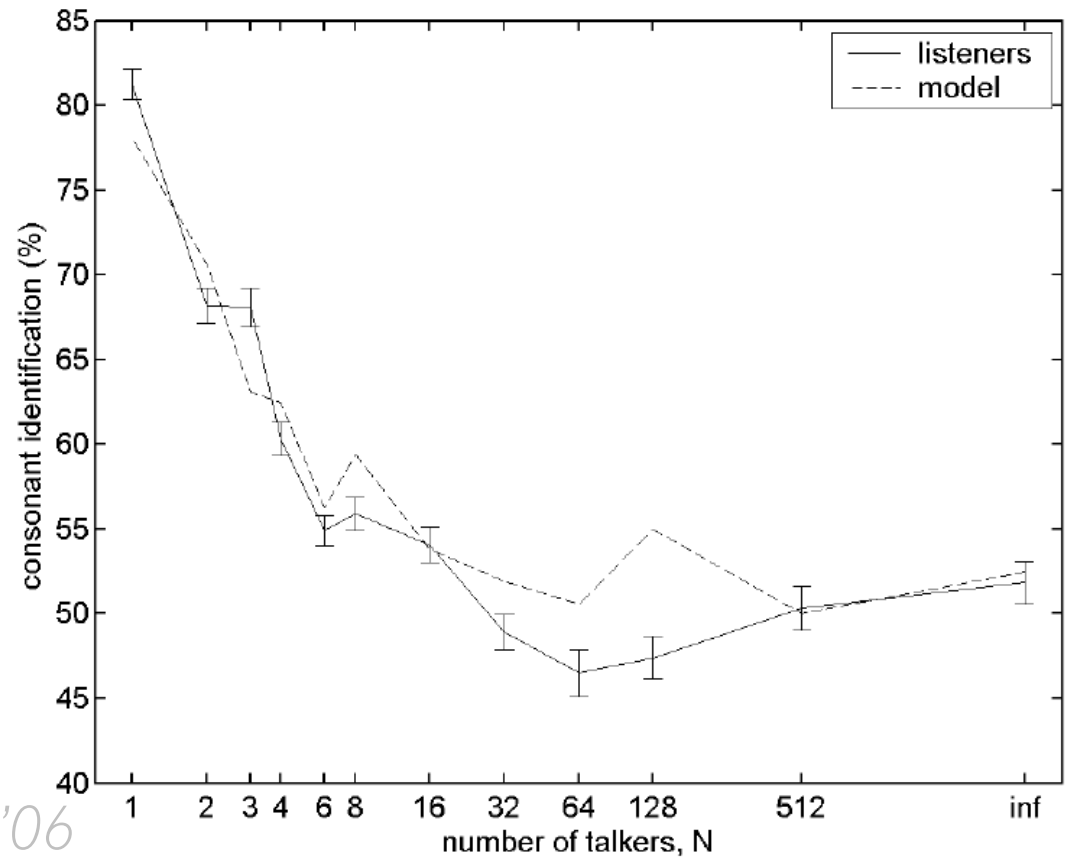
More Realistic Evaluation

- Real-world speech tasks
  - crowded environments
  - applications: communication, command/control, transcription
- Metric
  - human intelligibility?
  - 'diarization' annotation (not transcription)



Reconnecting to Perception

- People are (still) much better at speech recognition, including mixtures
- Can we model human separation with ASR?
  - "Glimpse model": MD ASR using oracle local SNR
  - Listeners identify high SNR islands?



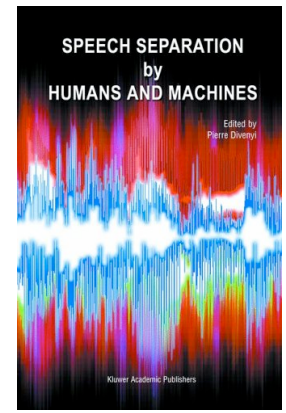
from Cooke'06

Summary & Conclusions

- Listeners do well separating speech
  - using spatial location
  - using source-property variations
- Machines do less well
  - difficult to apply enough constraints
  - need to exploit signal detail
- Models capture constraints
  - learn from the real world
  - adapt to sources
- Inferring state (≈ recognition) is a promising approach to separation

Sources / See Also

- NSF/AFOSR Montreal Workshops '03, '04
  - www.ebire.org/speechseparation/
  - labrosa.ee.columbia.edu/Montreal2004/
  - as well as the resulting book...



- Hanse meeting:
  - www.lifesci.sussex.ac.uk/home/Chris_Darwin/Hanse/
- DeLiang Wang's ICASSP'04 tutorial
  - www.cse.ohio-state.edu/~dwang/presentation.html
- Martin Cooke's NIPS'02 tutorial
  - www.dcs.shef.ac.uk/~martin/nips.ppt

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