Using Sound Source Models to Organize Mixtures

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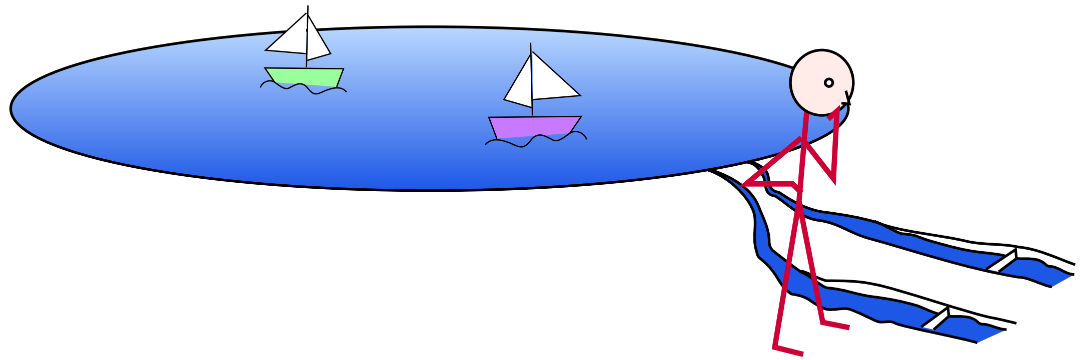
1. Mixtures and Models
2. Human Sound Organization
3. Machine Sound Organization
4. Ambient Sounds

The Problem of Mixtures

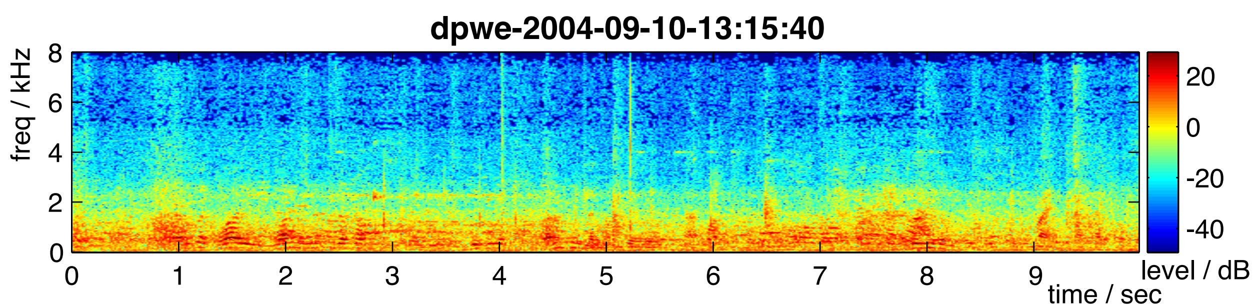


"Imagine two narrow channels dug up from the edge of a lake, with handkerchiefs stretched across each one. Looking only at the motion of the handkerchiefs, you are to answer questions such as: How many boats are there on the lake and where are they?" (after Bregman'90)

- **Received waveform is a mixture**
  - 2 sensors, N sources - underconstrained
- **Undoing mixtures: hearing's primary goal?**
  - .. by any means available

Sound Organization Scenarios

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



- Unmixing/remixing/enhancement...

How Can We Separate?

- By between-sensor differences (spatial cues)
  - ‘steer a null’ onto a compact interfering source
  - the filtering/signal processing paradigm
- By finding a ‘separable representation’
  - spectral? sources are broadband but sparse
  - periodicity? maybe – for pitched sounds
  - something more signal-specific...
- By inference (based on knowledge/models)
  - acoustic sources are redundant
    - → use part to guess the remainder
    - - limited possible solutions

Separation vs. Inference

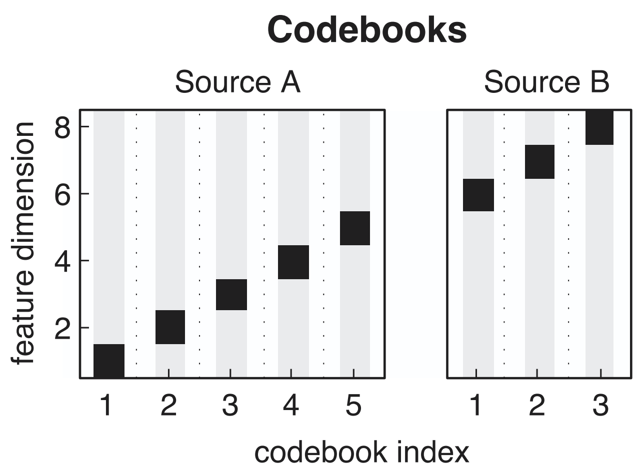
- Ideal separation is rarely possible
  - i.e. no projection can completely remove overlaps
- Overlaps → Ambiguity
  - scene analysis = find "most reasonable" explanation
- Ambiguity can be expressed probabilistically
  - i.e. posteriors of sources $\{S_i\}$ given observations X:

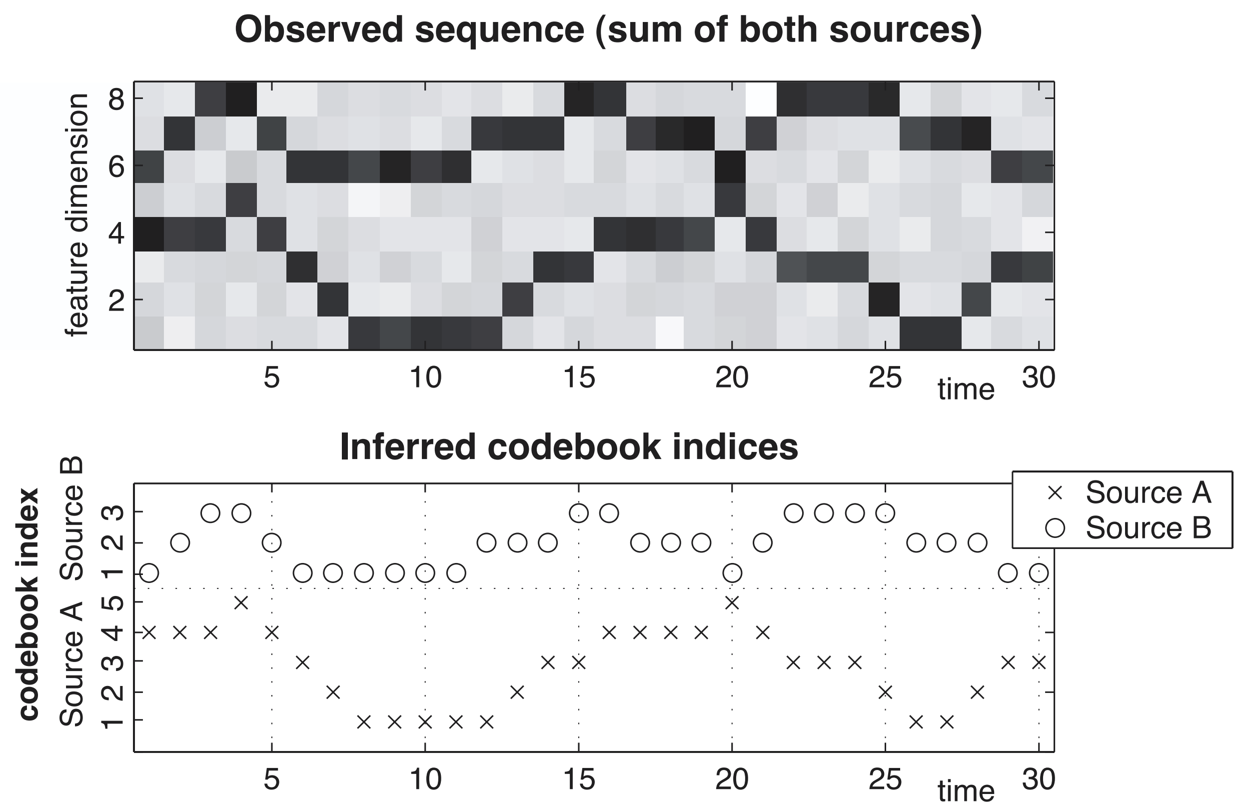
$$P(\{S_i\}|\,X) \propto \underbrace{P(X\,|\{S_i\})}_{\text{combination physics}}\;\underbrace{P(\{S_i\})}_{\text{source models}}$$

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

A Simple Example

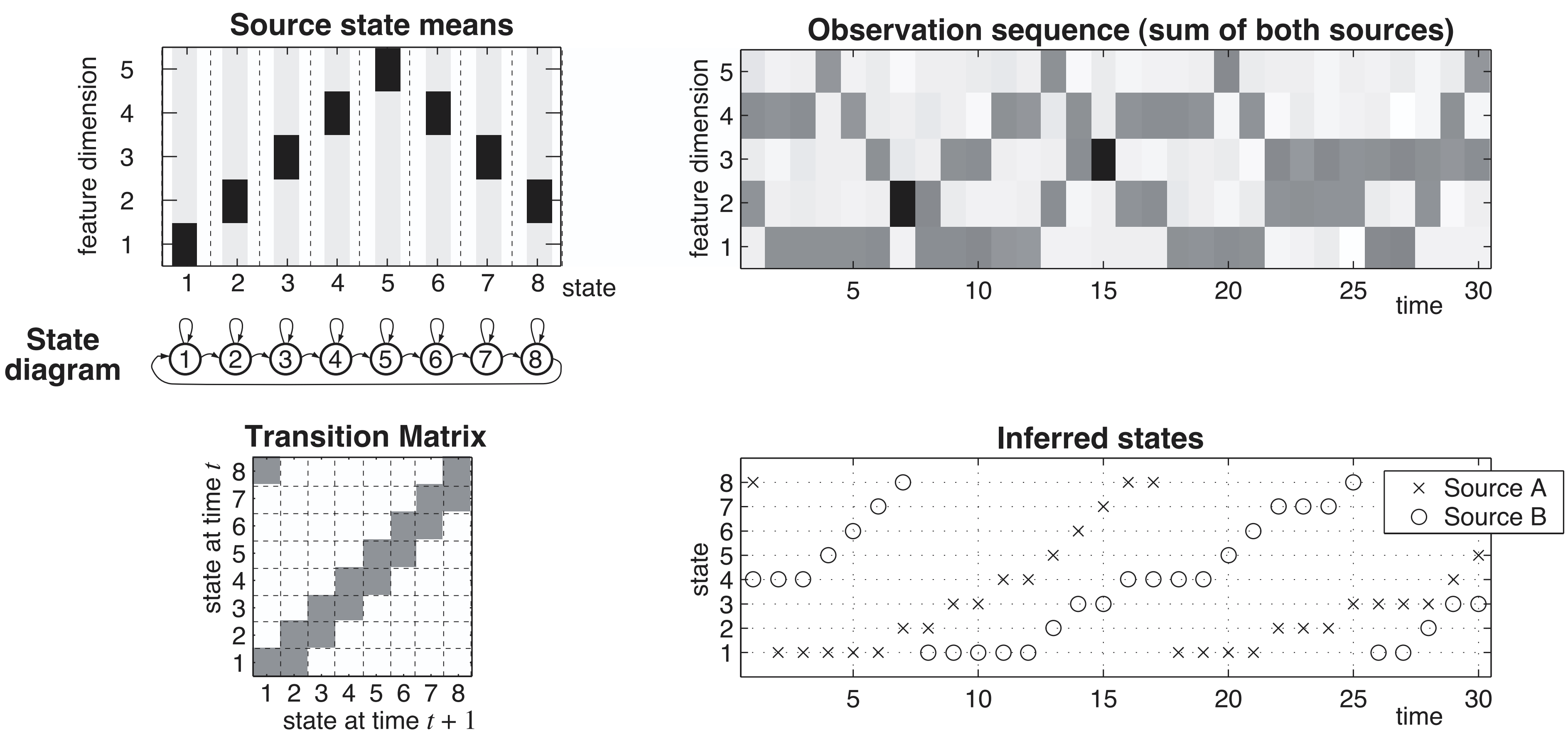
- Source models are codebooks from separate subspaces





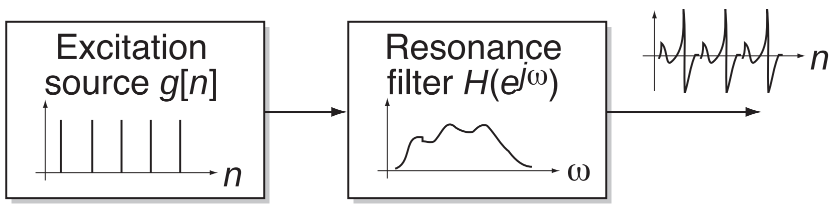
A Slightly Less Simple Example

- Sources with Markov transitions



What is a Source Model?

- Source Model describes signal behavior
  - encapsulates constraints on form of signal
  - (any such constraint can be seen as a model...)
- A model has parameters
  - model + parameters
    → instance



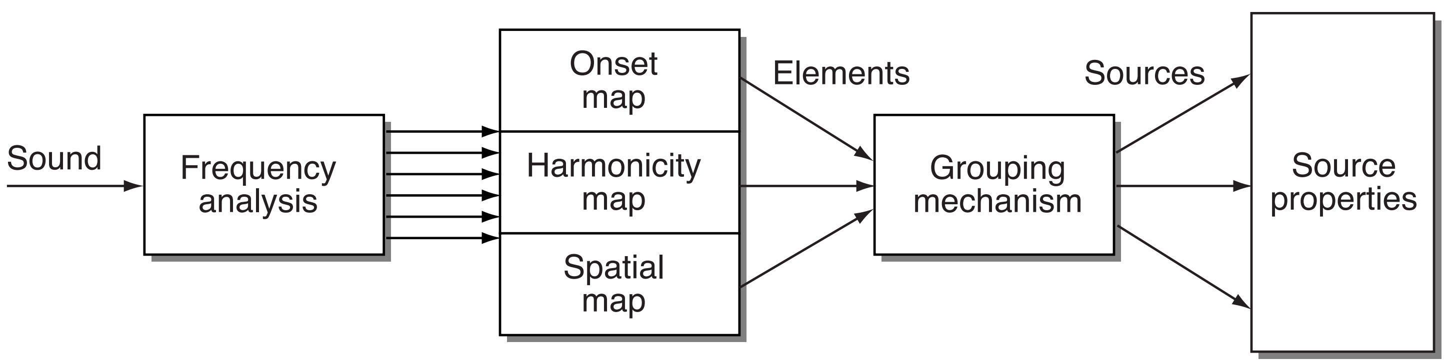
- What is *not* a source model?
  - detail not provided in instance
    e.g. using phase from original mixture
  - constraints on interaction between sources
    e.g. independence, clustering attributes

Outline

Auditory Scene Analysis

Bregman'90
Darwin & Carlyon'95

- How do people analyze sound mixtures?
  - break mixture into small elements (in time-freq)
  - elements are grouped in to sources using cues
  - sources have aggregate attributes
- Grouping rules (Darwin, Carlyon, ...):
  - cues: common onset/modulation, harmonicity, ...

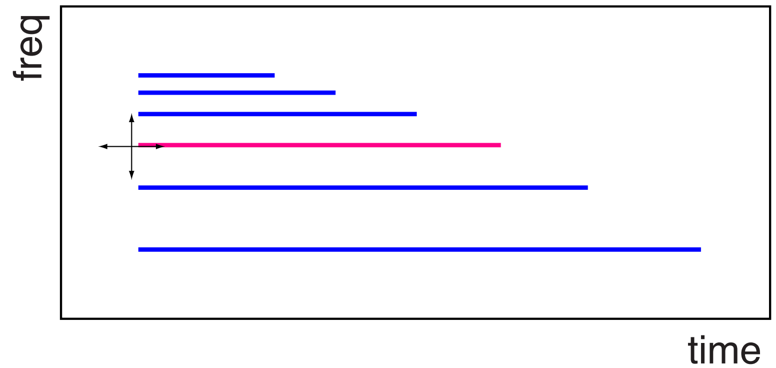


(after Darwin 1996)

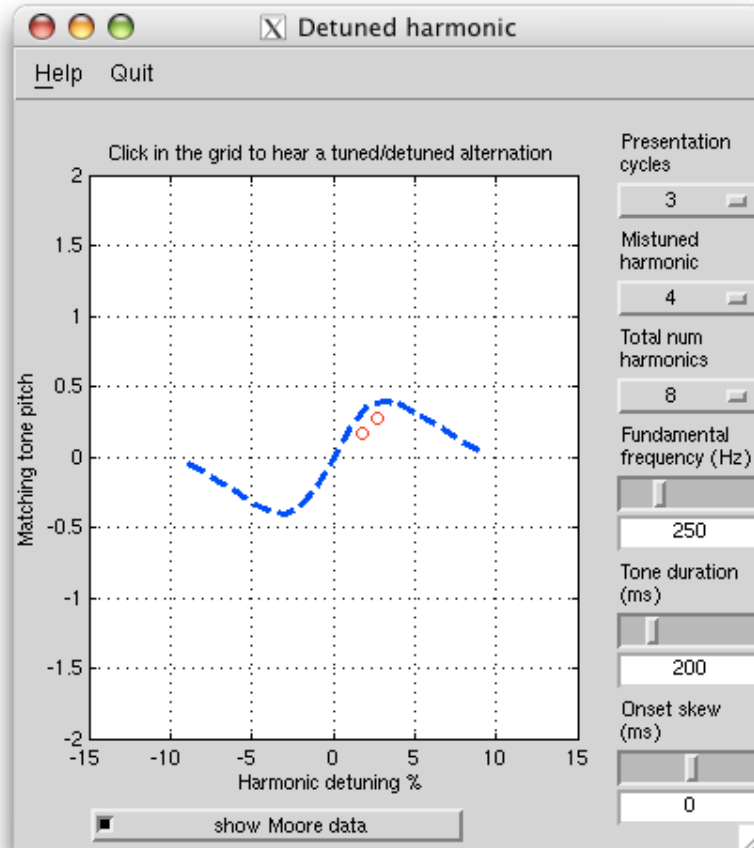
- Also learned "schema" (for speech etc.)

Perceiving Sources

- Harmonics distinct in ear, but perceived as one source ("fused"):



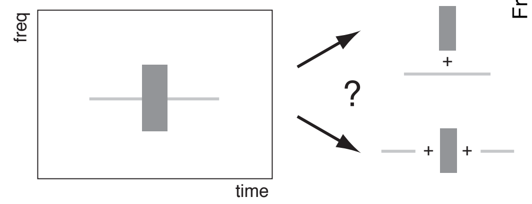
  - depends on common onset
  - depends on harmonics

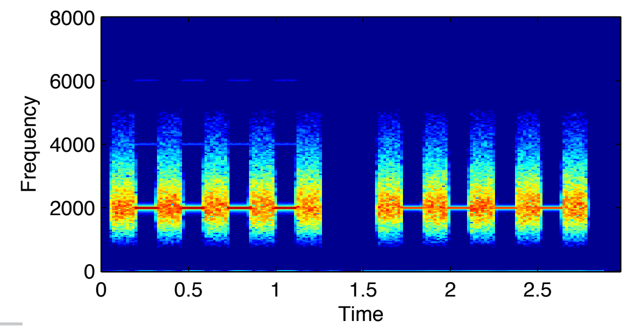


- Experimental techniques
  - ask subjects "how many"
  - match attributes e.g. pitch, vowel identity
  - brain recordings (EEG "mismatch negativity")

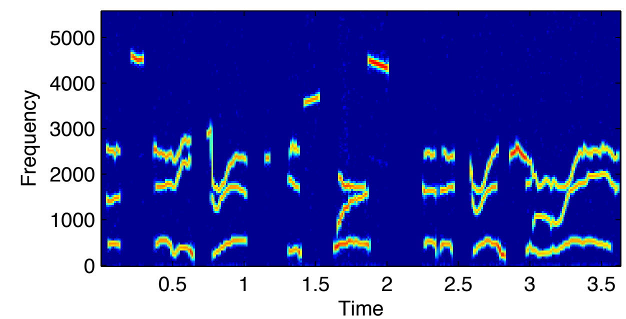
Auditory "Illusions"

- How do we explain illusions?
  - pulsation threshold

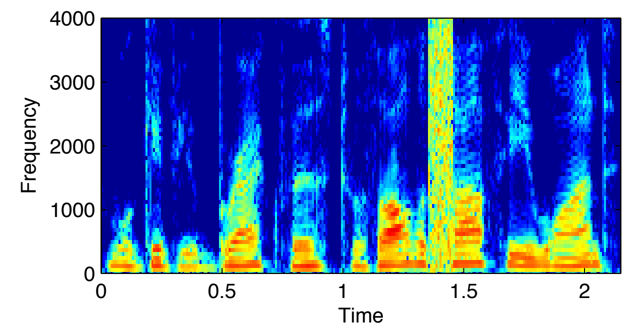




  - sinewave speech



  - phonemic restoration



- Something is providing the missing (illusory) pieces ... source models

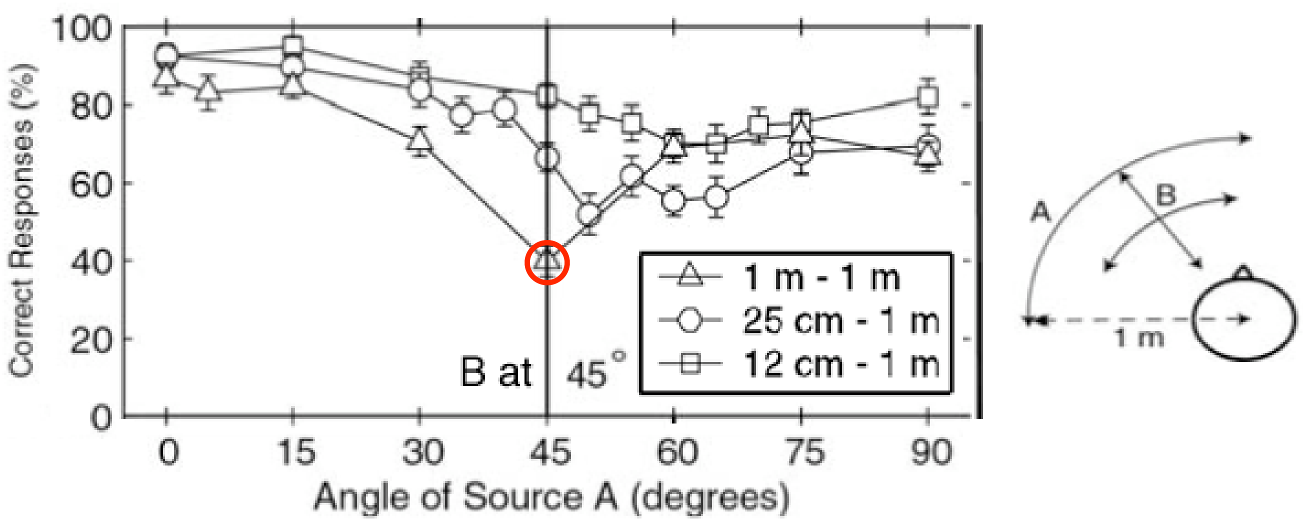
Human Speech Separation

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:

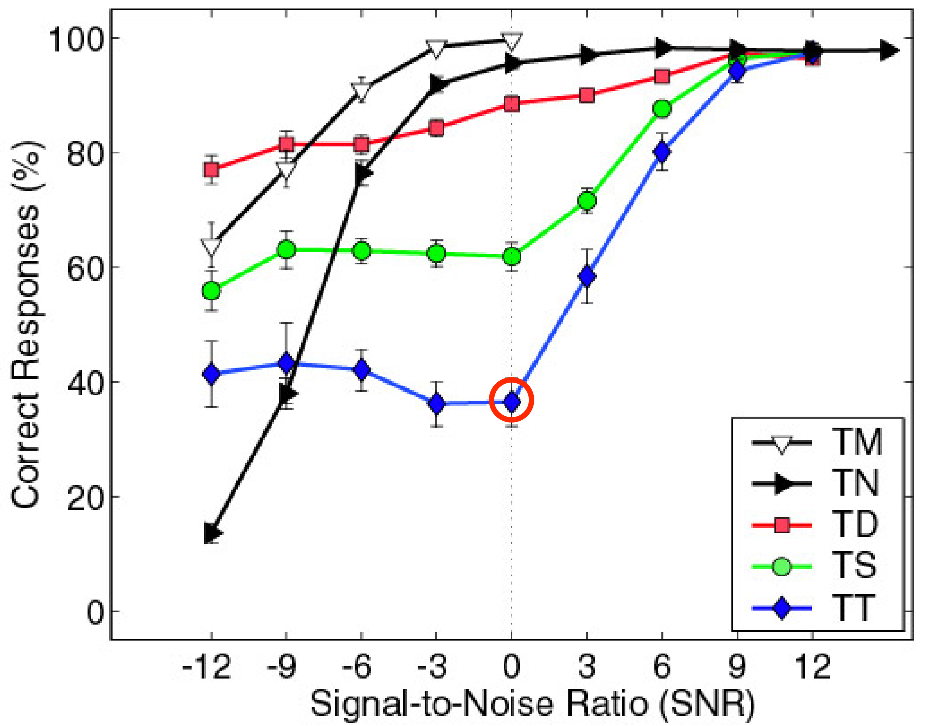


- A, B same speaker
- Range effect

Separation by Vocal Differences

Brungart et al.'01

- CRM varying the level and voice character



(same spatial location)

- energetic vs. informational masking
- more than pitch .. source models

Outline

1. Mixtures and Models
2. Human Sound Organization
3. Machine Sound Organization
   - Computational Auditory Scene Analysis
   - Dictionary Source Models
4. Ambient Sounds

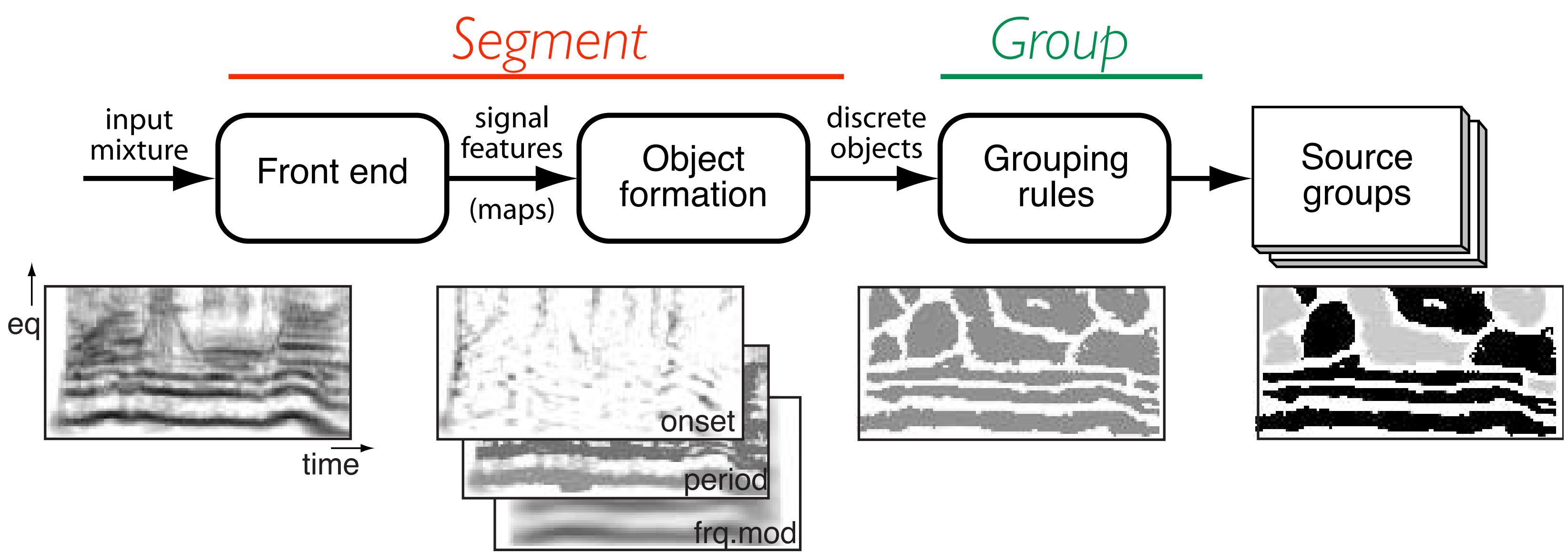
Source Model Issues

- Domain
  - parsimonious expression of constraints
  - nice combination physics
- Tractability
  - size of search space
  - tricks to speed search/inference
- Acquisition
  - hand-designed vs. learned
  - static vs. short-term
- Factorization
  - independent aspects
  - hierarchy & specificity

Computational Auditory Scene Analysis

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

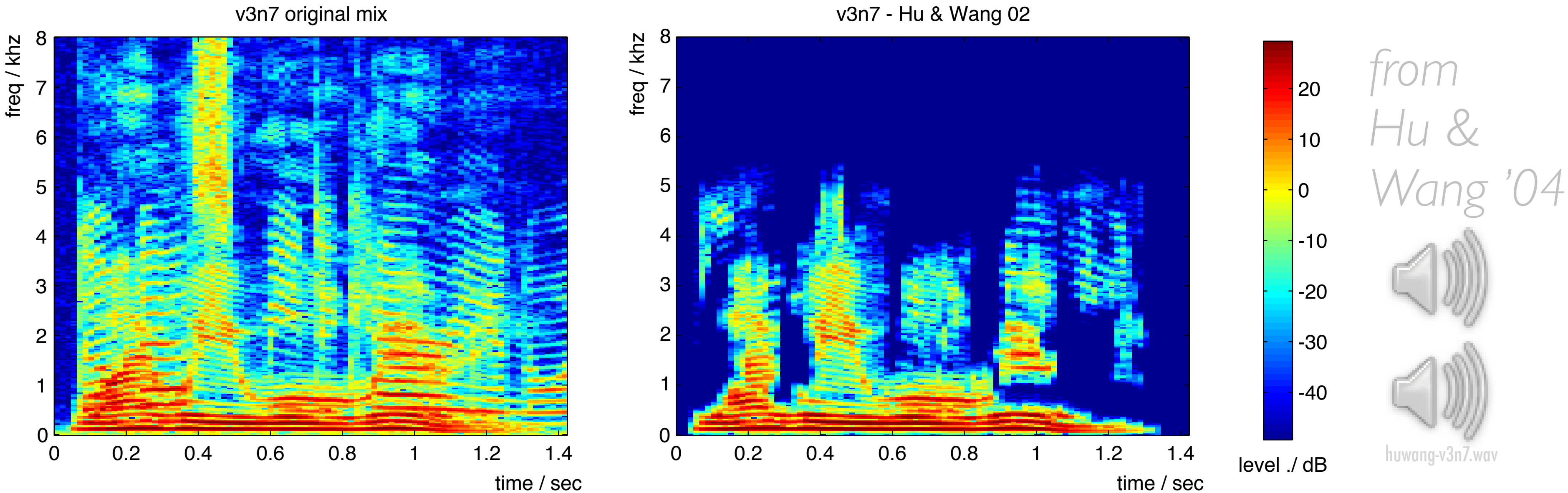
- Central idea:
  Segment time-frequency into sources based on perceptual grouping cues



  - ... principal cue is harmonicity

CASA limitations

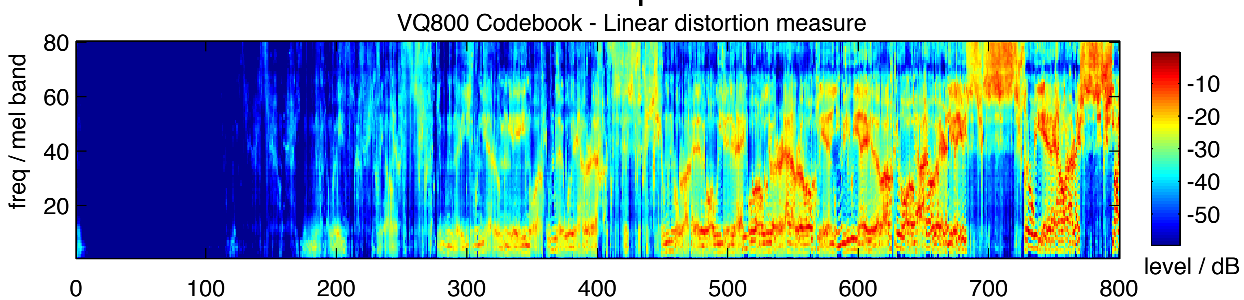
- **Limitations of T-F masking**
  - cannot undo overlaps – leaves gaps



- **Typically driven by local features**
  - limited model scope → no inference or illusions
- **Processing hand-defined, not learned**

Can Models Do CASA?

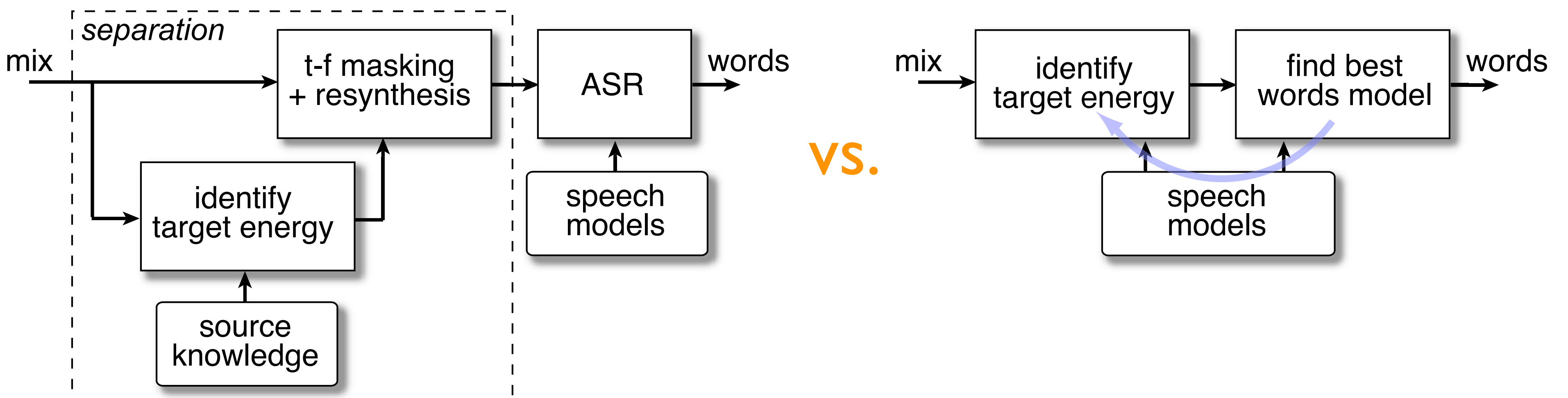
- Source models can learn harmonicity, onset
  - ... to subsume rules/representations of CASA



  - 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 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

Dictionary Models

Roweis '01, '03
Kristjannson '04, '06

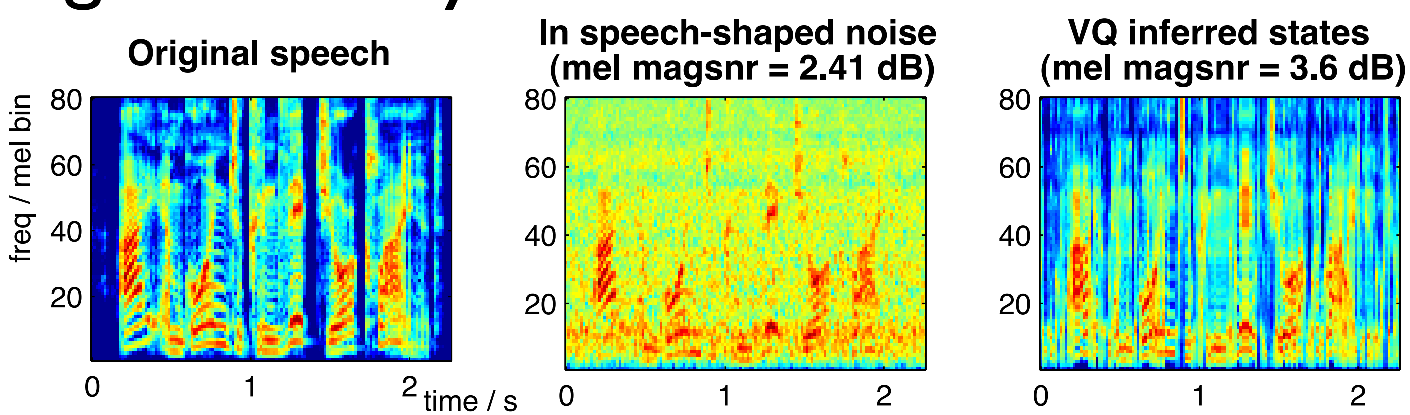
- Given models for sources, find "best" (most likely) states for spectra:

$$p(\mathbf{x}|i_1, i_2) = \mathcal{N}(\mathbf{x}; \mathbf{c}_{i1} + \mathbf{c}_{i2}, \Sigma)$$ combination model

$$\{i_1(t), i_2(t)\} = argmax_{i_1,i_2} p(\mathbf{x}(t)|i_1, i_2)$$ inference of source state

  - can include sequential constraints...
  - different domains for combining $\mathbf{c}$ and defining Σ

- E.g. stationary noise:



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Speech Recognition Models

- Cooke & Lee Speech Separation Challenge
  - short, grammatically-constrained utterances:

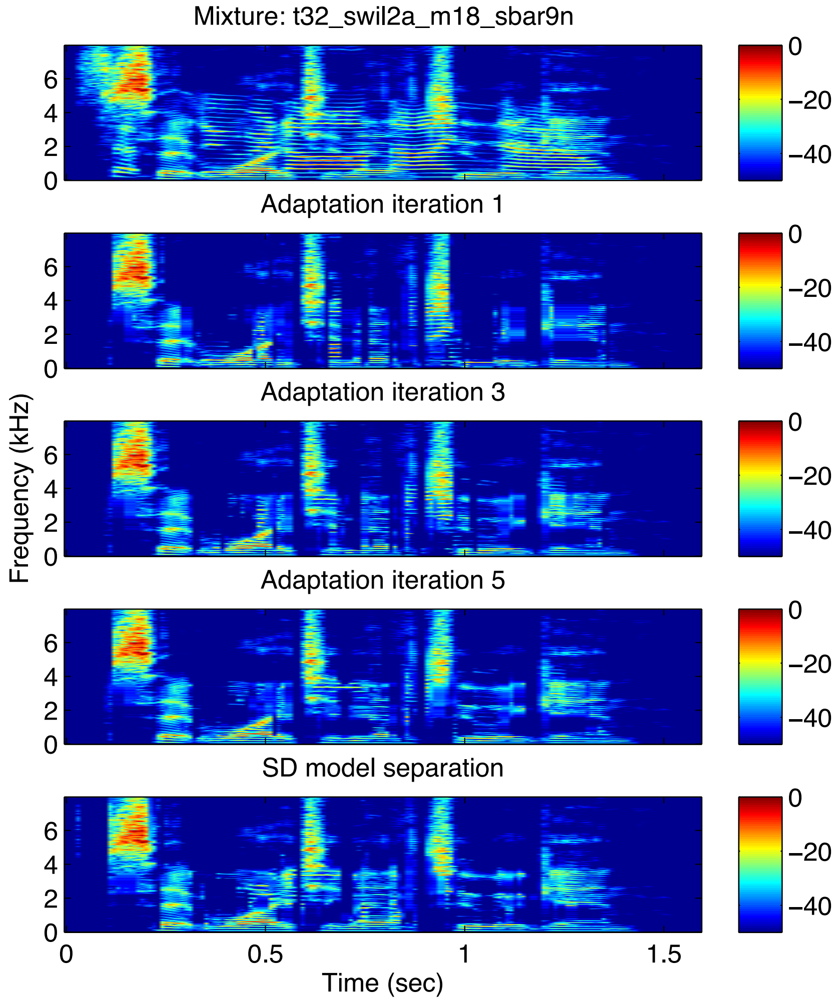
    <command:4><color:4><preposition:4><letter:25><number:10><adverb:4>

    e.g. "bin white by R 8 again"
  - task: report letter+number for "white"
- Decode with Factorial HMM
  - i.e. two state sequences, one model for each voice
  - exploit sequence constraints
  - exploit speaker differences
- IBM "superhuman" system *Kristjansson, Hershey et al. '06*
  - fewer errors than people for same speaker, level
  - exploits known speakers, limited grammar

Speaker-Adapted (SA) Models

Ron Weiss

- Factorial HMM needs distinct speakers

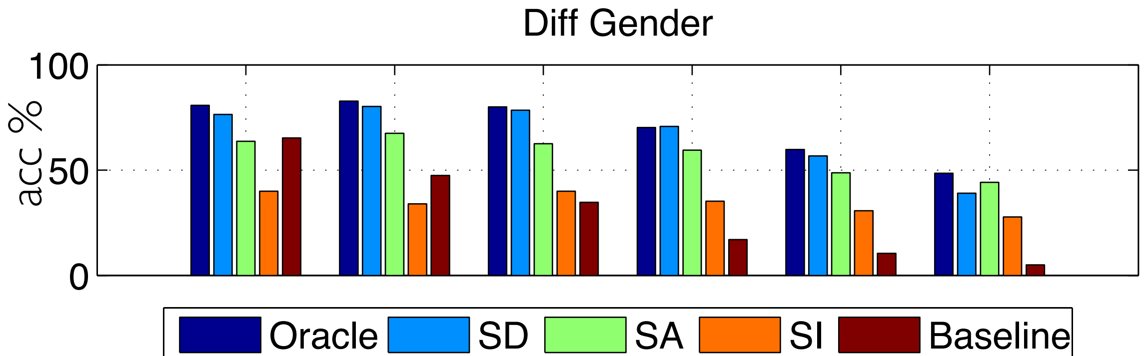


- use "eigenvoice" speaker space
- iterate estimating voice & separating speech
- performs midway between speaker-independent (SI) and speaker-dependent (SD)

SI

SA

SD

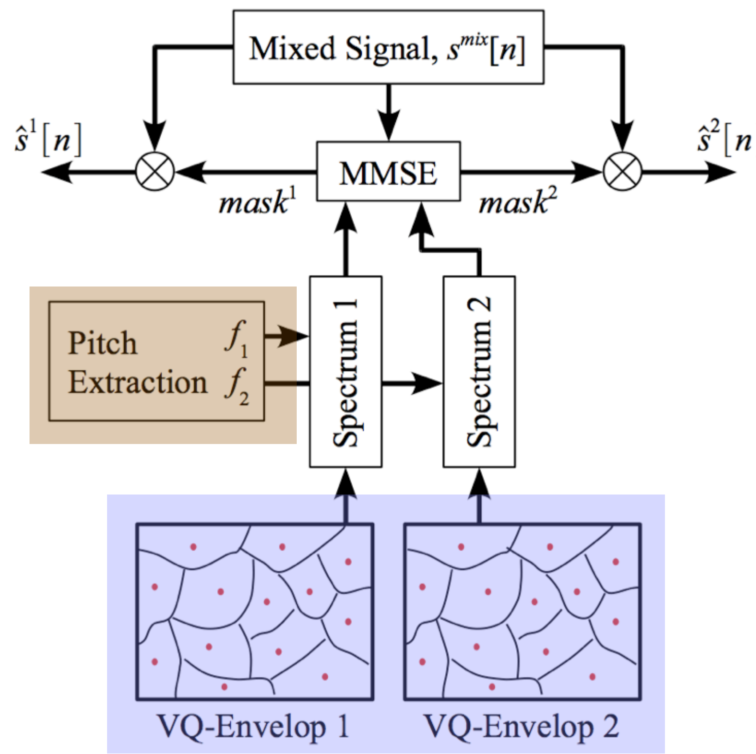


(Pitch) Factored Dictionaries

Ghandi & Has-John. '04
Radfar et al. '06

- Separate representations for "source" (pitch) and "filter"
  - *NM* codewords from *N+M* entries
  - but: overgeneration...

- Faster search
  - direct extraction of pitches
  - immediate separation of (most of) spectra



Outline

1. Mixtures & Models
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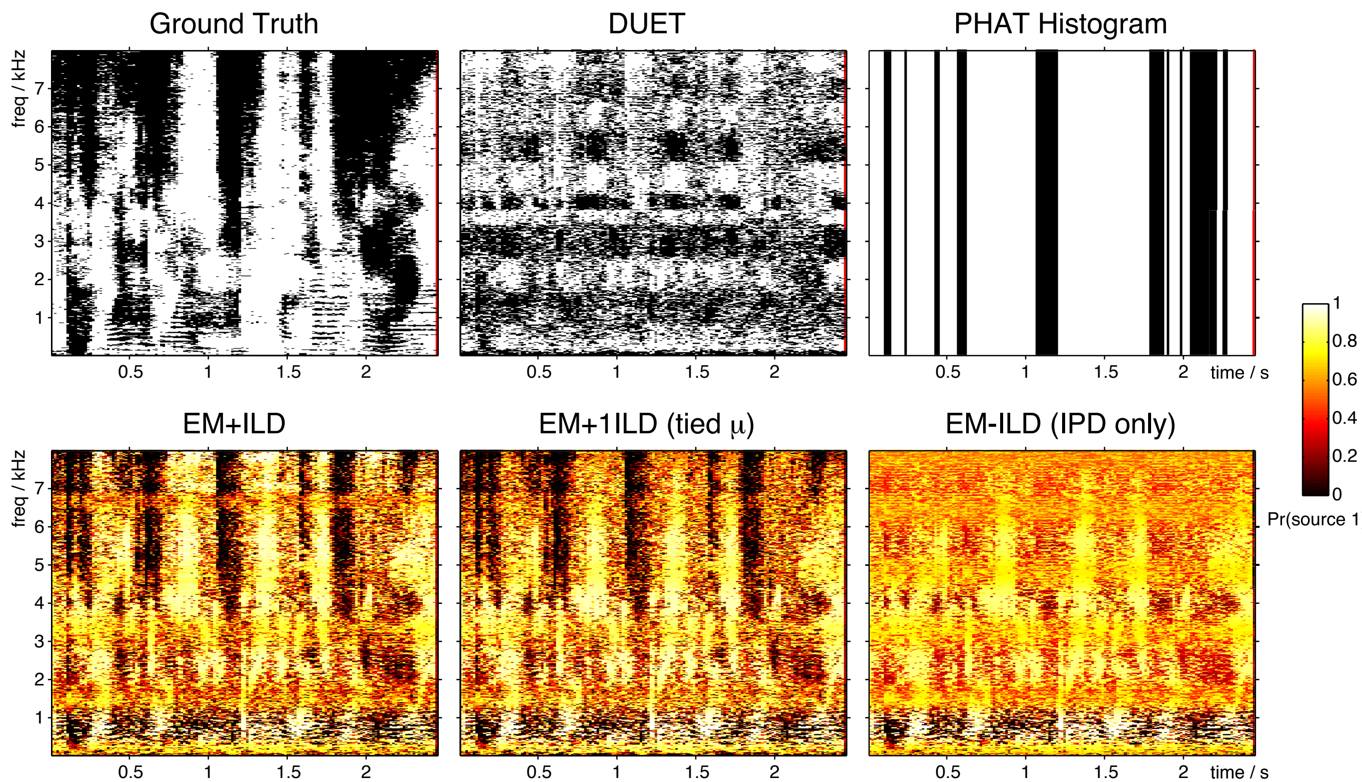
4. **Ambient Sounds**
    - binaural separation
    - “personal audio” analysis

Binaural Localization by EM

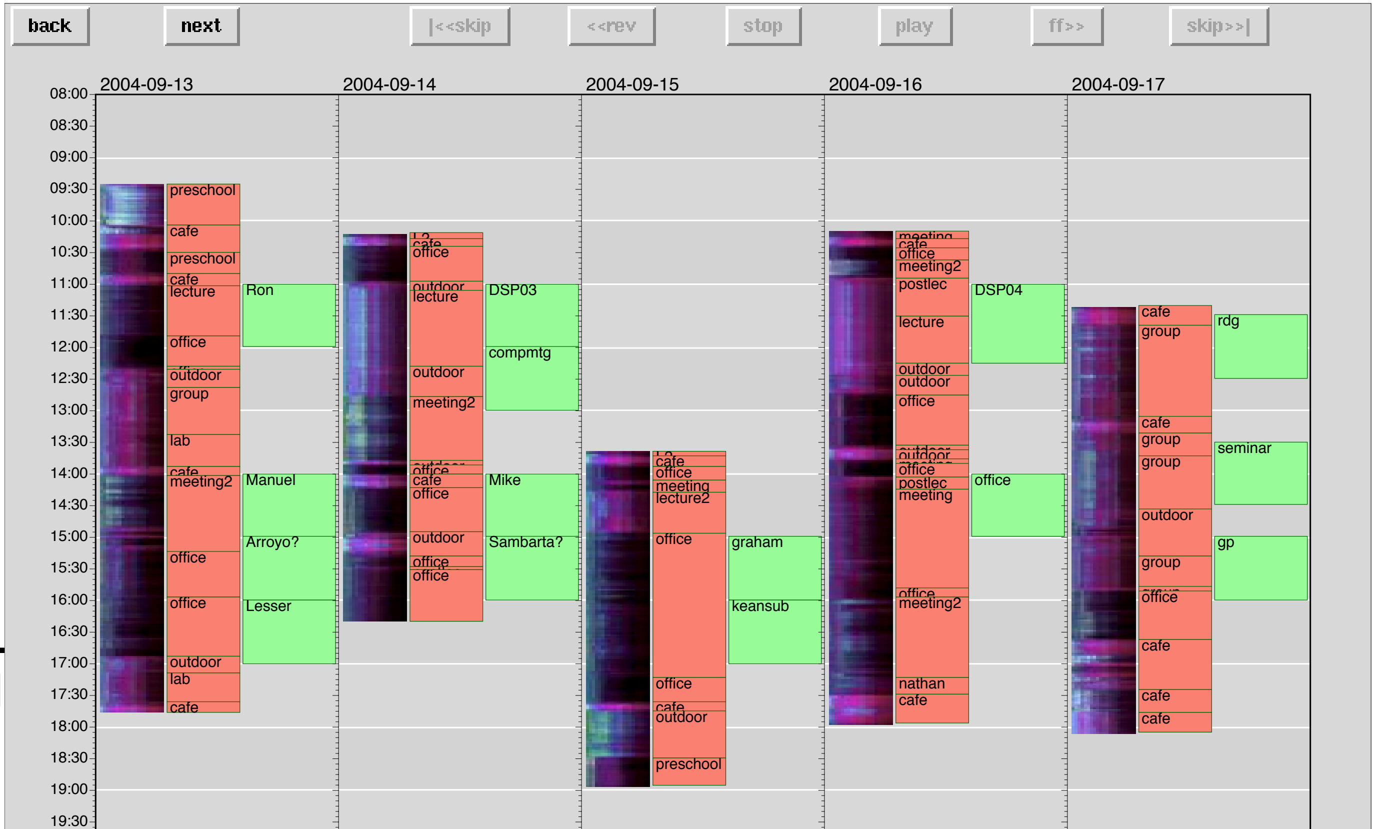
Mike Mandel, NIPS'06

- 2 or 3 sources in reverberation
- Iteratively estimate ILD, IPD
  - initialize from PHAT ITD histogram
  - output is soft TF mask



“Personal Audio” Archives

- Continuous recordings with MP3 player
- Segment / cluster “episodes”
  - .. by statistics of ~10 s segments
  - .. for browsing interface



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Sound

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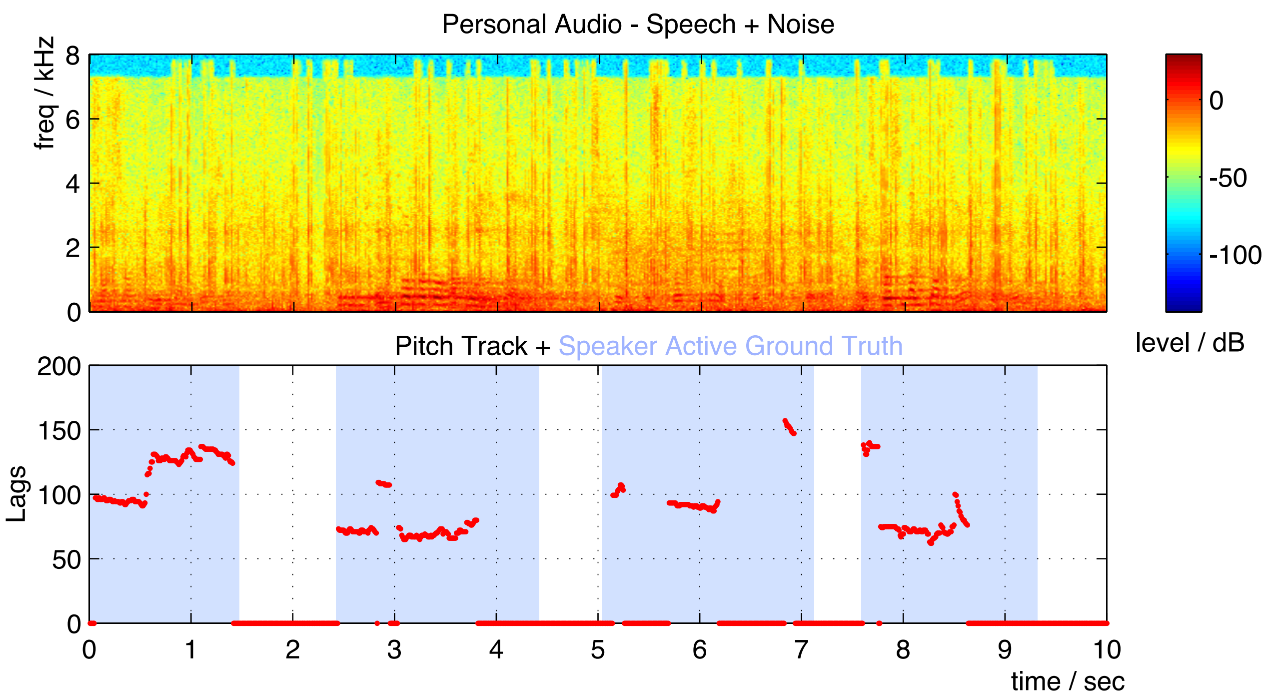
Personal Audio Speech Detection

Keansub Lee, Interspeech'06

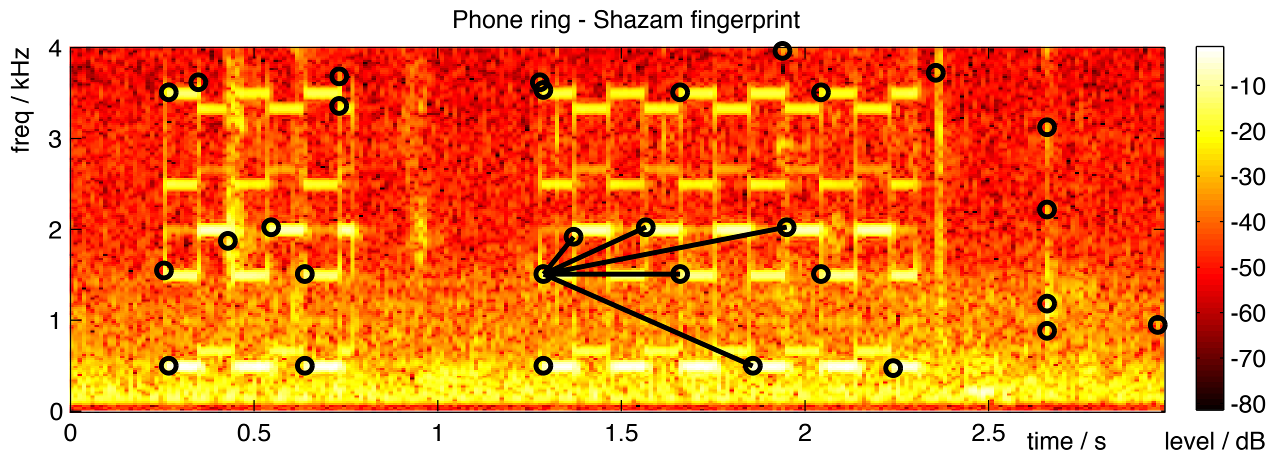
- **Pitch is last speech cue to disappear**
  - noise robust pitch tracker for voice detection
  - biggest problem was periodic noise (air conditioning)



Repeating Events in Personal Audio

Jim Ogle, ICASSP'07

- "Unsupervised" feature to help browsing
- Full NxN search is very expensive
  - use Shazam fingerprint hashes to find repeats



  - only works for exact repeats (alarms, jingles)
- O(N) scan for repeats
  - fixed-size hash table
  - multiple common hashes → confident match

Summary & Conclusions

- Listeners do well separating sound mixtures
  - using signal cues (location, periodicity)
  - 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
- Separation feasible only sometimes
  - describing source properties is easier