
Using Learned Source Models to Organize Sound Mixtures

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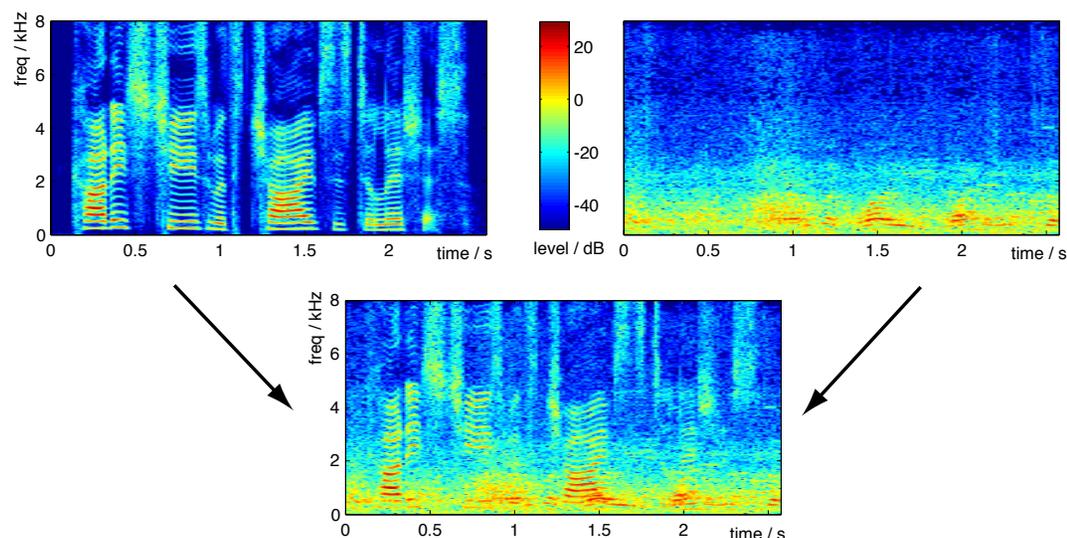
<http://labrosa.ee.columbia.edu/>

1. Source Models as Constraints
2. Examples of Model-Based Systems
3. Acquiring and Using Models
4. Biological Relevance?



The Problem of Scene Analysis

- How do we achieve ‘perceptual constancy’ of sources in mixtures?



- no obvious **segmentation** of objects
- **underconstrained**: infinitely many decompositions
- time-frequency overlaps cause **obliteration**

Scene Analysis as Inference

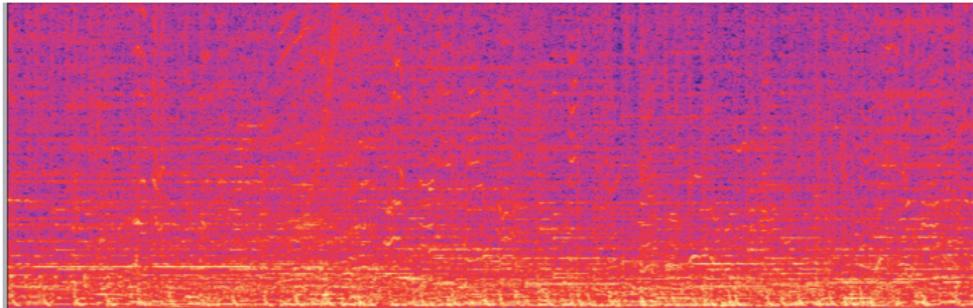
Ellis'96

- **Ideal** separation is rarely possible
 - i.e. no projection can completely remove **overlaps**
- **Overlaps** \Rightarrow **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** \rightarrow **better inference**
 - .. learn from **examples**?

An Example: Fingerprinting

- “Impossible” separation task (Avery Wang)

Simultaneous Mix Example



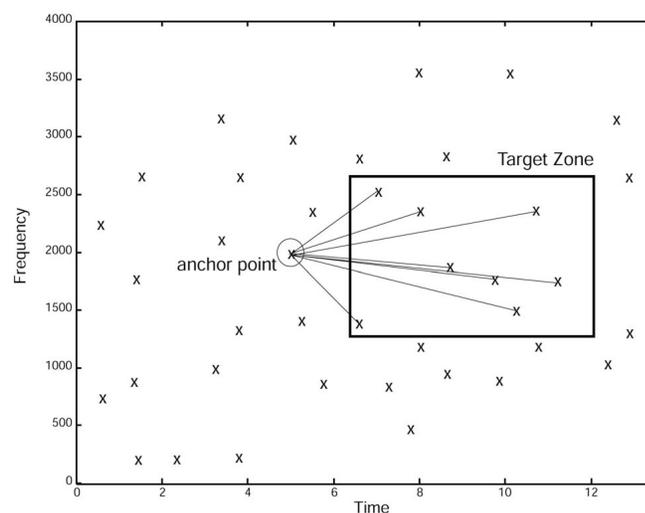
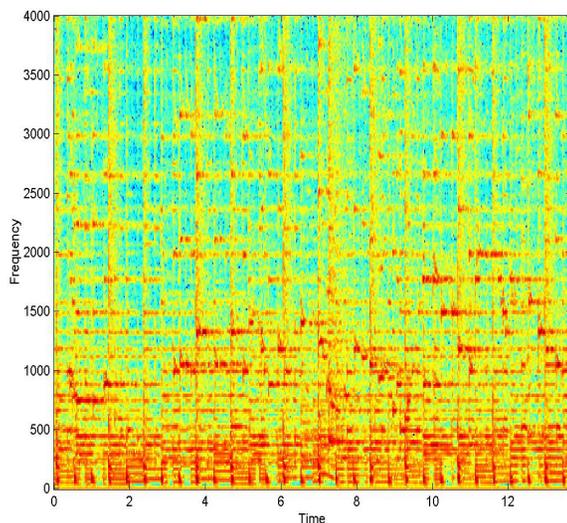
A spectrogram showing the frequency content of a simultaneous mix of seven audio tracks. The x-axis represents time and the y-axis represents frequency. The spectrogram is a dense, colorful pattern of red, orange, and blue, indicating a complex mixture of sounds.

1. Wim Mertens, *Struggle for pleasure*
2. Brahms, *Concerto for violin and Cello, A minor. Op. 102, allegro*
3. Ravel, *Bolero* (Dallas Symphony Orchestra)
4. Ravel, *Bolero* (London Symphony Orchestra)
5. Buena Vista Social Club, *Chan Chan*
6. Robert Miles, *Freedom*
7. M-People, *One Night in Heaven*

if it sounds good, tag it 

Fingerprinting: How it Works

- Library of songs ($> 1M$) described by **hashes**



- After ~ 10 s, song/segment identified **$> 98\%$**
- Key ideas:
 - **known-item** database of exact waveforms
 - **tiny part** of signal used (... the most **robust** part)

Example 2: Mixed Speech Recog.

- Cooke & Lee's **Speech Separation Challenge**

- short, grammatically-constrained utterances:

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

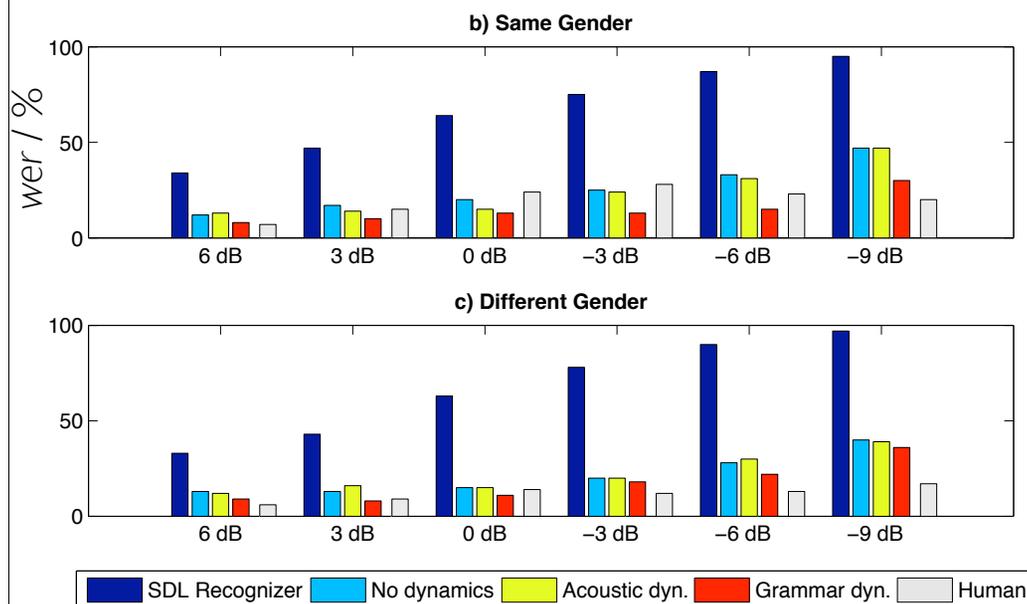
e.g. "bin white at M 5 soon"



t5_bwam5s_m5_bbilzp_6p1.wav

*Kristjansson et al.
Interspeech'06*

- IBM's "superhuman" recognizer:



- Model individual speakers (512 mix GMM)

- Infer speakers and gain

- Reconstruct speech

- Recognize as normal...

- Grammar constraints a big help



Scene Analysis as Recognition

- We don't want **waveforms**
 - limits to what listeners discriminate
 - .. especially over **long term**
- The outcome of perception is **percepts**
 - **source** identities (categories)
 - .. plus some salient **parameters**
- **Scene analysis: recovering source + params**
 - classification + parameter **estimation**
 - .. implies predefined set of **classes = source models**



What are the Models?

Models allow **world knowledge** (experience) to help **perception**

- **Explicit Models (dictionaries)**
 - can represent **anything** (“non-parametric”)
 - conceptually simple but **inefficient** in space/time
- **Parametric Models (subspaces)**
 - encapsulate broader **constraints** (e.g. harmonicity)
 - rely on actual **regularity** in the domain
 - may not be easy to apply (fit)
- **Middle ground?**
 - e.g. locally-learned **manifolds**
 - or dictionaries + parametric **transformations**



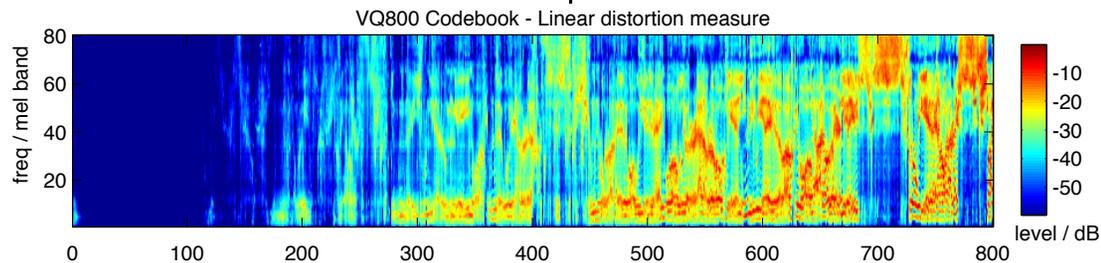
Learning, Representing, Applying

- Models encapsulate **experience**/environment
 - **evolutionary** scale (hardware)
vs. **lifetime** scale (conventional learning)
- Tradeoff between an **efficient** domain and a **flexible** learner
 - auditory percepts already factor out e.g. channel characteristics (phase, reflections, gain)
- Learned knowledge must be easy to **apply**
 - e.g. representations that are easier to recall/match



Dictionaries vs. CASA

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

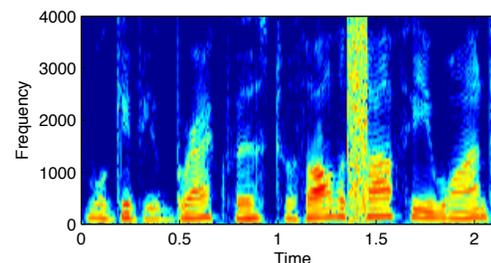
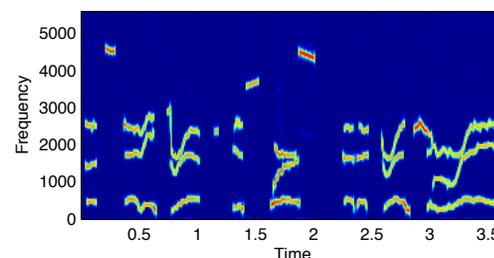
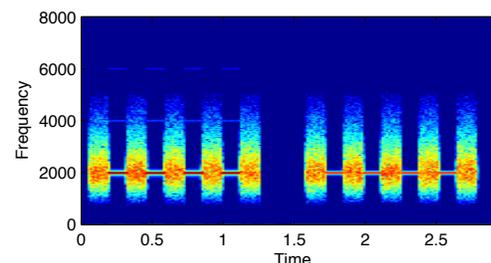


- can capture **spatial** info too [Pearlmutter & Zador'04]
- **Can also capture sequential structure**
 - e.g. consonants follow vowels
 - ... like people do?
- **Maybe equivalent results in the end**
 - .. i.e. algorithm, not **computational theory**

Biological Relevance of Models

- How do we explain **illusions**?

- pulsation threshold
- sinewave speech
- phonemic restoration



- **Something** is providing the missing (**illusory**) pieces

Summary

- Scene Analysis is possible only thanks to **constraints**
 - most sound combinations are **unlikely**
- Listeners care about individual **sources**
 - .. in a wide range of combinations
- **Statistical source models** can be **learned** from the environment
 - exactly how is more of a detail...

