# Computational Auditory Scene Analysis

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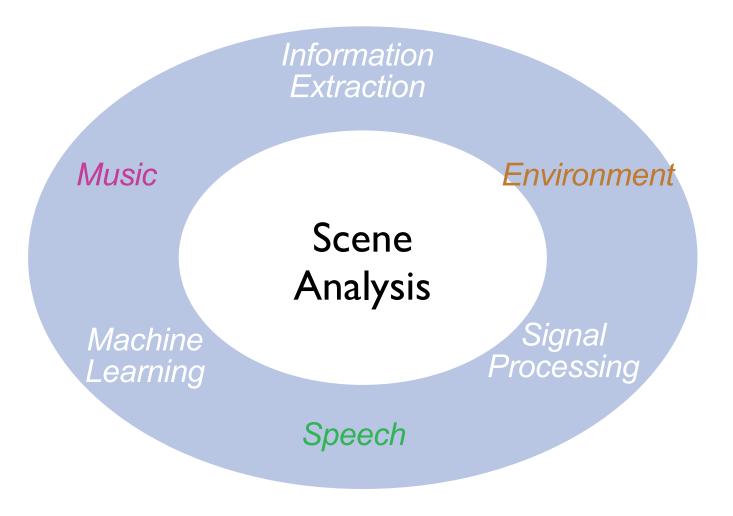
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- I. The Scene Analysis problem
- 2. ASA and CASA
- 3. Issues in CASA





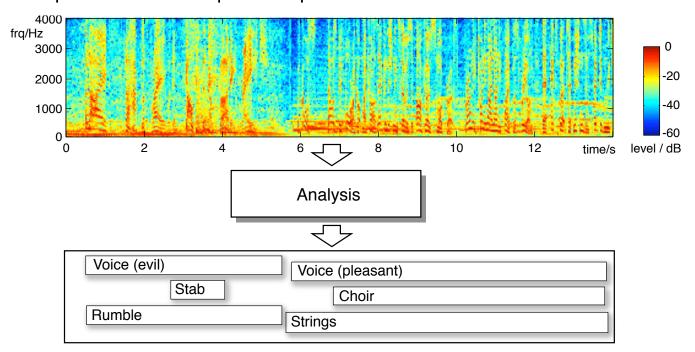
### LabROSA Overview





# 1. Scene Analysis

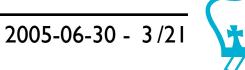
- Recover individual sources from scenes
  - .. duplicate the perceptual effect



- Problems competing sources, channel effects
- Dimensionality loss
  - o need additional constraints

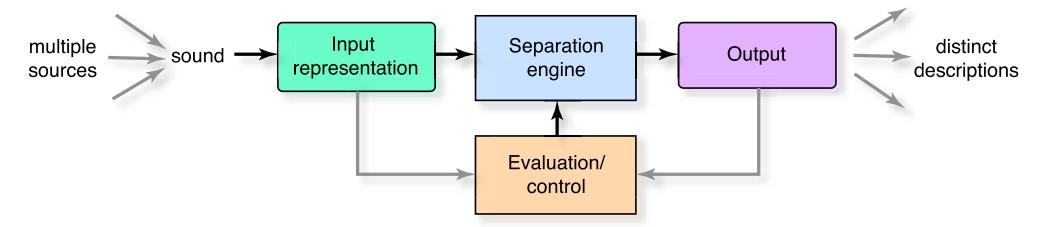


Comp. Aud. Scene Analysis - Dan Ellis



# Scene Analysis Systems

- "Scene Analysis"
  - o not necessarily separation, recognition, ...
  - scene = overlapping objects, ambiguity
- General Framework:

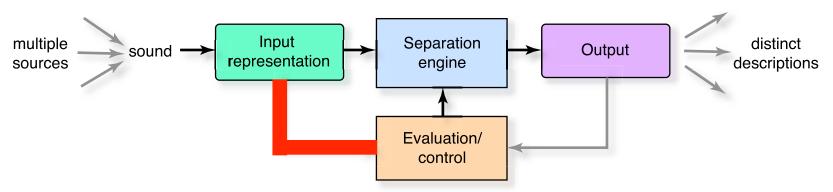


- o distinguish input and output representations
- distinguish engine (algorithm) and control (constraints, "computational model")





# Human and Machine Scene Analysis

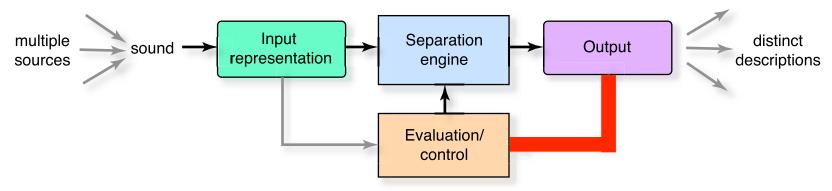


- CASA (Brown'92 et seq.):
  - o Input: Periodicity, continuity, onset "maps"
  - Output: Waveform (or mask)
  - Engine: Time-frequency masking
  - o Control: "Grouping cues" from input
    - or: spatial features (Roman, ...)





# Human and Machine Scene Analysis

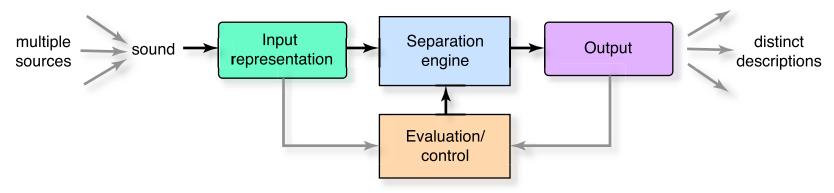


- CASA (e.g. Brown'92):
- ICA (Bell & Sejnowski et seq.):
  - o Input: waveform (or STFT)
  - Output: waveform (or STFT)
  - Engine: cancellation
  - Control: statistical independence of outputs
    - or energy minimization for beamforming





# Human and Machine Scene Analysis



- CASA (e.g. Brown'92):
- ICA (Bell & Sejnowski et seq.):
- Human Listeners:
  - Input: excitation patterns ...
  - o Output: percepts ...
  - o Engine:?
  - o Control: find a plausible explanation

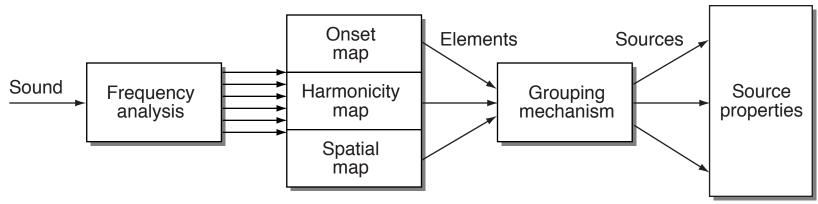




# 2. Auditory Scene Analysis

(Bregman 1990)

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





(after Darwin 1996)

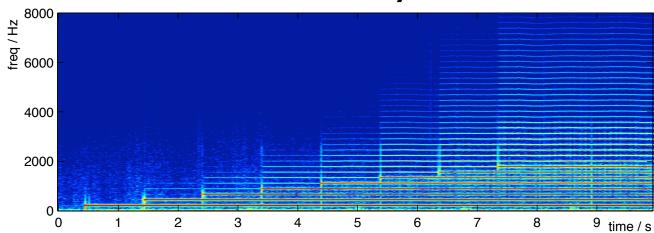
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# Grouping cues

Main cues: Harmonicity + Onset





(from Pierce 1980)

- o not necessarily consistent!
- Other cues:
  - spatial information
  - o 'schema' learned patterns
- Cues ≈ constraints



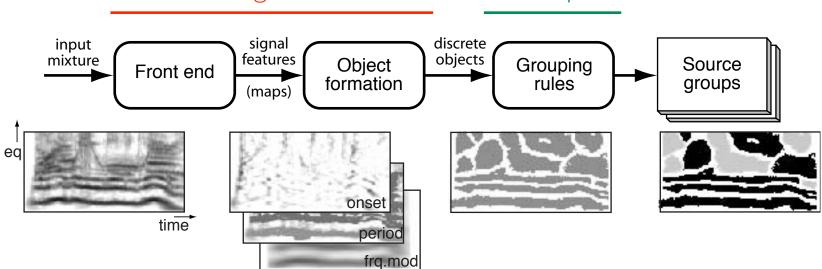


# Bottom-up CASA

(Brown'92, Hu & Wang'02)

Segment

Group



- Literal implementation of psychoacoustics
  - o segment time-frequency into elements
  - o group into sources
- Output via time-frequency masking
  - o i.e. time-varying filter

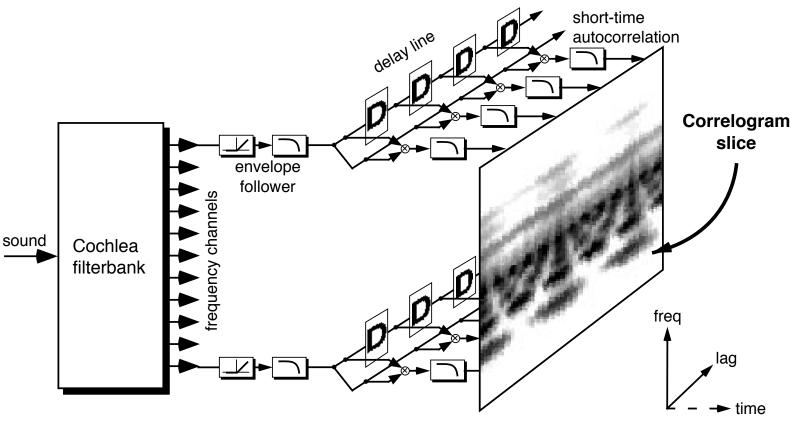




# Correlogram front-end

(Slaney'90 et seq.)

- Periodic modulation as 3rd separating axis
  - o envelope to handle unresolved harmonics



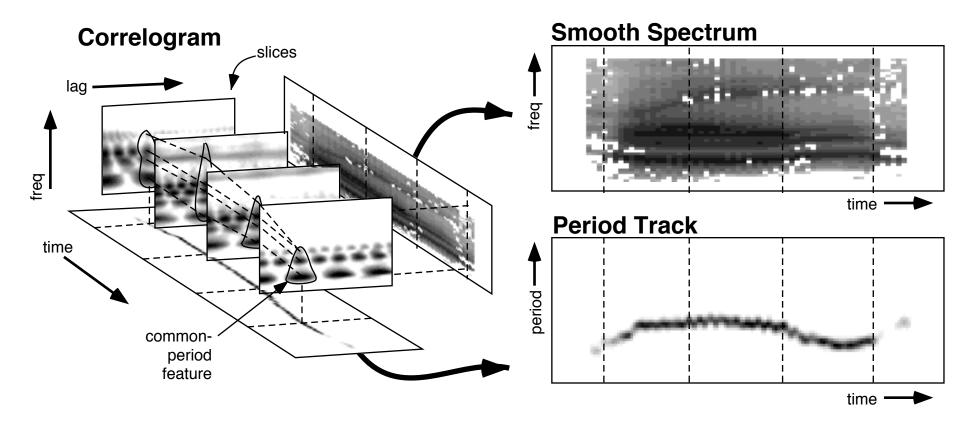


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## "Weft" Periodic Elements

(Ellis'96)

Represent harmonics without grouping?



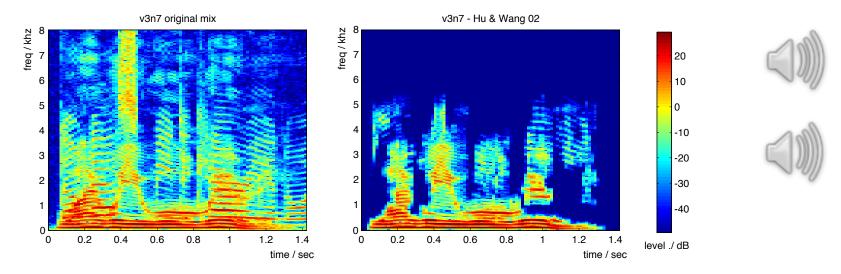
hard to separate multiple pitch tracks





# **CASA** Output

Time-Frequency masked reconstruction



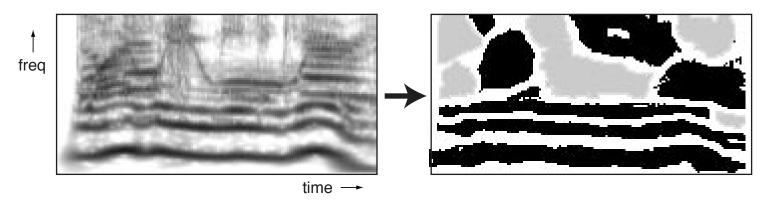
- works surprisingly well (for speech?)
- o cannot undo overlapping energy (< 20%?)
- o applicable to reverberation also?
- Or: parametric resynthesis
  - o e.g. 'wefts', speech synthesizer







# Challenges for CASA

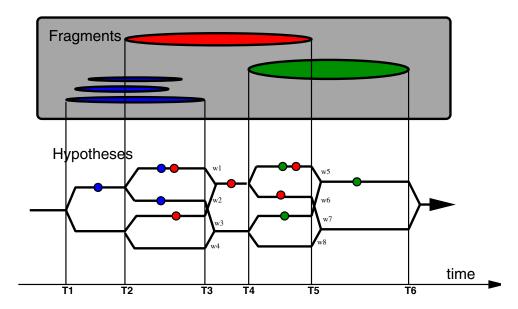


- Circumscribing time-frequency elements
  - o need to have 'regions', but hard to find
- Periodicity is the primary cue
  - o how to handle aperiodic energy?
- Bottom-up leaves no ambiguity or context
  - o how to model illusions/interpolations?
- Need to group over longer timespans
  - o local properties not enough



# Model-based integration

- How to represent high-level constraints?
   How to integrate disparate fragments?
- "Speech fragment decoder" (Barker et al. '05)



model of source (e.g. speech recognition HMM)
 to say which parts go together



# Disambiguation

- Scene ⇒ multiple possible explanations
   Analysis ⇒ choose most reasonable one
- Most reasonable means...
  - consistent with grouping cues (CASA)
  - independent sources (ICA)
  - o consistent with experience ... (human)
  - $\bullet \max P(\{S_i\} | X) \propto \frac{P(X | \{S_i\})}{P(\{S_i\})} \frac{P(\{S_i\})}{P(\{S_i\})}$

combination physics source models

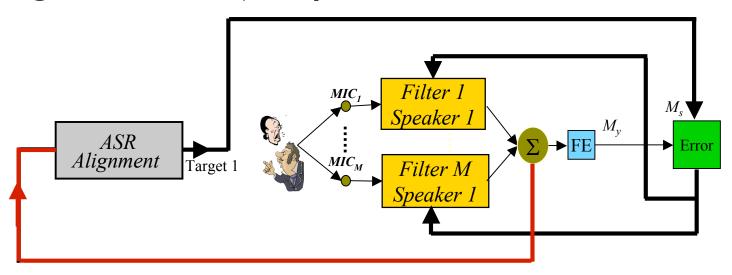
- i.e. some kind of constraints to disambiguate
  - Learning as the source of this disambiguation knowledge





# Recognition for Separation

- Speech recognizers embody knowledge
  - o trained on 100s of hours of speech
  - o use them as a 'reasonableness' measure
- e.g. Seltzer, Raj, Reyes:



from Manuel Reyes's WASPAA 2003 presentation

 speech recognizer's best-match provides optimization target



# Obliteration and Outputs

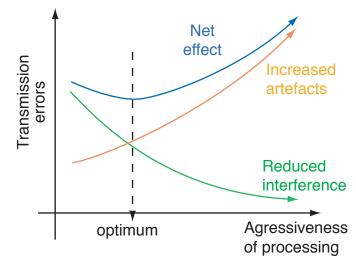
- Perfect separation is rarely possible
  - o e.g. cancellation after psychoacoustic coding?
  - o strong interference will obliterate part of target
- What should the output be?
  - o can fill-in missing-data holes using source models
    - 'pretend' we observed the full signal
    - but: hides observed/inferred distinction
  - o output internal model state instead?
    - e.g. ASR output
    - synthesize with "minimally informative noise"





#### Practical CASA?

- When will CASA be useful?
  - o no agreed way to measure progress!
  - o intelligibility is a novel idea
- Obstacles:
  - o graceful degradation
    - effect of distortions
  - unpitched sounds
  - computation
    - look-ahead
  - o integration with multichannel techniques
    - sequential or all-at-once?





#### Current CASA work

- Handling unvoiced events (OSU)
- Partial recognition & grouping (Sheffield)
- Model-based separation (Columbia)
- Spatial cues?
- Dereverberation?





#### Conclusions

- Framework for scene analysis
  - o Input, Output, Engine, Control
- Auditory Scene Analysis
  - o in humans and machines
- Scene analysis as Disambiguation
  - finding the additional constraints
- Big problems still to overcome



