



HEARING SYSTEMS



Mechanisms and models of normal and impaired hearing

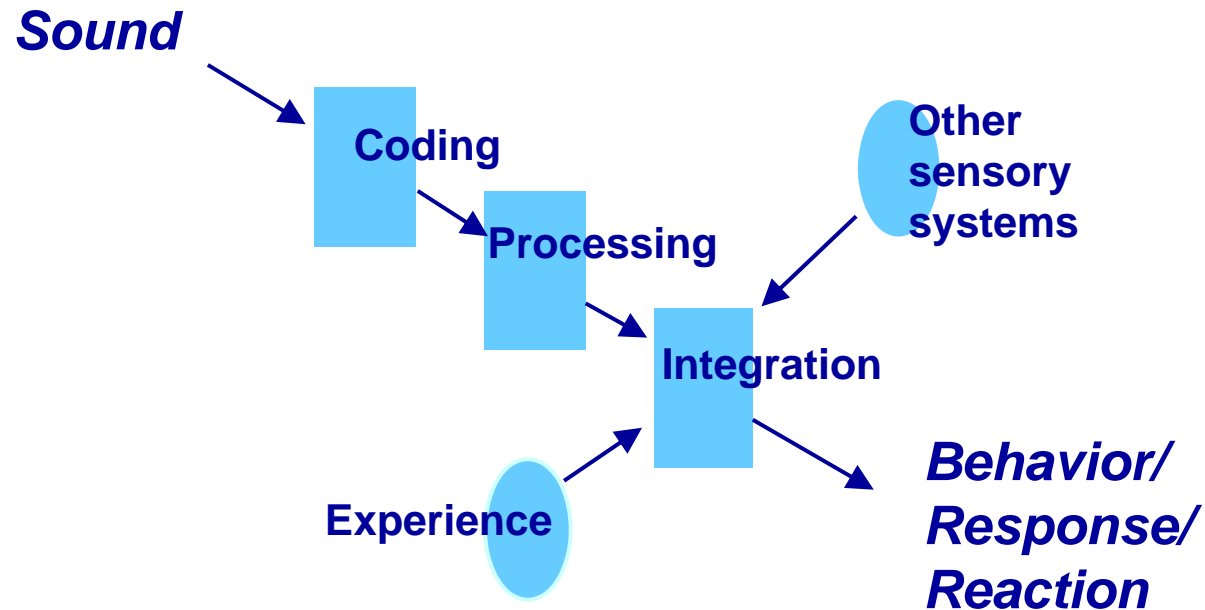
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Hearing Systems

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Technical University of Denmark



Hearing: Information processing system



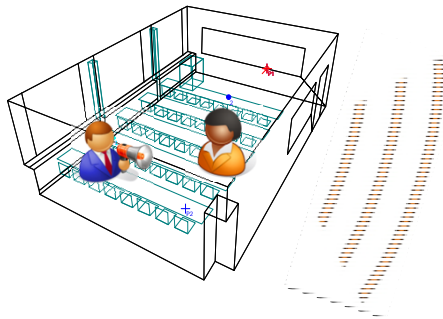
Challenges:

- Representation and processing of signal information in the auditory system; neural correlates of perception.
- Modelling auditory signal processing and perception.
- Integration of processing strategies in technical and clinical applications.

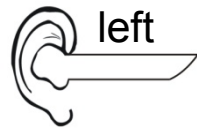


Various challenges

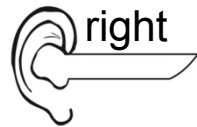
Physical domain



Complex sound field

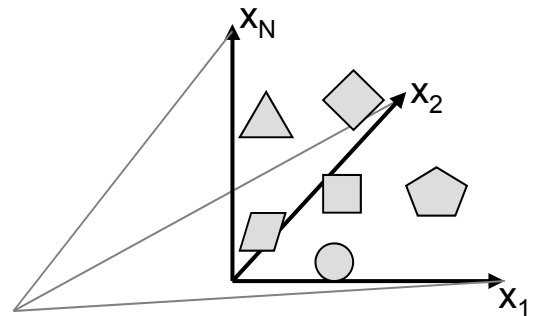


left



right

*1-dim.
input signal*



features: time, freq, level,
location, modulation, ...

Coding
*Multi-dimensional
feature representation*



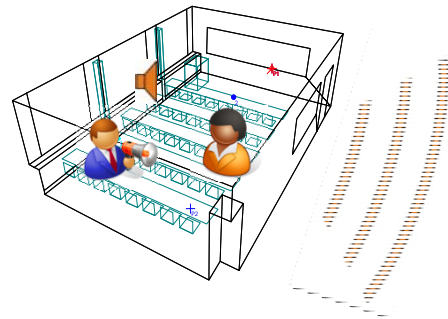
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Various challenges

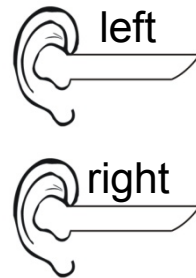


Psychophysical domain

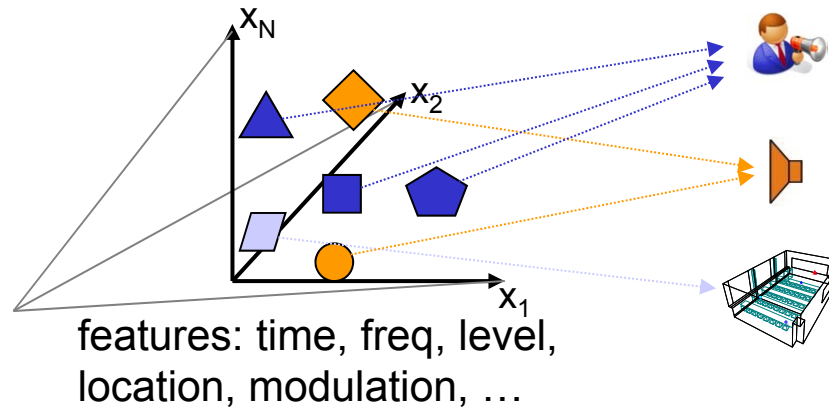
Physical domain



Complex sound field



1-dim. input signal



Coding
Multi-dimensional feature representation

Decoding
Segmentation, feature binding

- intelligibility
- loudness
- ...
- pitch
- distance
- ...
- room size
- envelopment
- ...

Outcome measure

Some "hot topics":

- Solving the cocktail-party problem
- Solving the dynamic range problem
- Coding of spatial sounds in humans
- Neural correlates of learning and attention



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The “cocktail-party” problem



In “cocktail-party” situations, normally-hearing listeners effortlessly segregate different sources. No artificial system performs anywhere near as well.



The “cocktail-party” problem

Key problem: Hearing-impaired people have **difficulty with speech communication** (even with hearing aids) when background noise is present.



- What gets lost in the **impaired system** (besides sensitivity)?
- How can we **compensate** for the deficits with **hearing instruments**?
- What are the **properties** that makes the **intact** auditory system so **special**?
- Why is the intact auditory system so **robust** in **challenging** situations?



Can auditory models help?

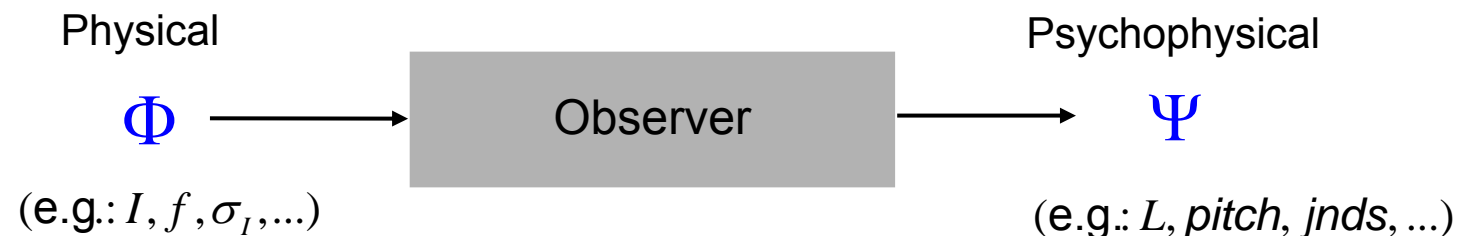


- Main goals:
- To represent the results from experiments within one framework
 - To explain the functioning of the system

- Specifically:
- Models can help generate hypotheses that can be explicitly stated.
 - Models can help determine how a deficit in one or more components affects the operation of the system.
 - Models can illustrate how complex a problem is.

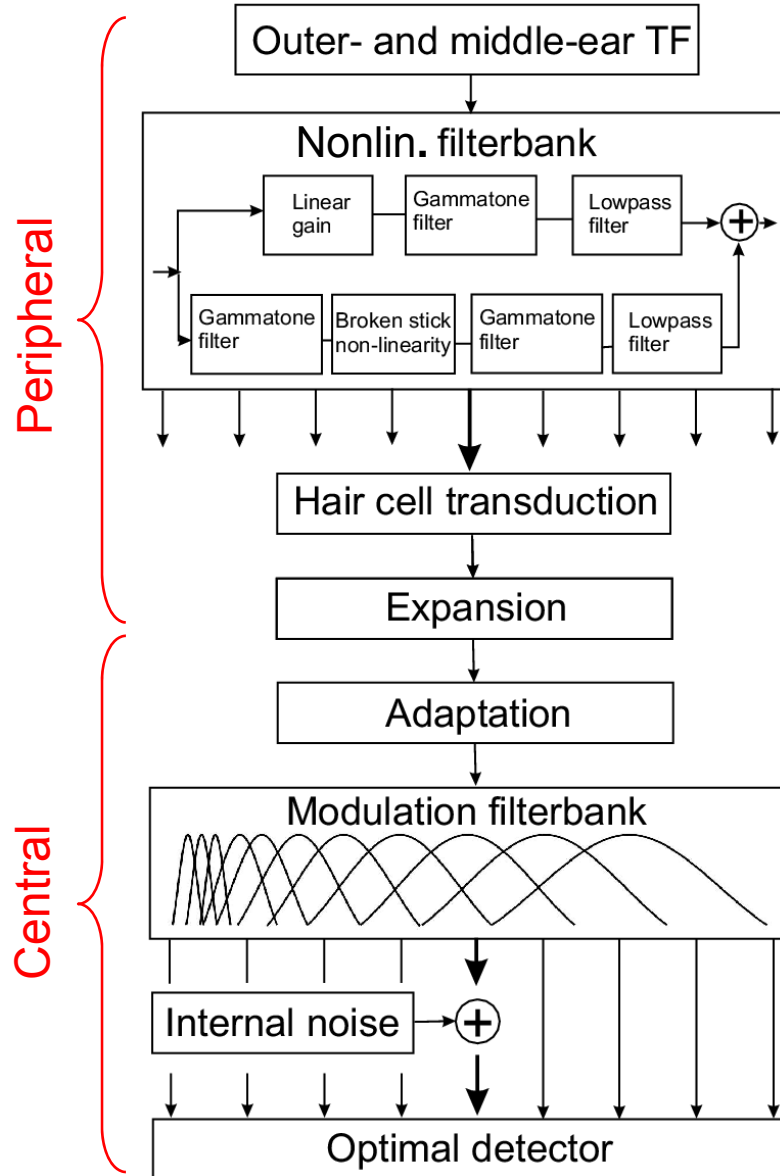
Classes of models: Conceptual, biophysical, physiological, mathematical, computational, ... **perceptual models**, depending on which aspects are considered.

Example





Example for a perception model (from an engineering point of view)



Model focusses on limitations in resolution rather than predictions of sensations.

Focus on the simulation of perception data (inspired by physiology)

Computational auditory signal processing and perception model

CASP

Jepsen *et al.* (2008) (based on Dau *et al.*, 1997)



Overview



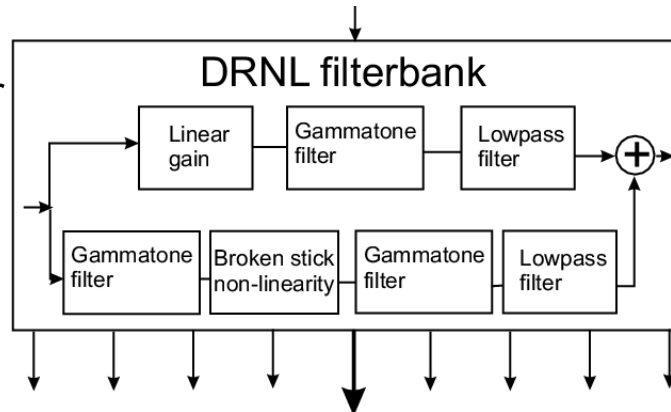
- Key aspects of **nonlinear cochlear processing** for auditory perception
- **Across-channel processing** and coincidence detection
- **Adaptation**: Steady-state compression and dynamic contrast enhancement
- Processing of **temporal and spectral modulations** and consequences for speech perception
- Computational **auditory scene analysis**: An approach based on coherence



Nonlinear cochlear filtering

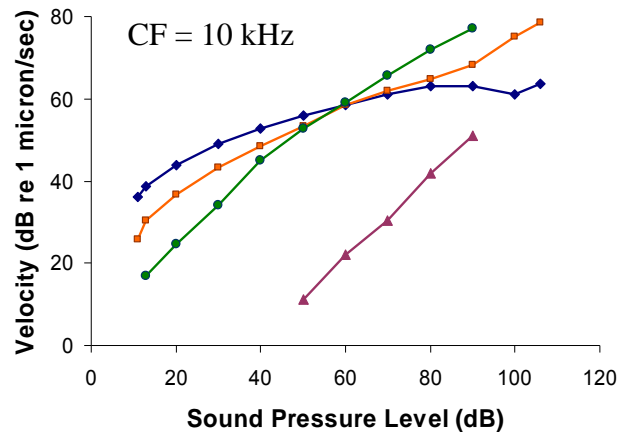
Dual Resonance Nonlinear (DRNL) filtering

Meddis *et al.* (2001)

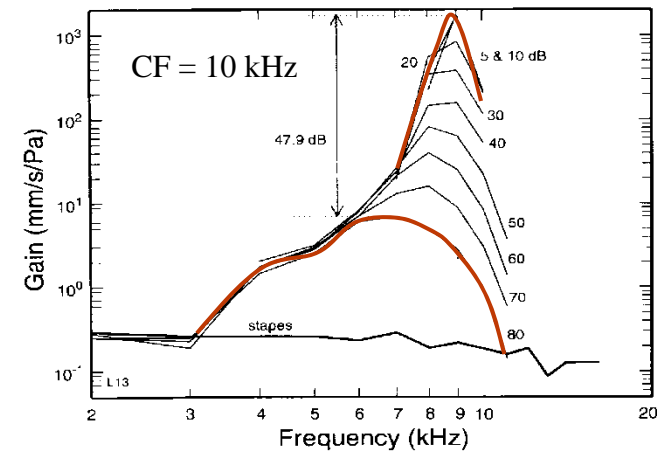


Alternative models:

e.g., Heinz *et al.* (2001); Zilany and Bruce (2006); Irino and Patterson (2007), ...



Ruggero *et al.* (2001)



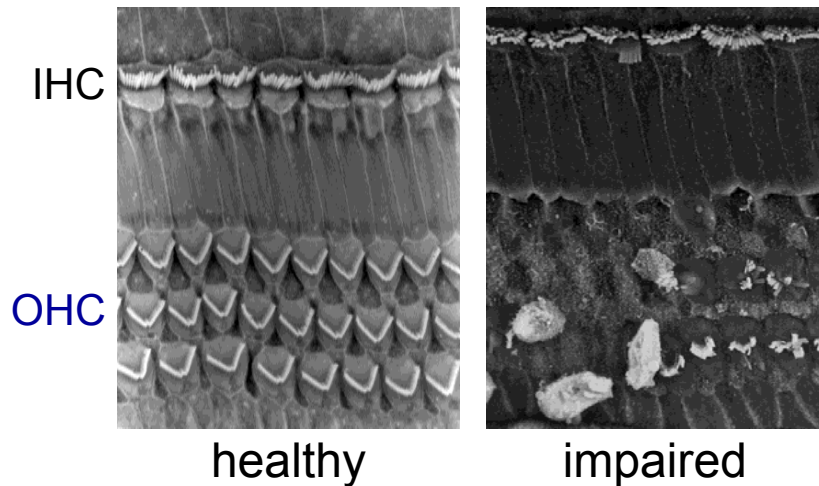
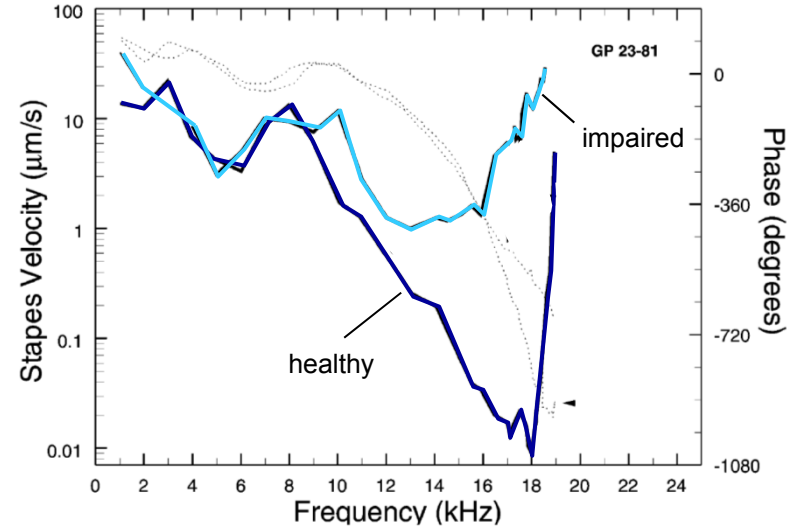
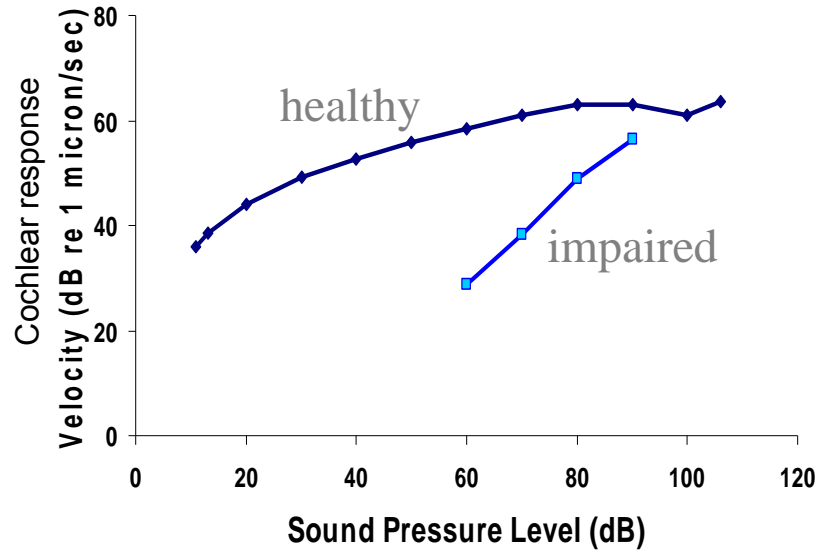
- Amplification and compression only at the characteristic frequency (CF).
- Linear response properties for off-freq. stimulation.

- Frequency selectivity is level dependent.
- Largest gain at low stimulation levels



Cochlear damage

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Simulation of loss of frequency selectivity (broadening factor of 3) but no threshold elevation.



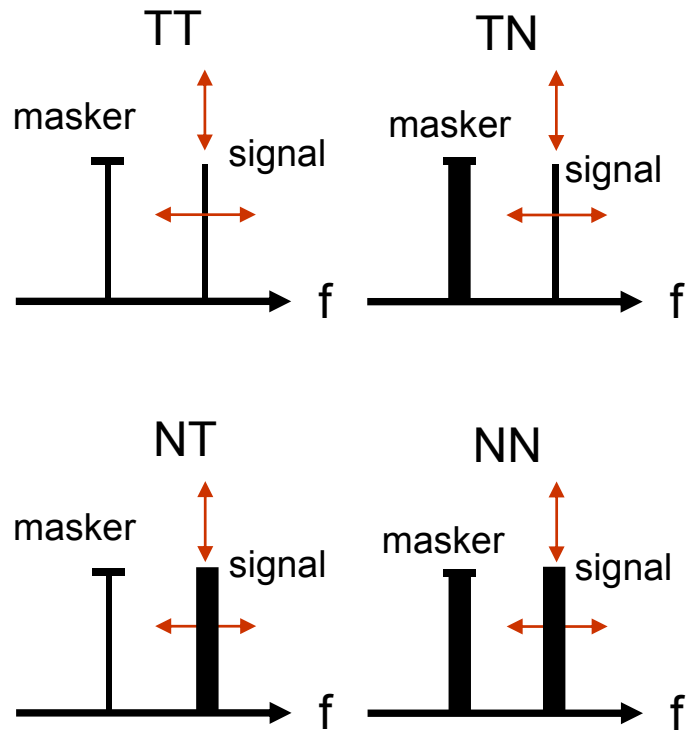
Moore (1995)



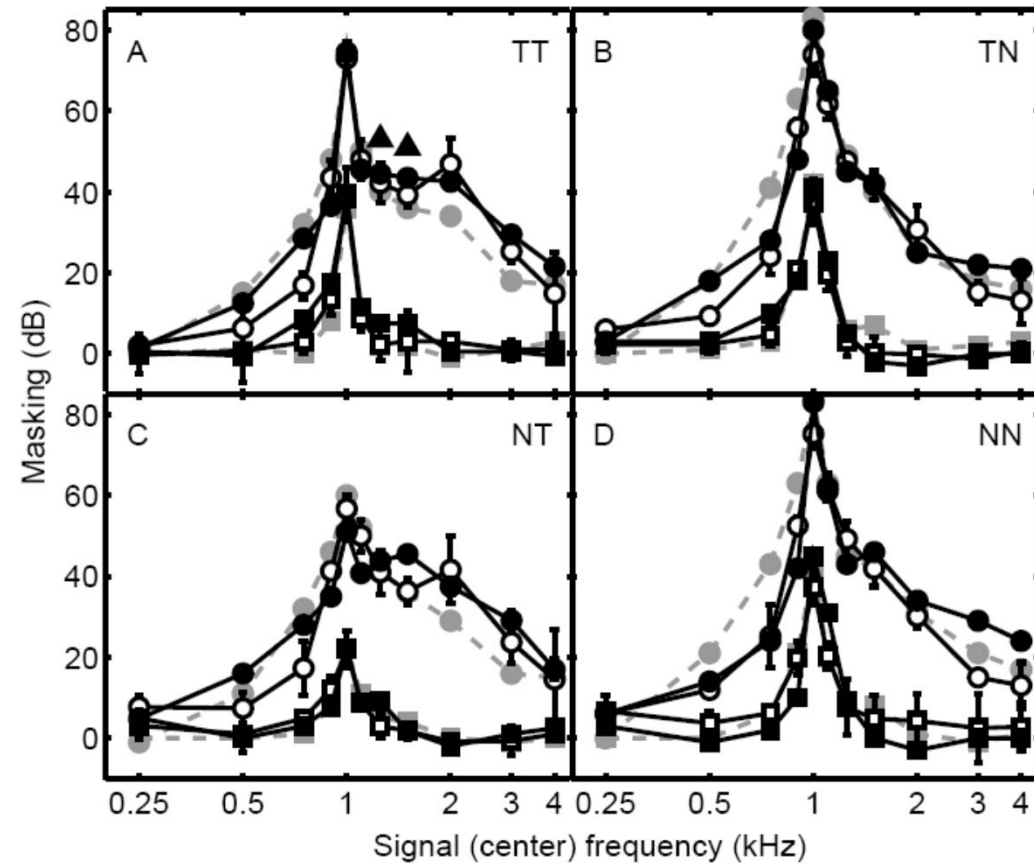
Spectral masking patterns (NH)



Jepsen *et al.* (2008)



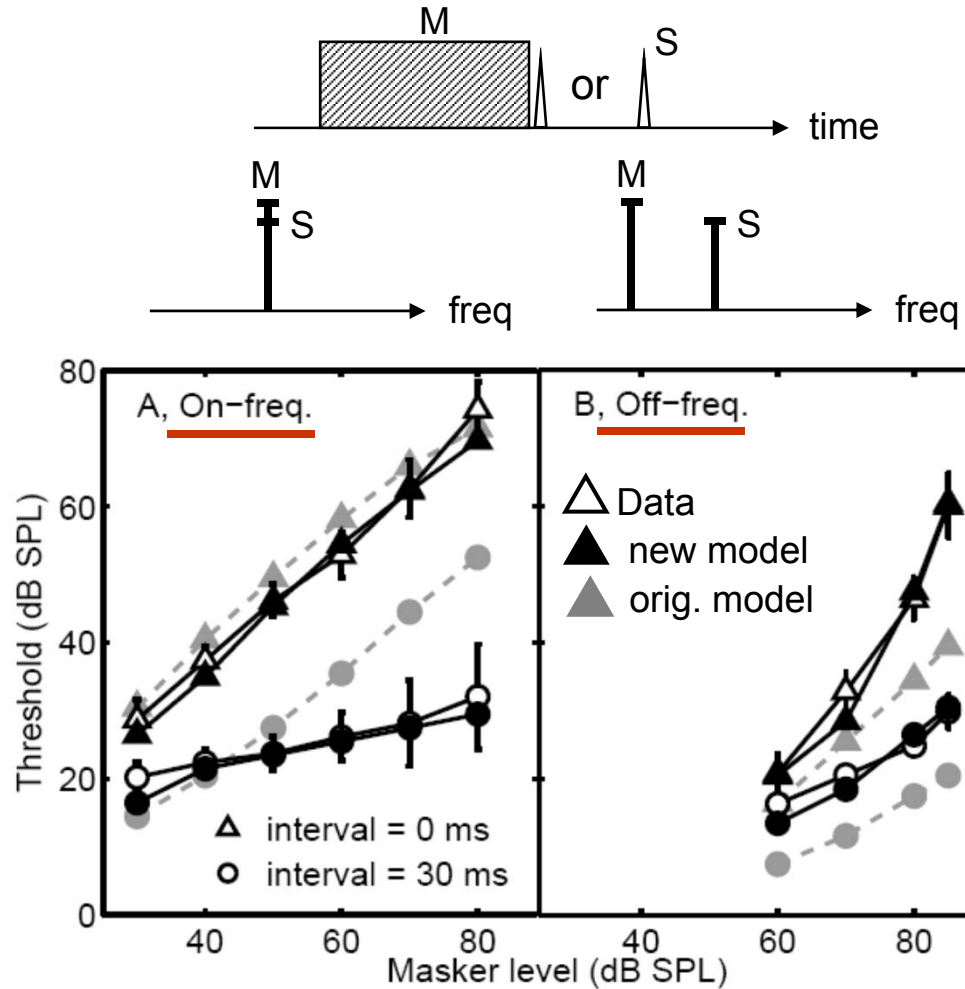
Masker level: 45 or 85 dB SPL



- ○ Data (Moore *et al.*, 1998)
- ● Model
- ● Original model (with *linear* BM)

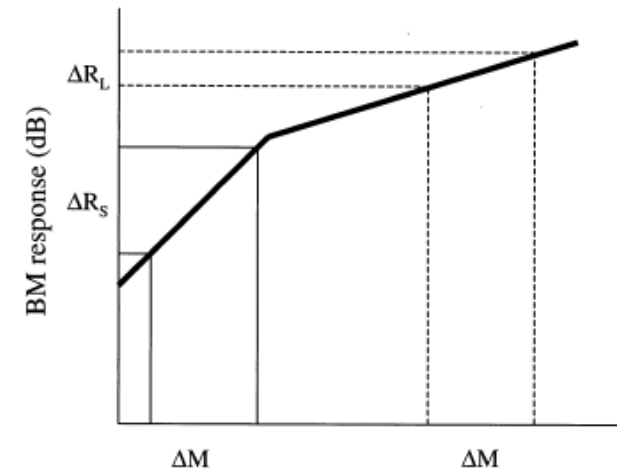


On- versus off-frequency forward masking (NH)

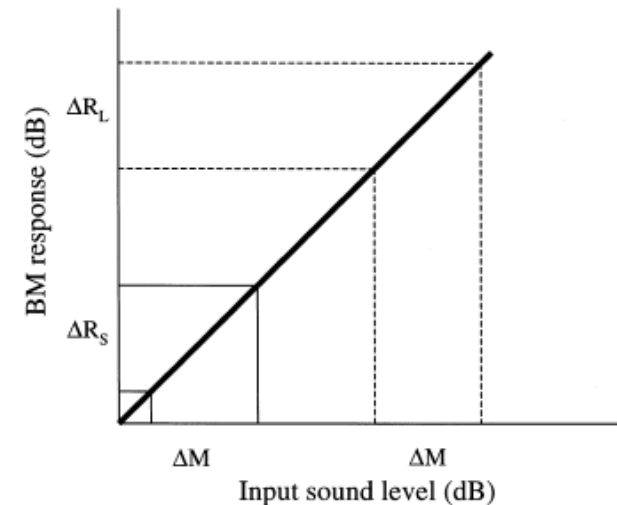


⇒ Model accounts for effects of BM processing on forward masking (NH).

(a) On-frequency



(b) Off-frequency

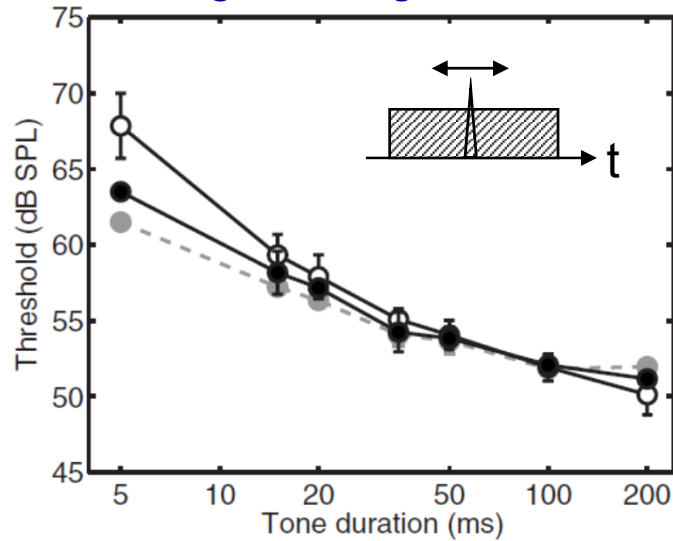




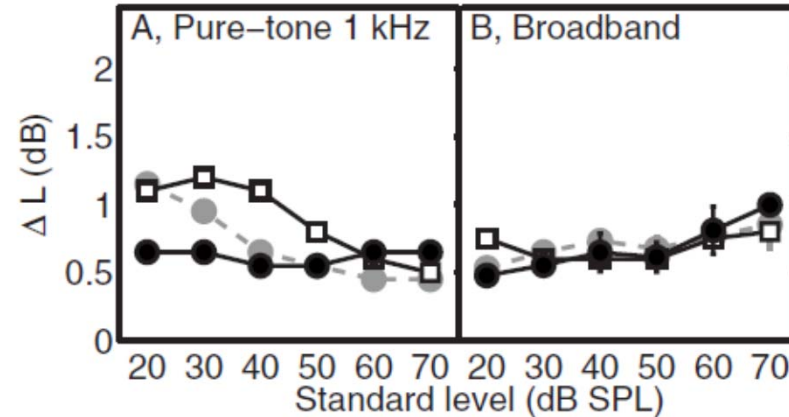
Intensity discrimination, signal integration and AM detection (NH)



Signal integration

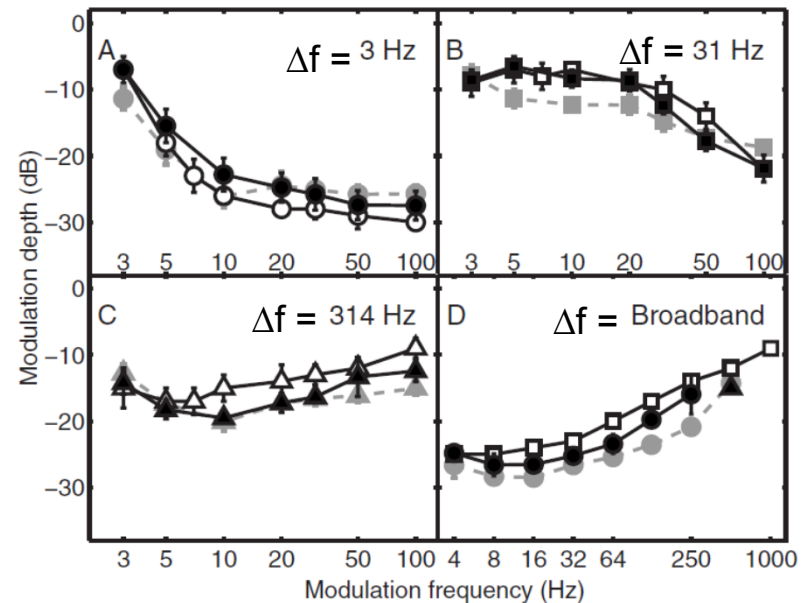


Intensity discrimination



... and modulation detection

Modulation transfer functions

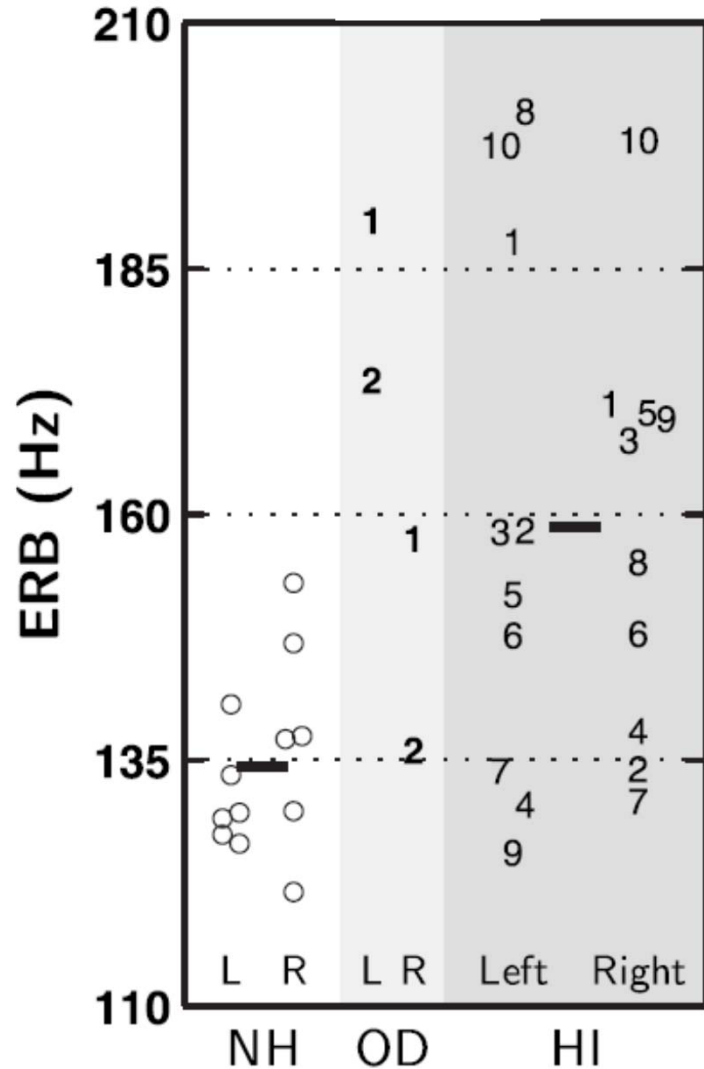


... resulting from the properties of optimal detector, adaptation stage and modulation filterbank

Jepsen *et al.* (2008)



Modelling variability in the data?



So far so nice. **Preprocessing** has also been successful as front end in certain applications - for *mean NH listeners*.

However, a **model** is **missing** that accounts for the **variability** in the data (particularly in **HI** listeners).

(**Example**: Frequency selectivity @750 Hz in listeners with normal audiogram at low frequencies.)

1. step: **Characterisation** of HI ("auditory profile").
2. step: **Prediction** of individual HI ("basic" functions).
3. step: **Evaluation** in other tasks (e.g. speech).

Strelcyk and Dau (2009)



Modelling individual hearing impairment?

Measures of **basic auditory functions** provide information about **individual deficits**

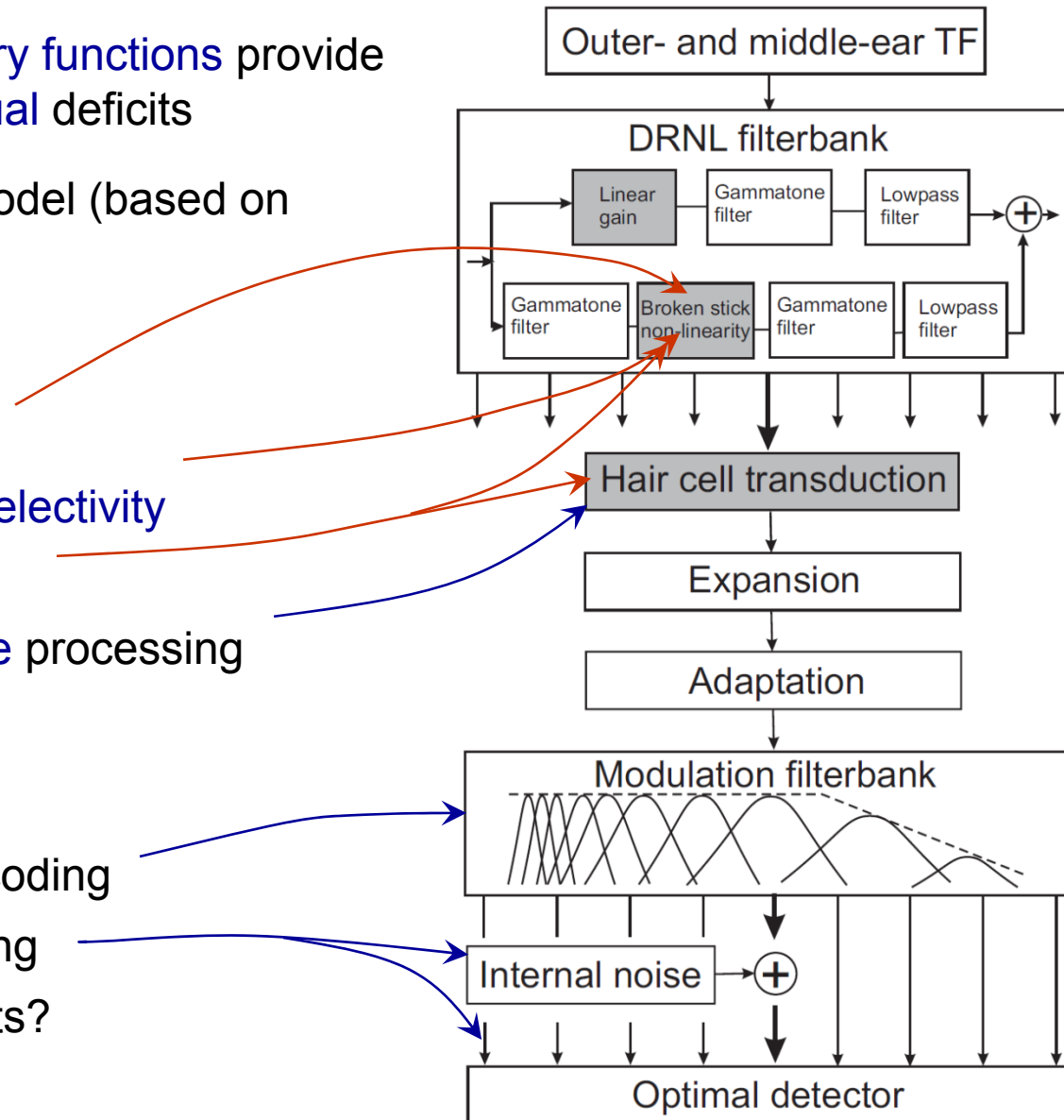
⇒ **Modifications** in the model (based on auditory profile)

Peripheral stages:

- Reduced **compression**
- Change of **frequency selectivity**
- Reduced **sensitivity**
- Degraded **fine-structure** processing
- ...

Later stages:

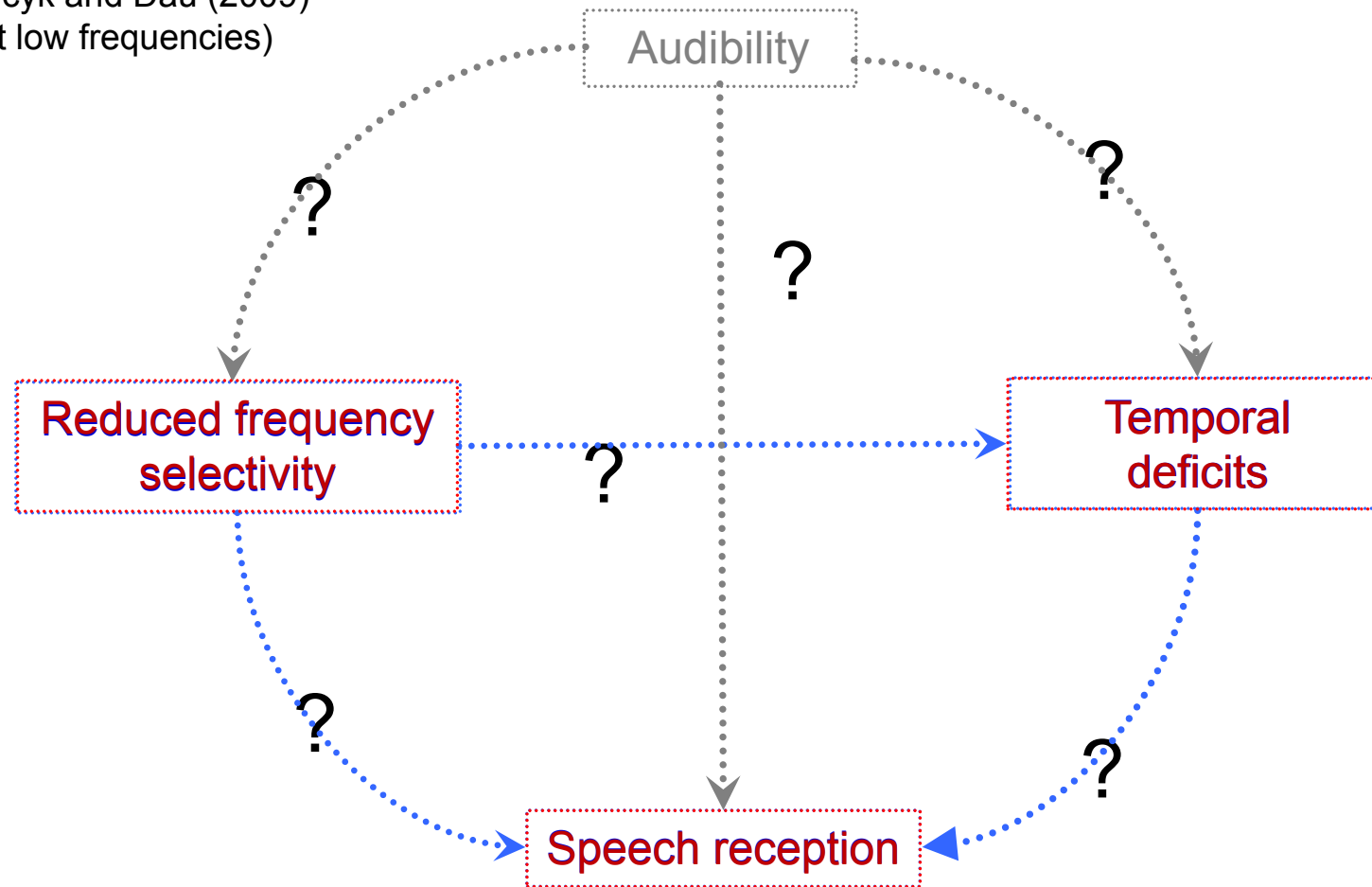
- Deficits in **modulation coding**
- "Sub-optimal" processing
- **Central/cognitive** deficits?





Relations between functions in impaired hearing

Strelcyk and Dau (2009)
(at low frequencies)



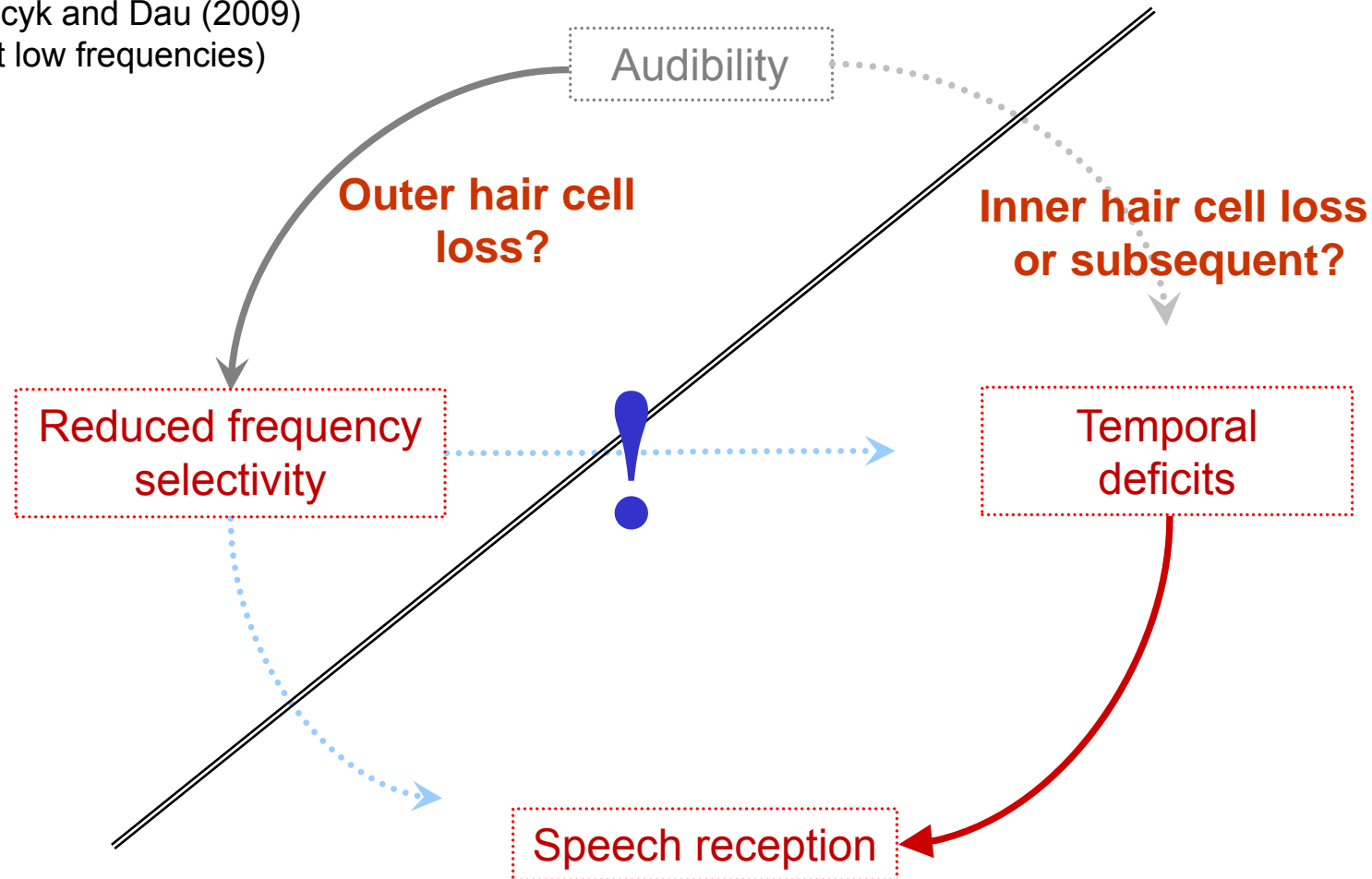


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Relations between functions in impaired hearing



Strelcyk and Dau (2009)
(at low frequencies)



in two-talker and lateralized noise,
but not in modulated noise
⇒ Important for **spatial segregation** and **talker separation**?



Overview



- Key aspects of nonlinear cochlear processing for auditory perception
- **Across-channel processing** and coincidence detection
- Adaptation: Steady-state compression and dynamic contrast enhancement
- Processing of temporal and spectral modulations
- Computational auditory scene analysis: An approach based on coherence



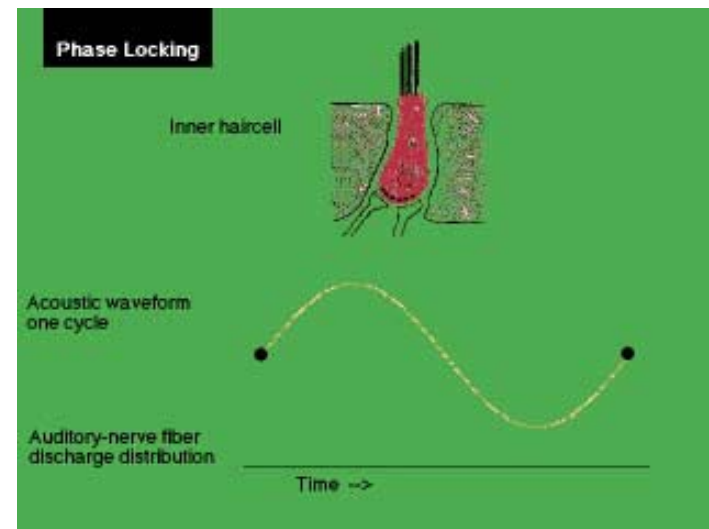
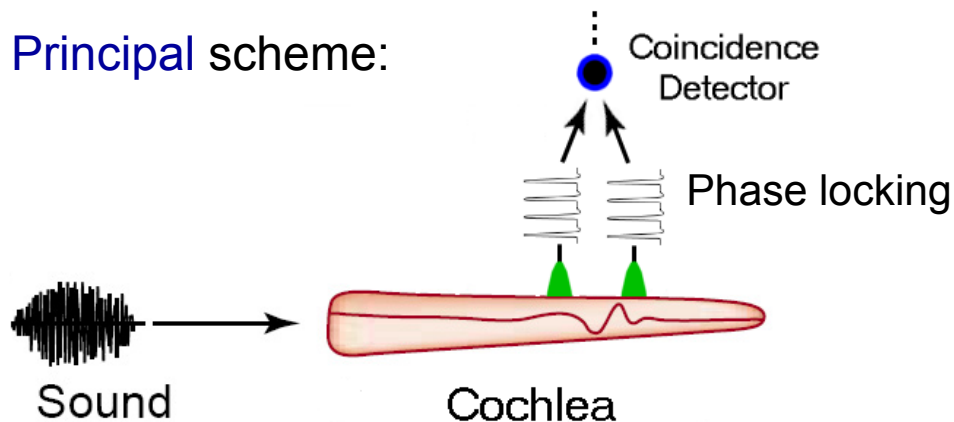
Across-channel processing

Reduced frequency selectivity thus represents only **one** impairment factor. Probably **not sufficient** to explain the major problems in noisy environments.

Hypothesis: Across-channel processing is important for **robust** signal encoding (Loeb *et al.*, 1981; Carney *et al.*, 2002).

Spatio-temporal models: Idea: To **extract information** from the **spatio-temporal** pattern of cochlear activity.

Principal scheme:

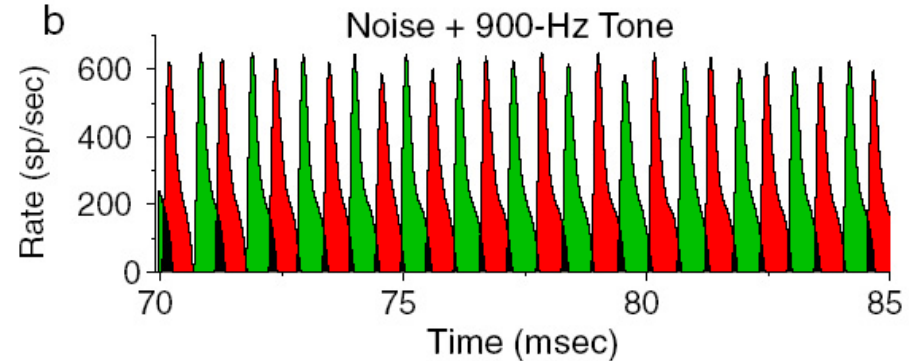
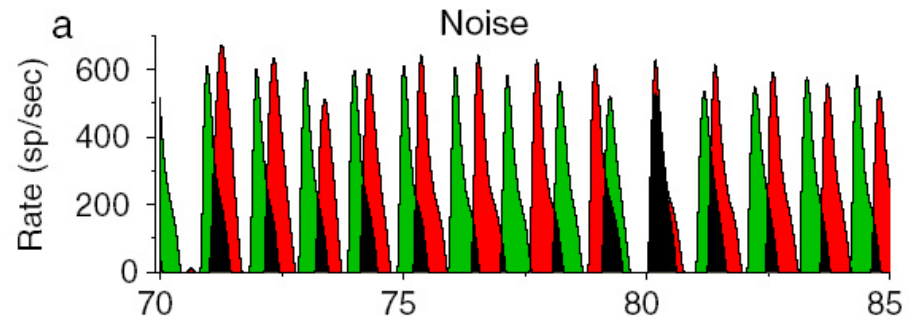
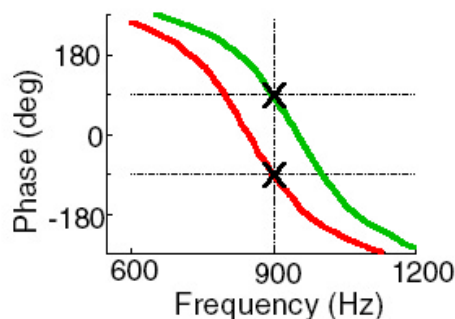
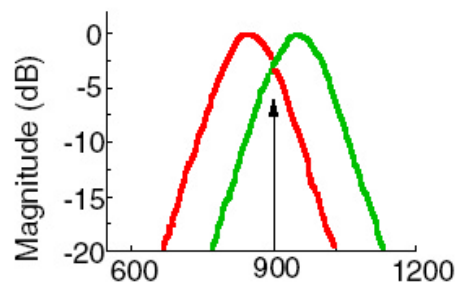
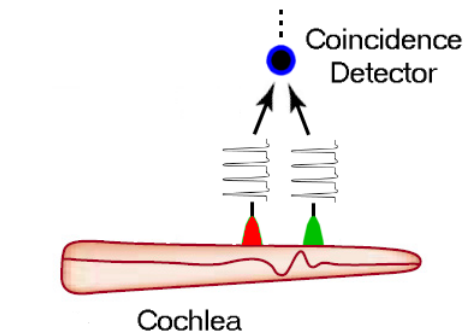




Across-channel model for signal-in-noise detection



Detection of formants and tones in noise (e.g., Deng & Geisler, 1987; Carney *et al.*, 2002)



Presence of the **signal** (e.g., formant): **Reduction** in the rate of cross-frequency coincidence.

Response pattern is **very robust** to overall level changes (as long as the 3 "components" are intact).



Cochlear damage and across-channel processing

Typical consequences of cochlear damage:

1. Reduced **frequency selectivity** as a consequence of loss or reduction of compression (outer hair cells)
2. Deterioration of the encoding of temporal fine structure, by:
 - i) Reduced precision of **phase locking** in AN fibers
 - ii) Reduced **number of cochlear hair cells** → reduction of converging inputs
 - iii) Loss of **coincidence detectors**

Effect on the output of spatio-temporal processing:



Cochlea

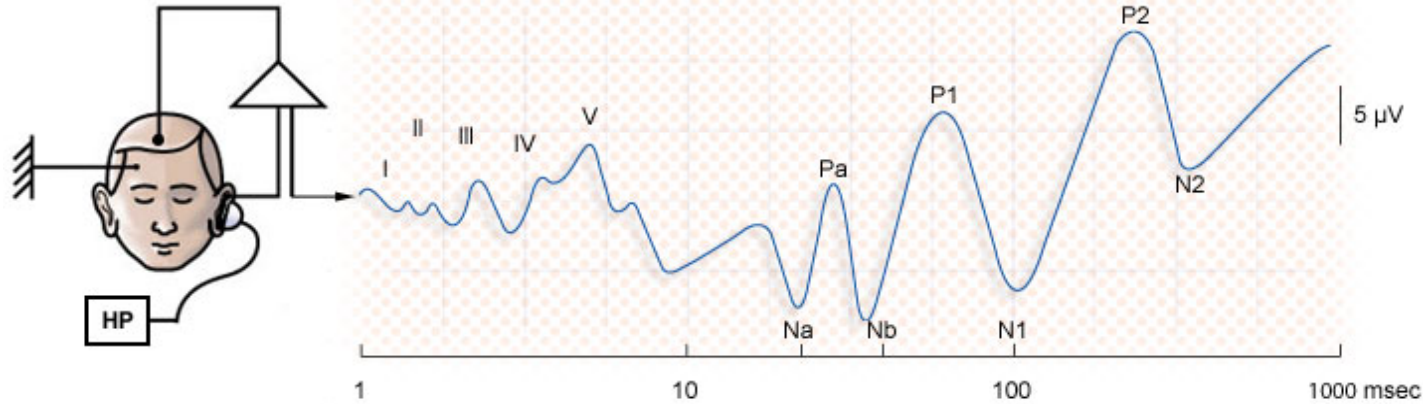


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How can we measure phase locking in humans?



Evoked potentials



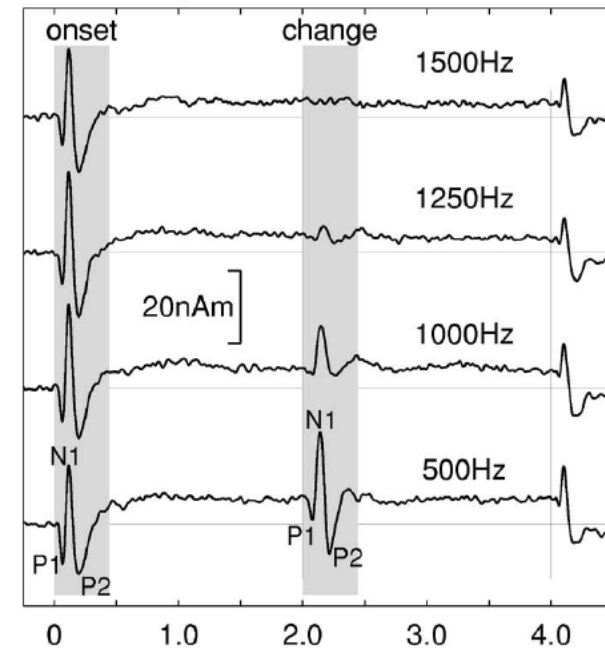
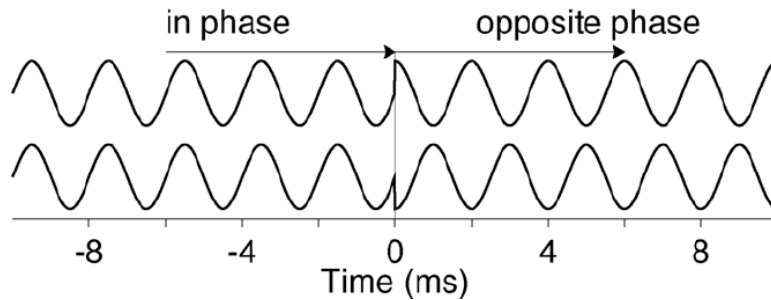
Ross *et al.* (2007)

Sound stimulation

Responses

Left ear:

Right ear:





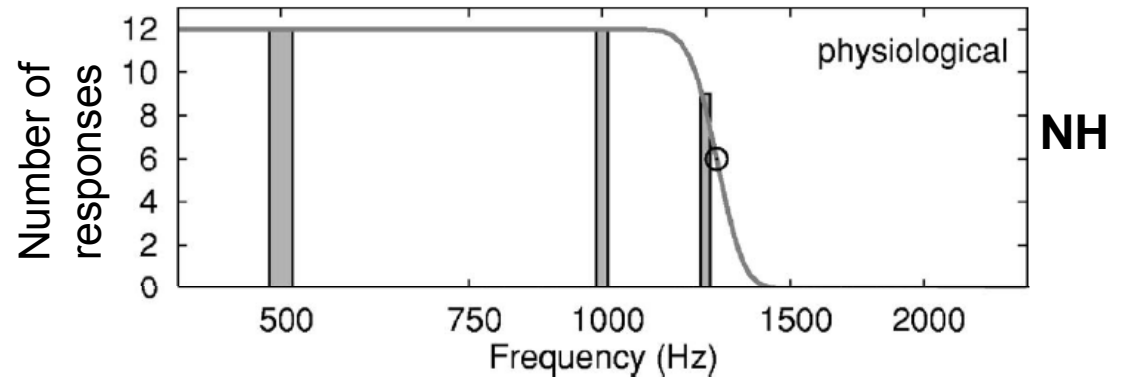
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Phase locking in normal versus impaired hearing



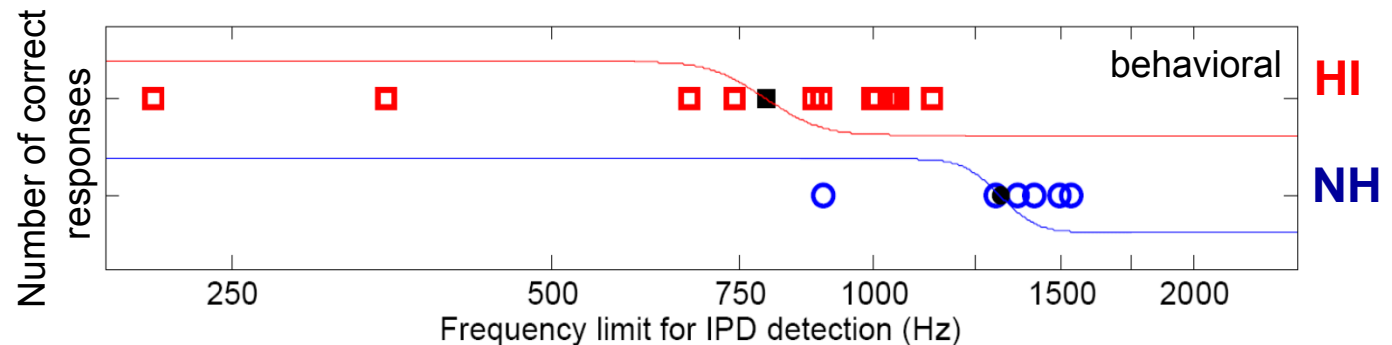
Physiological results

Ross *et al.* (2007)
(MEG study)



Behavioral results

Santurette and Dau (2009)

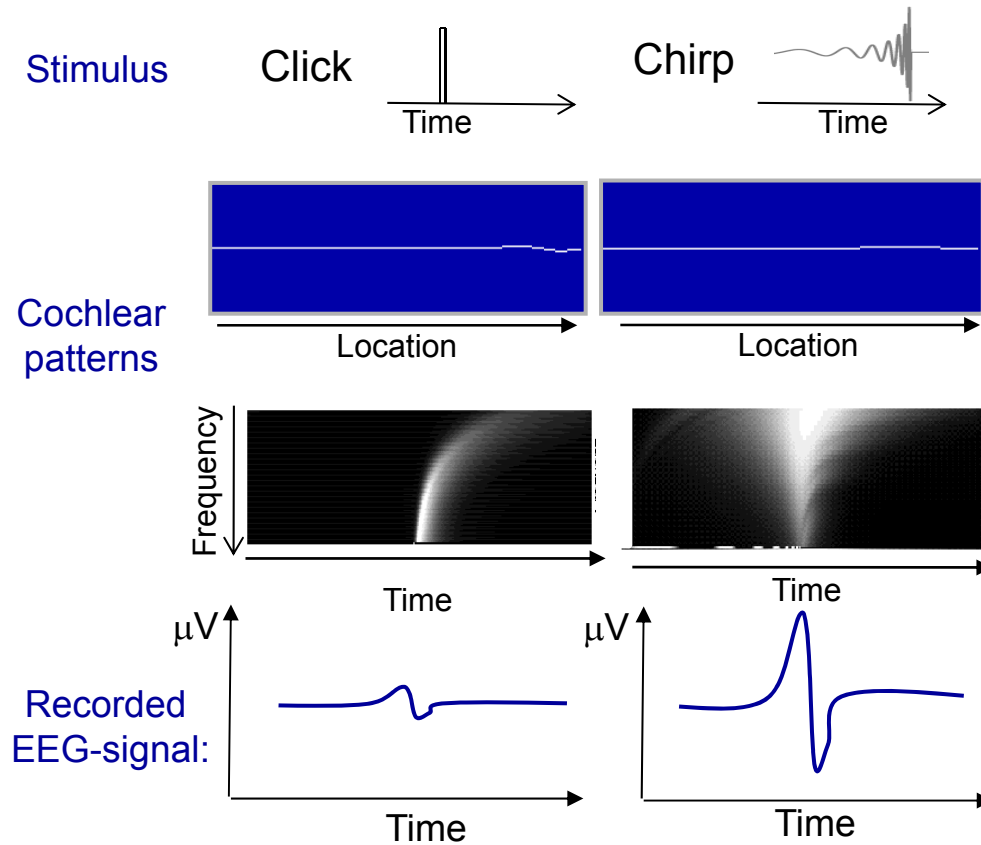


- ⇒ Good correspondence between physiological and behavioral estimates
- ⇒ Most hearing-impaired listeners show a lower frequency limit - either due to degraded monaural phase locking or deficits in the "binaural operator".



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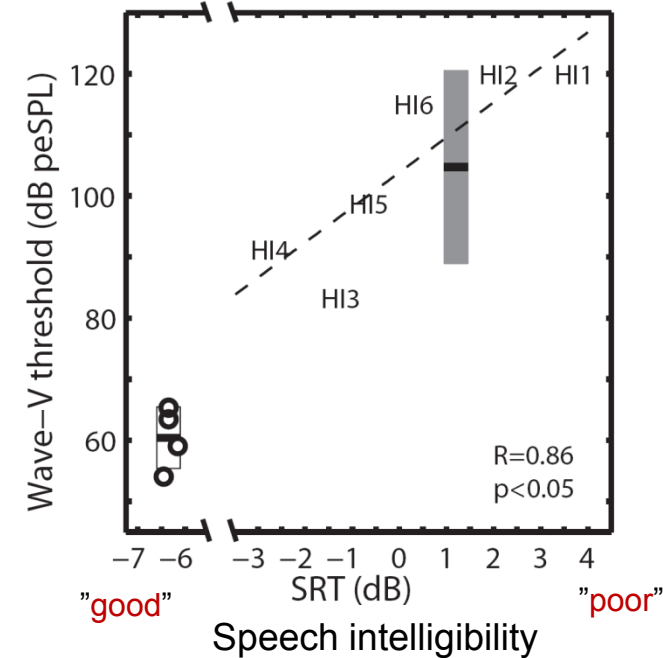
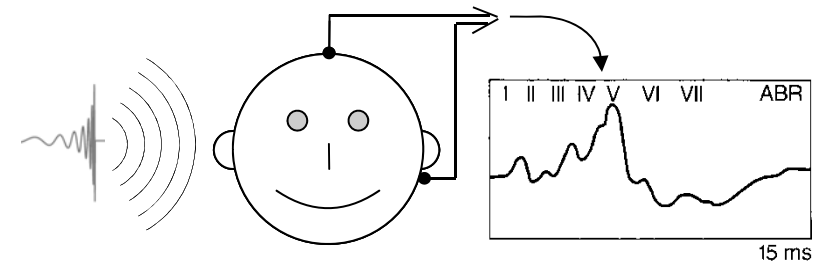
Relation between speech intelligibility and measures of temporal processing



Dau *et al.* (2000); Harte *et al.* (2010)

⇒ The amount of neural synchronization across frequency is correlated with speech intelligibility (but not with audibility).

Auditory-evoked potentials (ABR)



Papakonstantinou *et al.* (2011)



Overview



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- **Adaptation**: Steady-state compression and dynamic contrast enhancement
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Level adaptation



We can hear sounds extending over a huge range of sound levels (of 120 dB).

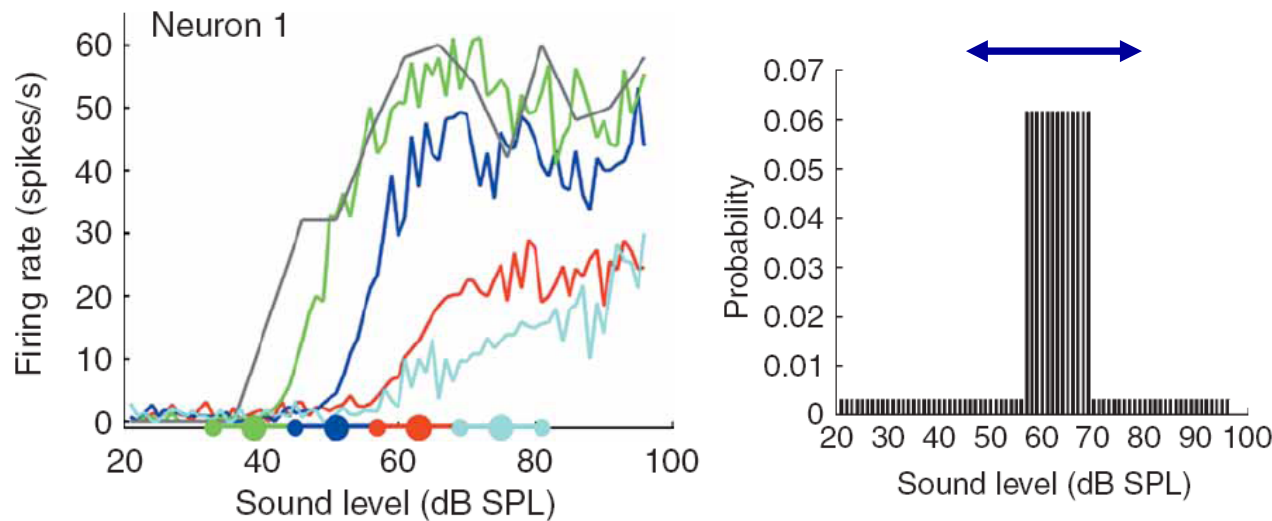
At the same time, we can hear level changes of about 1 dB across entire level range.

However: The neural dynamic range of individual neurons is very limited as studied extensively in the cochlea (auditory nerve).

Which mechanisms exist that extend the range of coding?

Possible solution:

Dean *et al.* (2005)



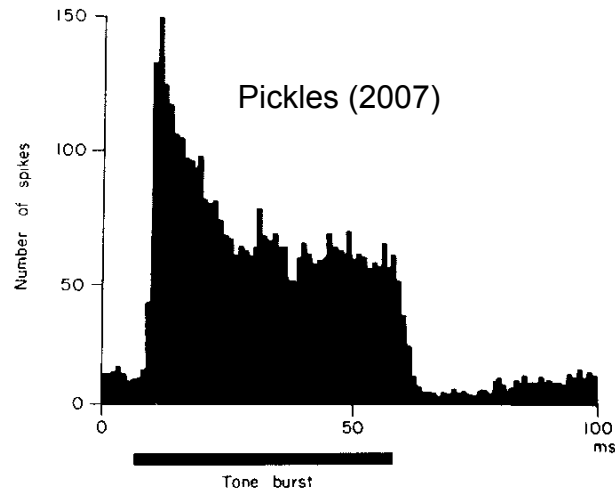
⇒ Adaptive processes of neurons throughout the auditory system (here: brainstem).



Dynamic adaptation



Dynamic changes: Temporal pattern of adaptation is similar throughout auditory pathway but “**time constants**” change from *ms* to *s*.

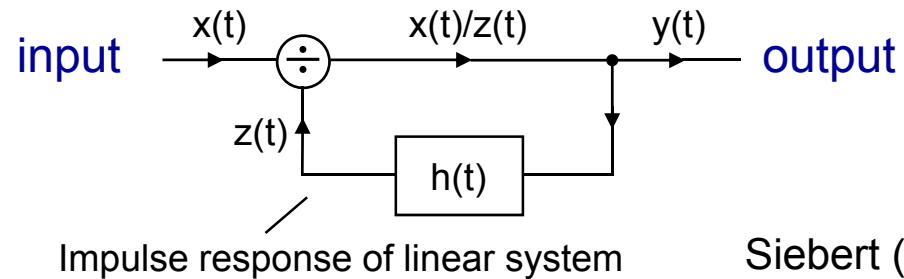


Firing patterns of many neurons show a form of **adaptation** to a sudden change in stimulus level.

Auditory nerve: **rapid** adaptation

Phenomenological
model of adaptation:

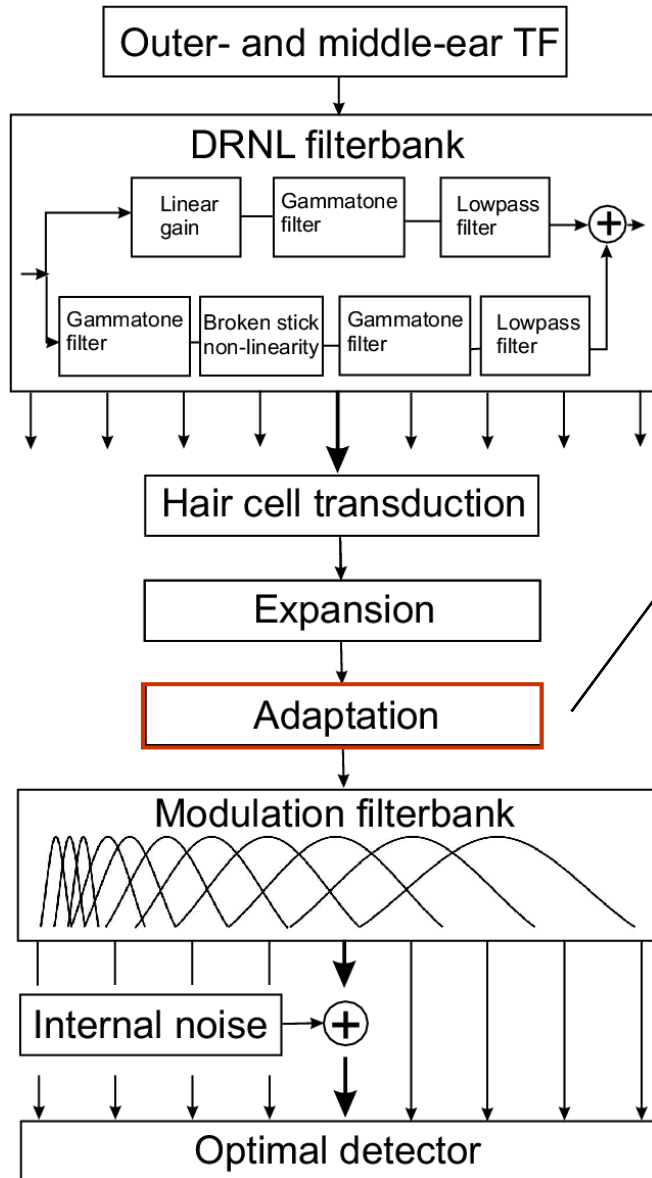
⇒ **Steady-state compression**
and **contrast enhancement**



Siebert (1968);
Dau *et al.*(1996)



Model including an adaptation circuit



- + Simple circuit that accounts for large variety of behavioral data
- + Provides robust internal representation in model applications
- No explanation of the mechanisms underlying adaptation

Jepsen et al. (2008)
(based on Dau *et al.*, 1997)



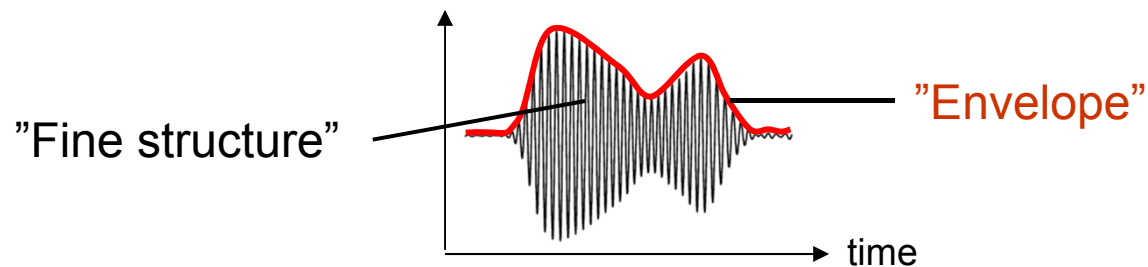
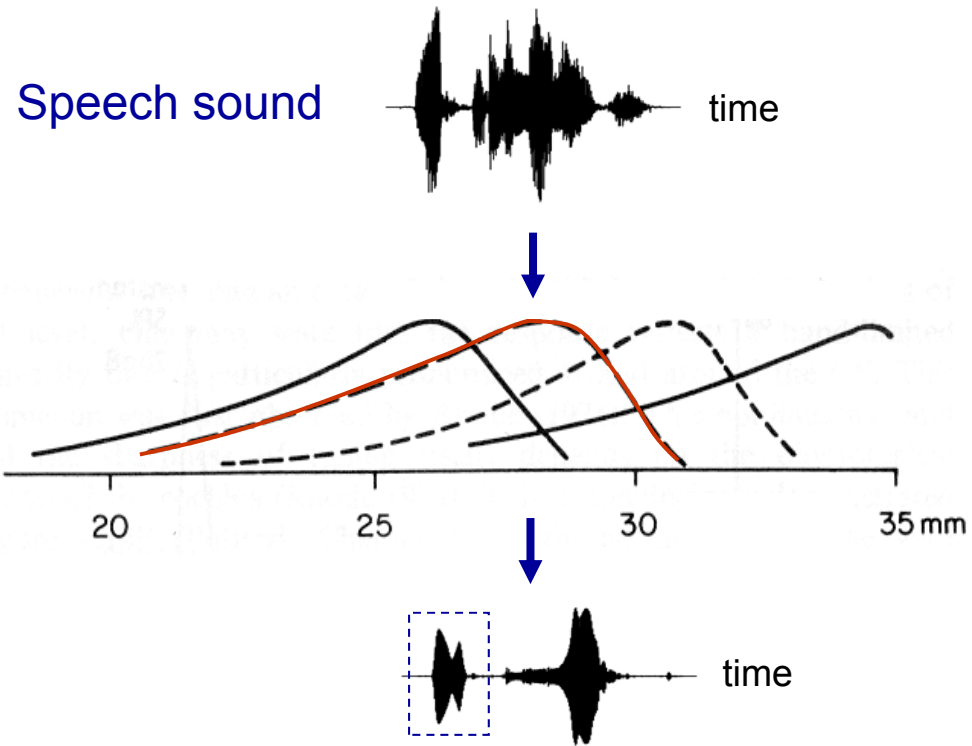
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How is the envelope coded in the auditory system?



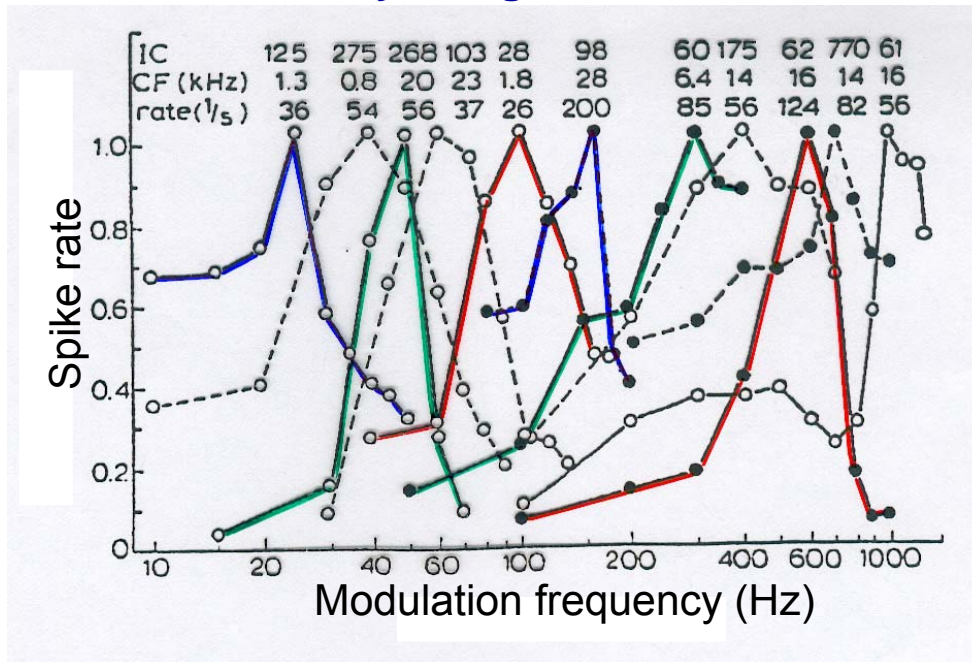


Modulation selectivity

Evidence from physiological and perceptual data: **Decomposition of the temporal envelope** at the output of each cochlear filter.

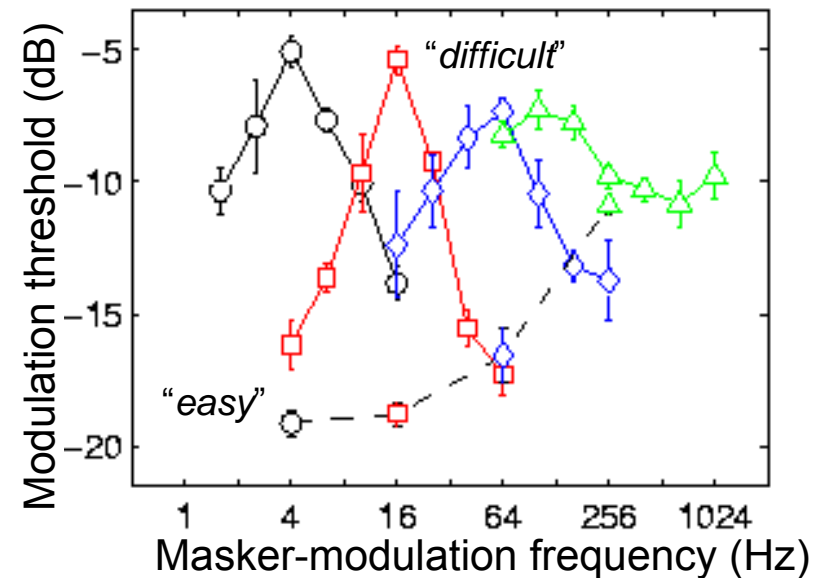
Langner (1992)

Physiological data



Dau *et al.* (1997);
Ewert & Dau (2000)

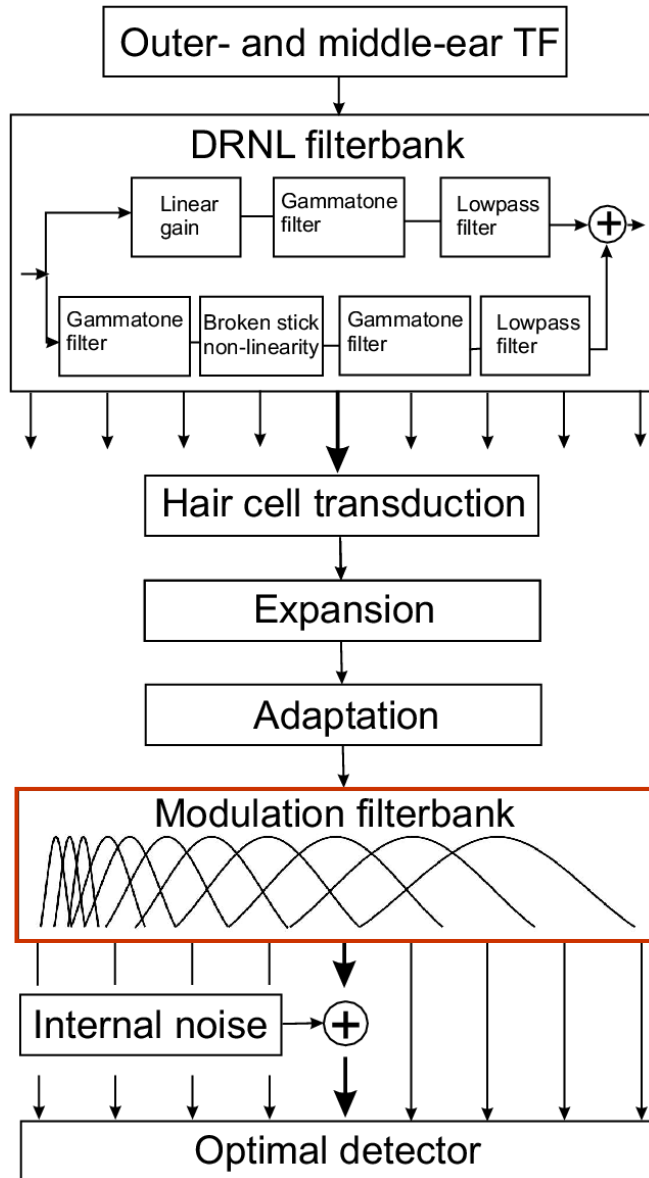
Psychophysical data



⇒ **Modulation frequency-to-place** transformation in the brain.



(1-D) Modulation filterbank model



Speech perception:

- Modulation filterbank consistent with concept of **speech transmission index (STI)** (e.g., Houtgast and Steeneken, 1985).
- **RASTA** algorithm (Hermansky, 1994) in speech recognition systems: filters out “irrelevant” temporal modulations.

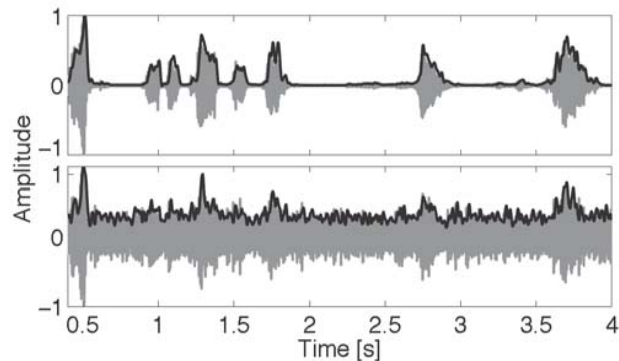
Dau *et al.* (1997); Jepsen *et al.* (2008)



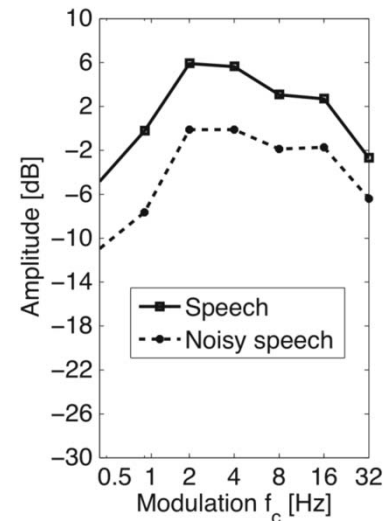
Speech intelligibility prediction: The STI concept



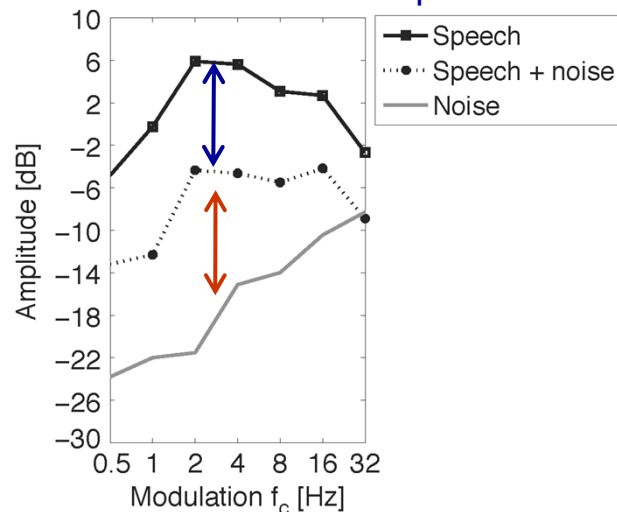
Speech signal
(1/3 oct. filtered @ 2kHz)



No processing



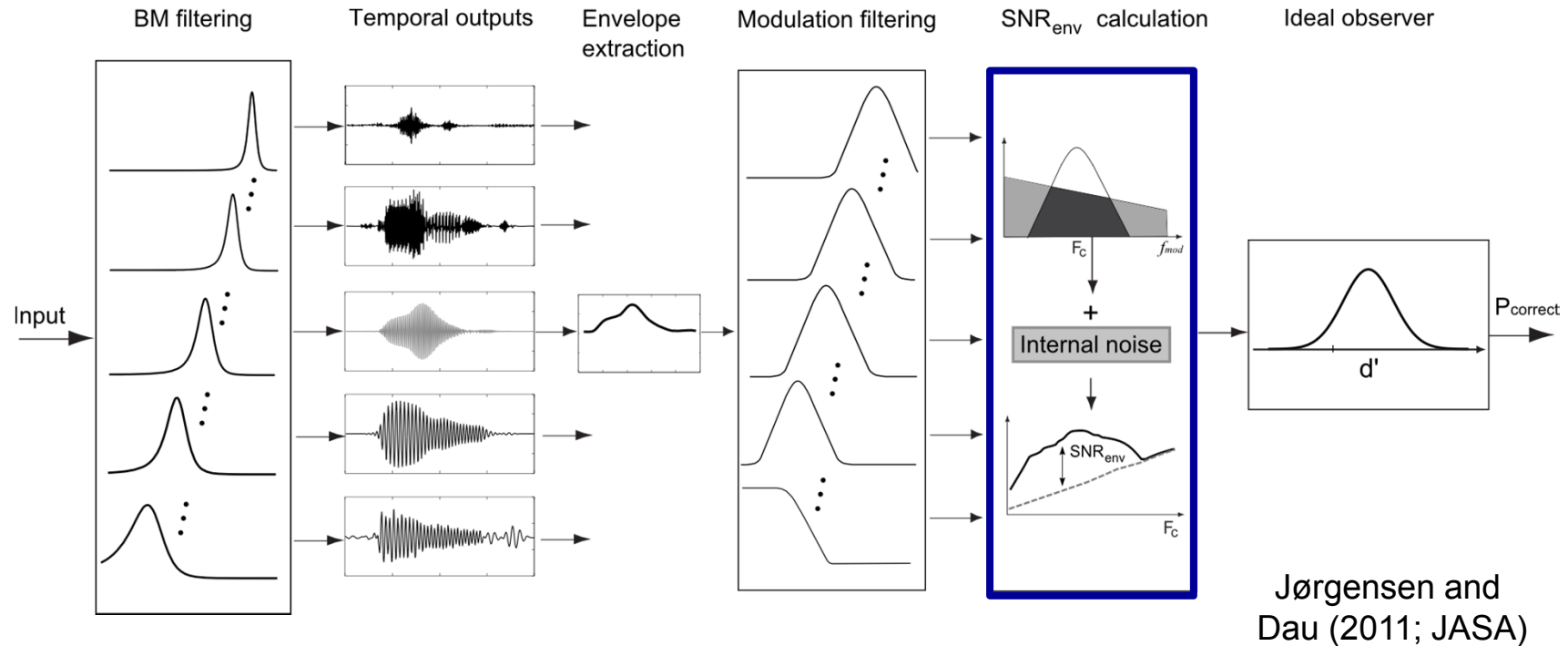
Modulation spectra



- STI accounts for effects of **additive noise**.
- **Noise reduction** (via spectral subtraction) *increases* the SNR (in the audio domain) and the STI.
⇒ **Prediction of increase** in intelligibility.
- However, **data** typically show a **decreased** speech intelligibility.
⇒ **Noise reduction paradox**



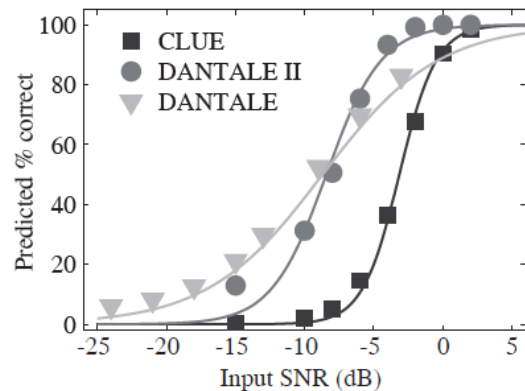
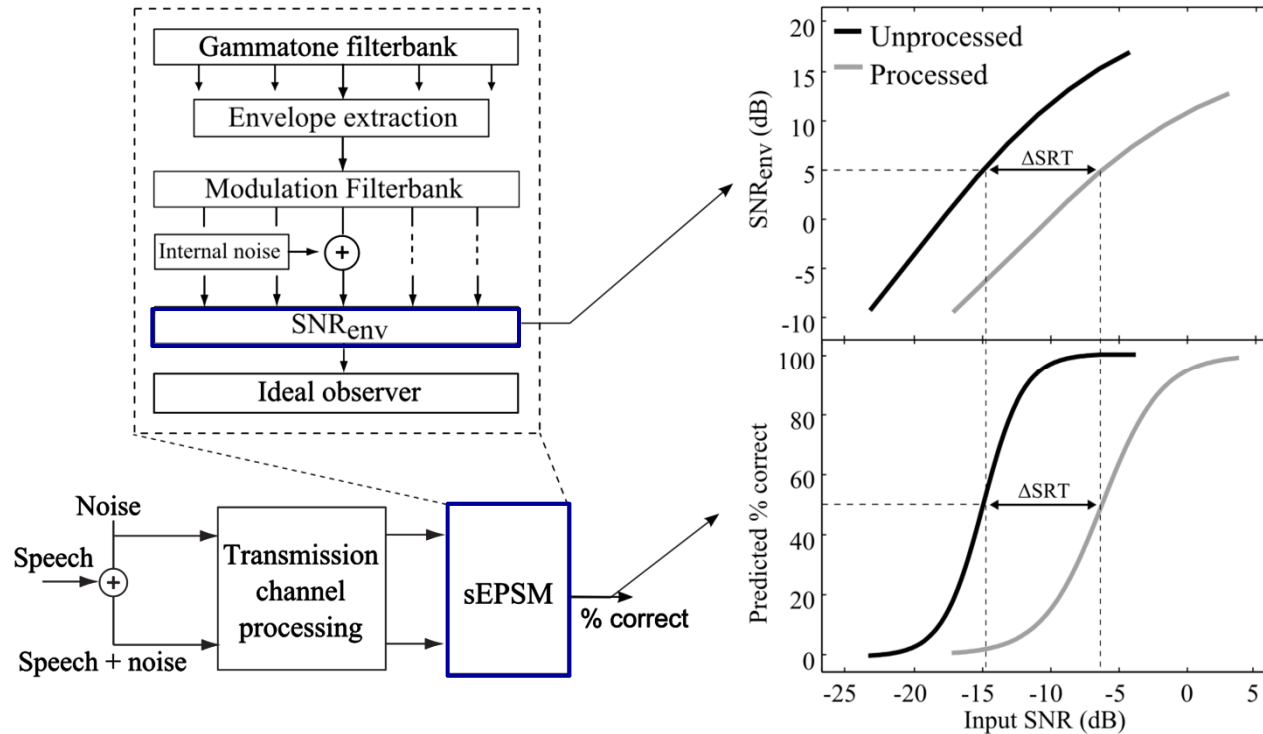
Speech-based envelope power spectrum model (sEPSM)



- Based on the EPSM (Ewert and Dau, 2000) used for prediction of **modulation detection** and masking.
- **Key component:** Metric based on the **signal-to-noise ratio** in the envelope domain (**SNR_{env}**).



Components of the framework



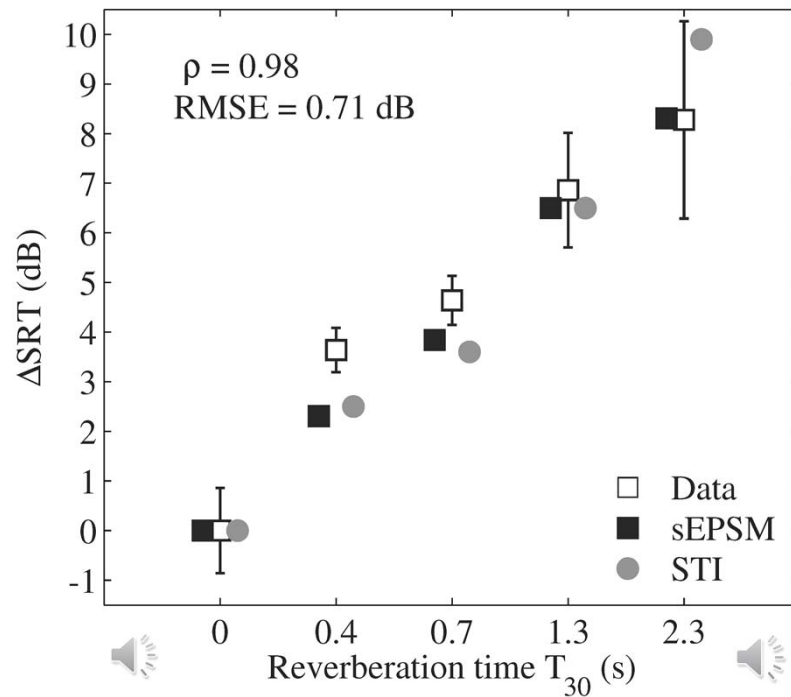
The *ideal observer* makes assumptions about the **response alternatives and redundancy** (m, σ) of a given speech material \Rightarrow shape of psych. function.

However, the "key" measure affected by the transmission channel is considered to be **SNR_{env}**.

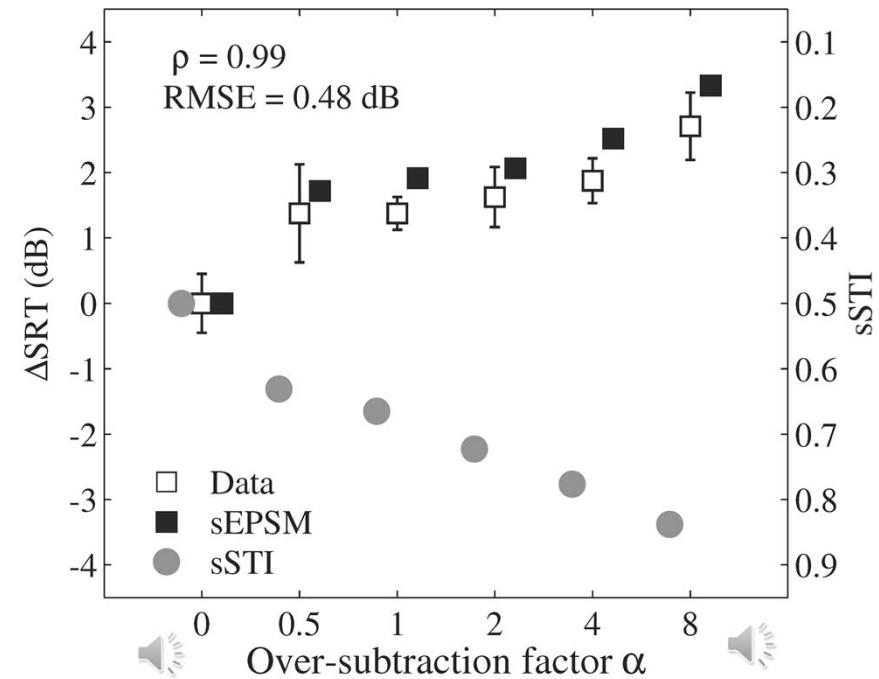


Data and simulations

Reverberation



Spectral subtraction



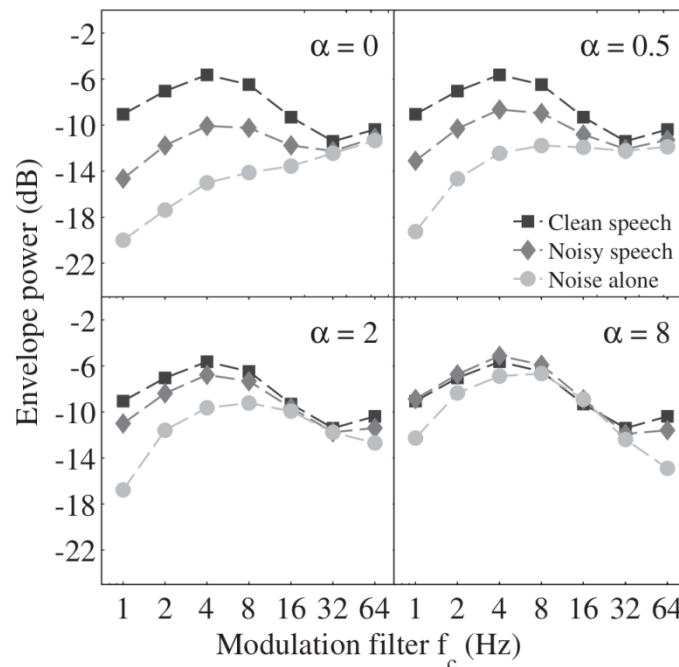
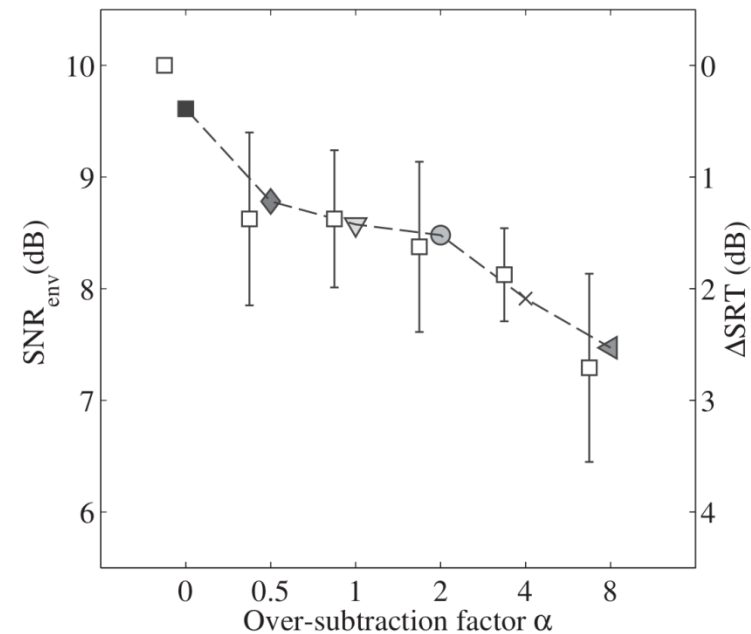
- ⇒ In conditions of **reverberation**, STI and sEPSM perform **similarly** (and successfully).
- ⇒ In conditions of **spectral subtraction**, the sEPSM accounts for the data while the **STI fails** completely (Jørgensen and Dau, 2011).



Model analysis (for spectral subtraction)



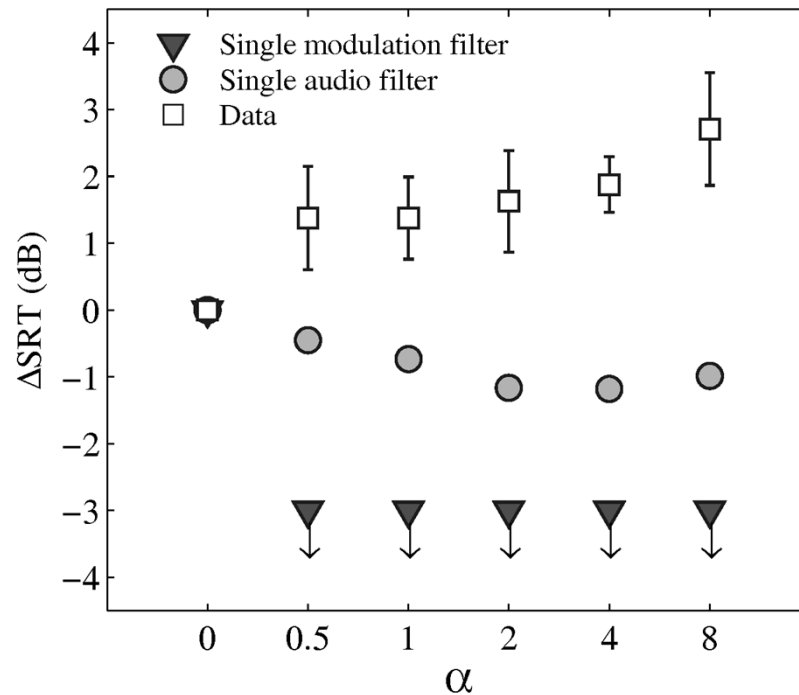
Modulation spectra @ 1 kHz

 $\text{SNR}_{\text{env}}(\alpha)$ 

- **No contributions** from modulations ≥ 32 Hz (consistent with earlier work).
 - The envelope power of the noisy speech increases with α ; However, the envelope power of the (estimated) **noise floor increases more strongly** with α .
- \Rightarrow Thus, SNR_{env} **decreases with α** as does the measured speech intelligibility.



Further model analysis



Is **frequency selectivity** in audio and envelope frequency domain **critical**?

Additional simulations with:

- one "broad" auditory filter
- a 150-Hz modulation LP filter

In both cases, the **modified model fails** to account for the data.

⇒ The **integration** of SNR_{env} information **after frequency-selective** processing (in both domains) is crucial for speech-intelligibility prediction.

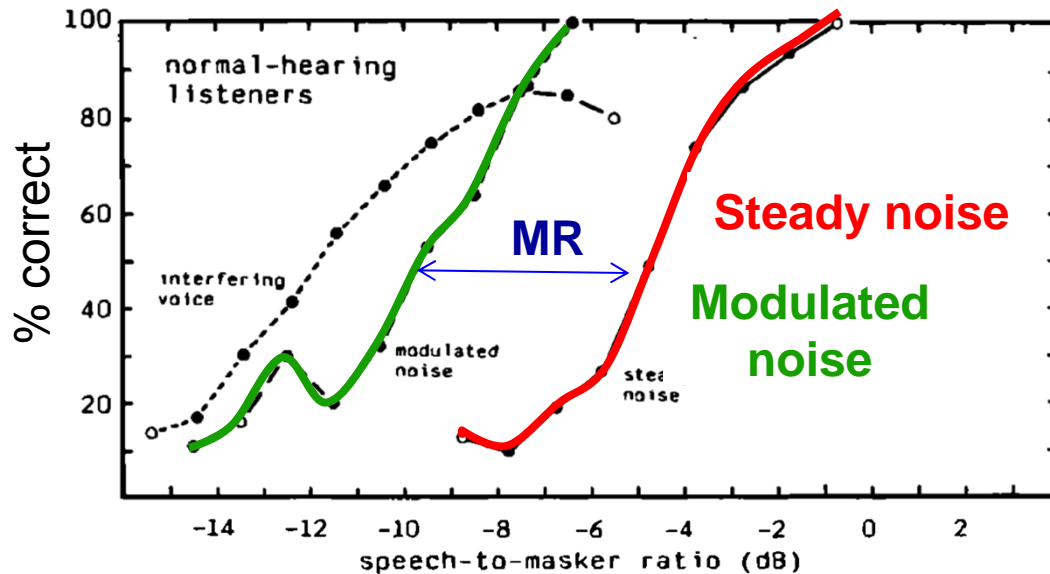
However, the model does **not reflect**, which modulations contribute at which time and (carrier) frequency to speech intelligibility.



Speech masking release in modulated interferers



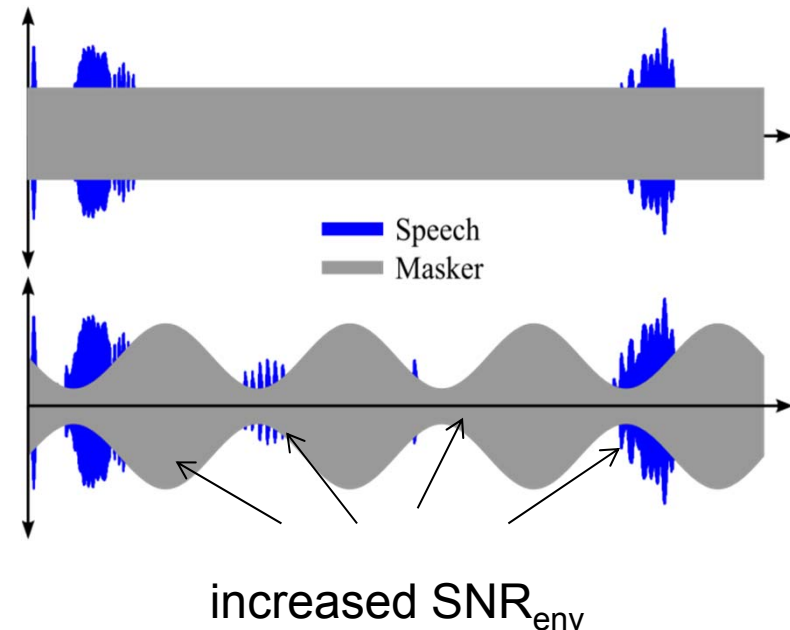
Festen and Plomp (1990)



Speech perception in **fluctuating noise** enhanced compared to a stationary noise interferer

Large **masking release (MR)** observed due to the ability to "listen in the dips".

Speech masking release

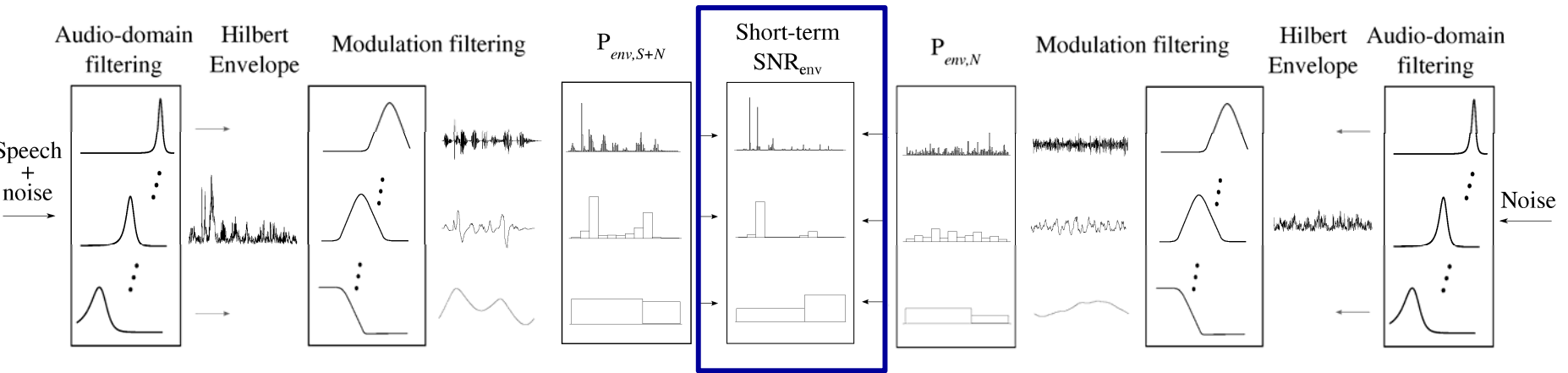


Hypothesis: The **SNR_{env}** might be increased in the dips.

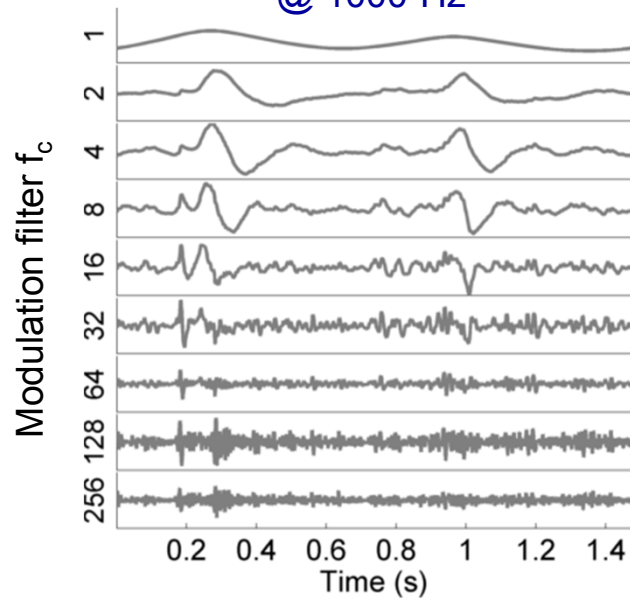
"Short-term" **SNR_{env}** calculation required



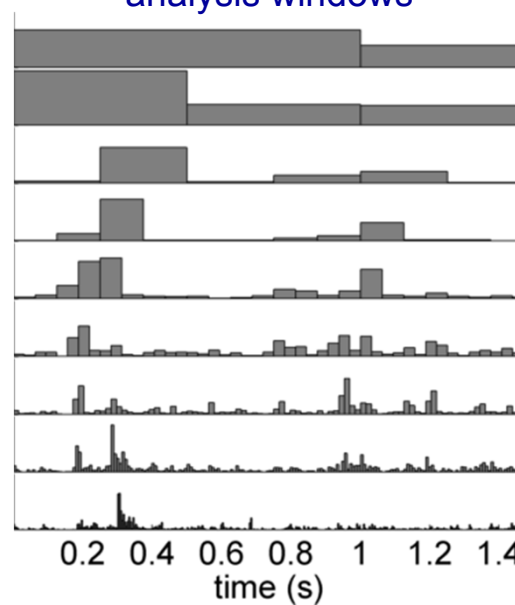
“Multi-resolution” sEPSM



Internal representation
@ 1000-Hz



Channel-dependent
analysis windows



(Jørgensen, Ewert and Dau)
JASA 2013

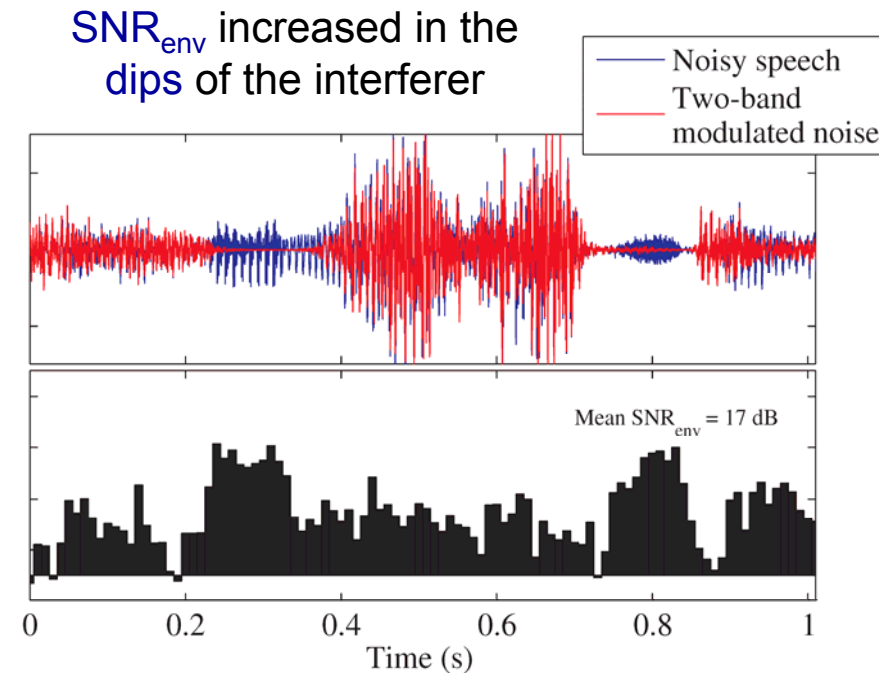
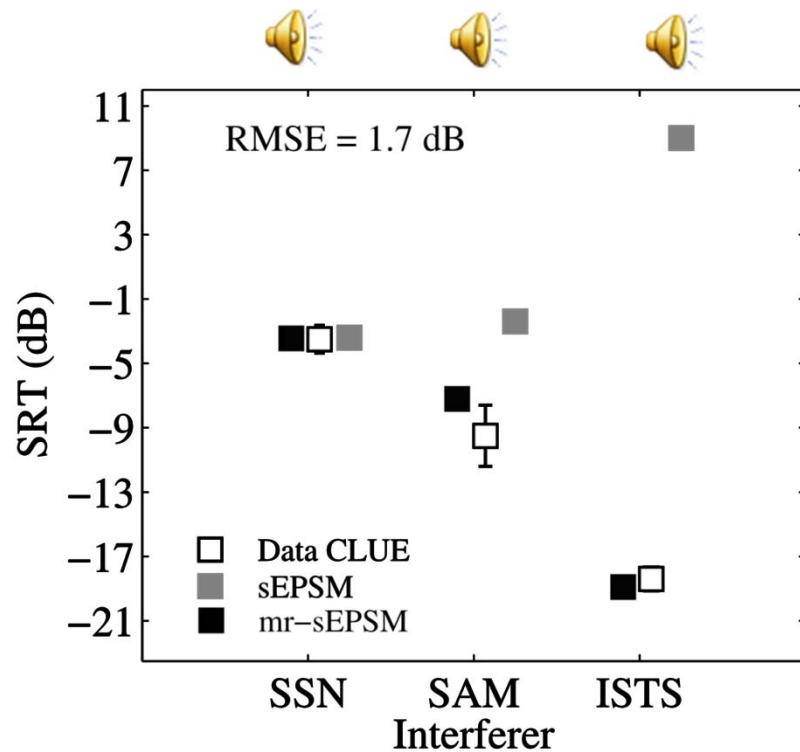
Envelope power
calculation

$$\text{(with } \tau \sim \frac{1}{\Delta f} \text{)}$$



Modulated-noise and speech-like interferers

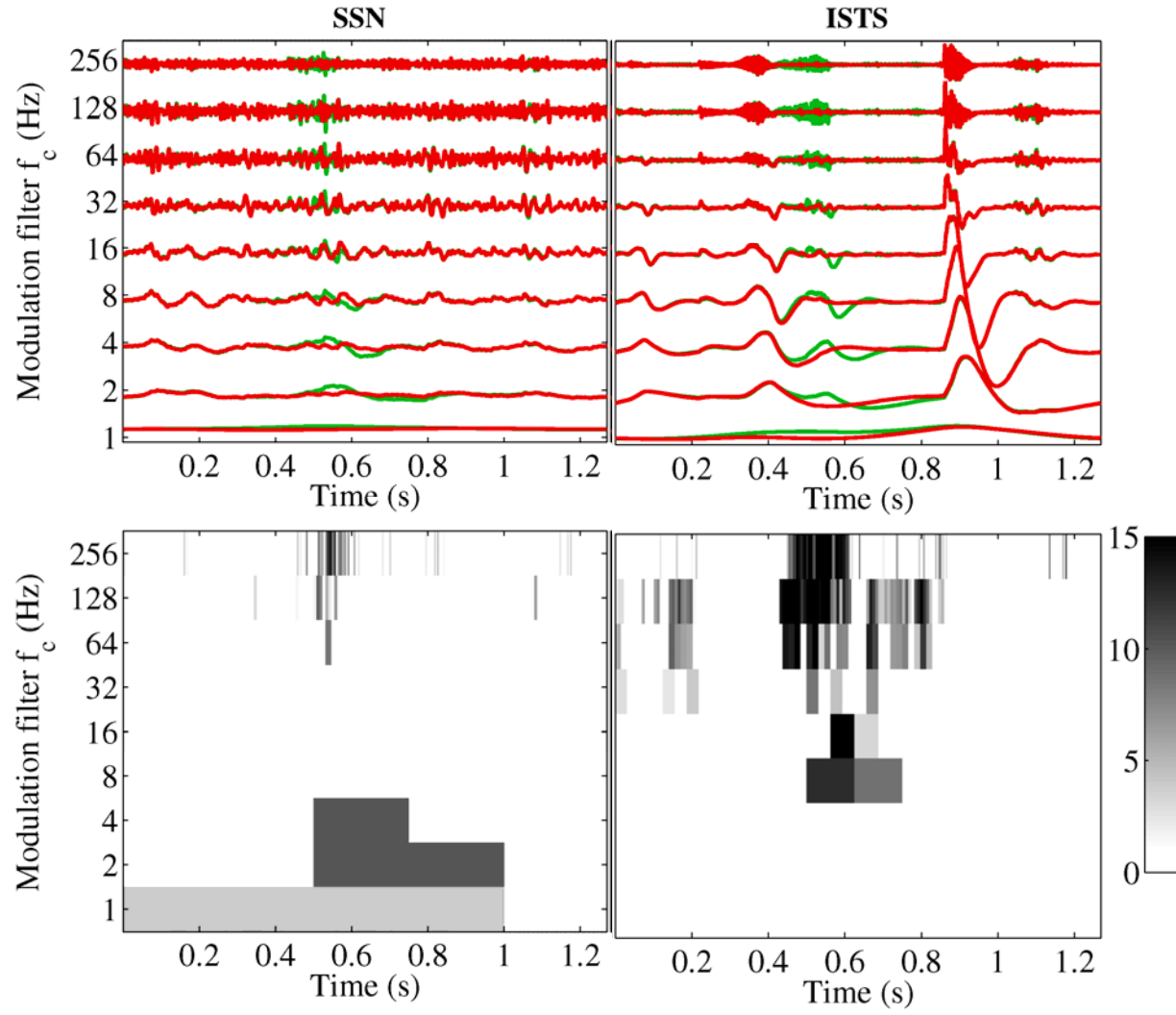
- Three conditions: **SSN** - as the stationary reference condition
SAM - 8-Hz modulated noise (e.g., Festen, 1987)
ISTS - International speech test signal (Holube *et al.*, 2010).



In fact, the **simulations suggest** that **high-frequency modulations** (>30 Hz) contribute effectively to speech intelligibility in the case of the **SAM** and **ISTS** interferers.



The role of fast modulations



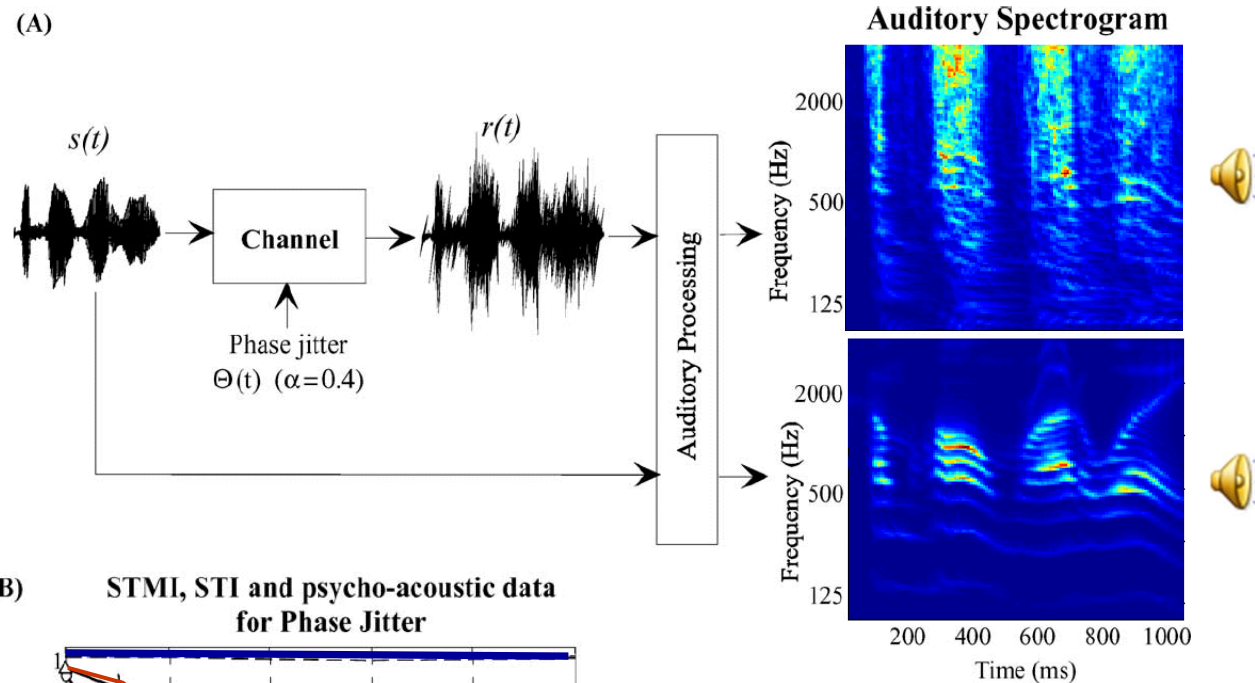
Model-output from audio-filter @1 kHz



Another challenge: Phase jitter (nonlinear) distortion

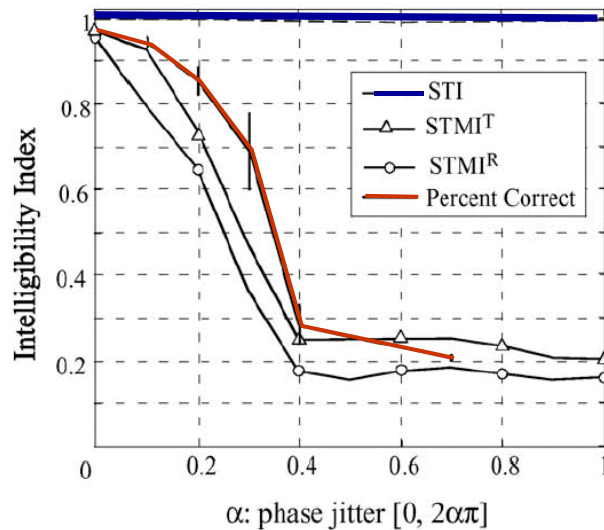


(A)



Elhilali *et al.*
(2003)

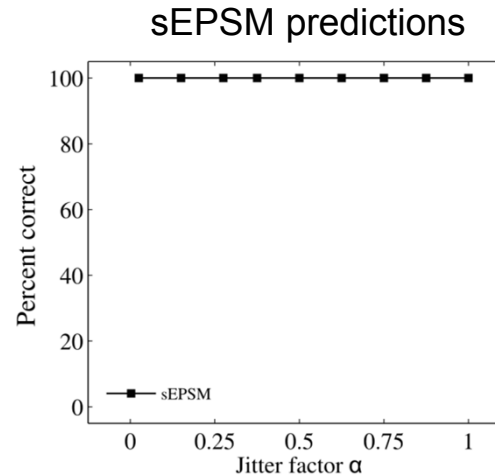
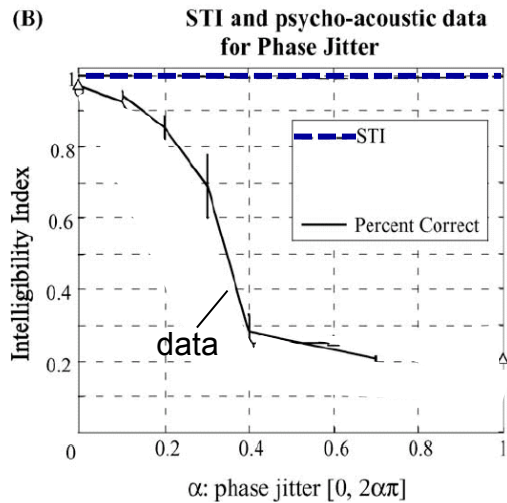
(B) STMI, STI and psycho-acoustic data
for Phase Jitter



- Temporal modulations appear not to be sufficient.
- Spectro-temporal modulation index (STMI) was defined to account for the degraded spectral (ripple) representation.



Phase jitter distortion



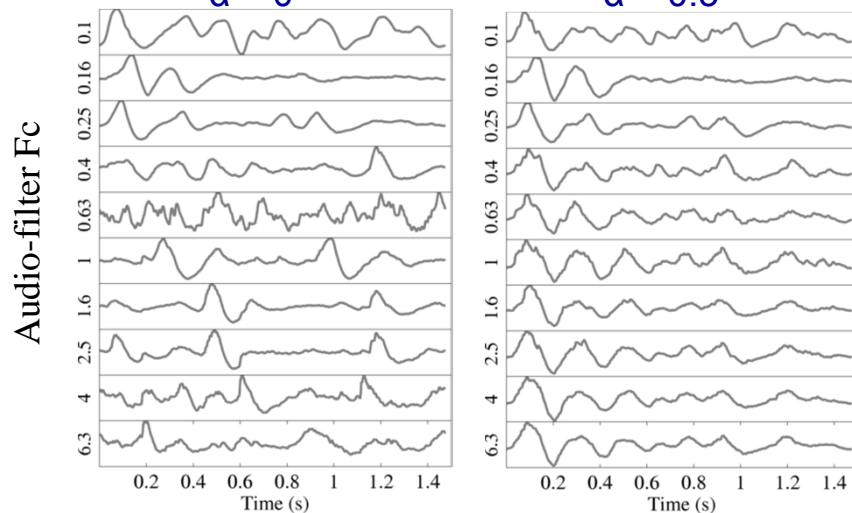
As the STI, the sEPSM fails in this condition.

Both models are insensitive to across-frequency distortions

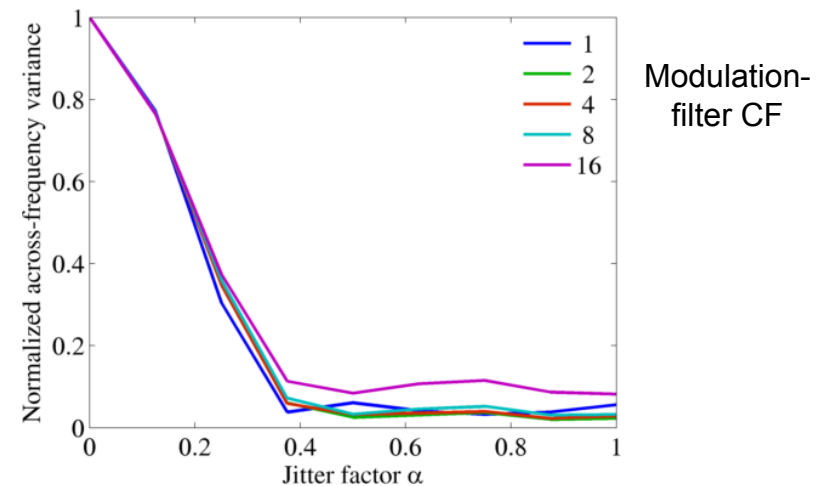
Internal representation at output of 4-Hz modulation filter

$\alpha = 0$

$\alpha = 0.5$



⇒ Across audio-frequency variance decreases with increasing phase jitter

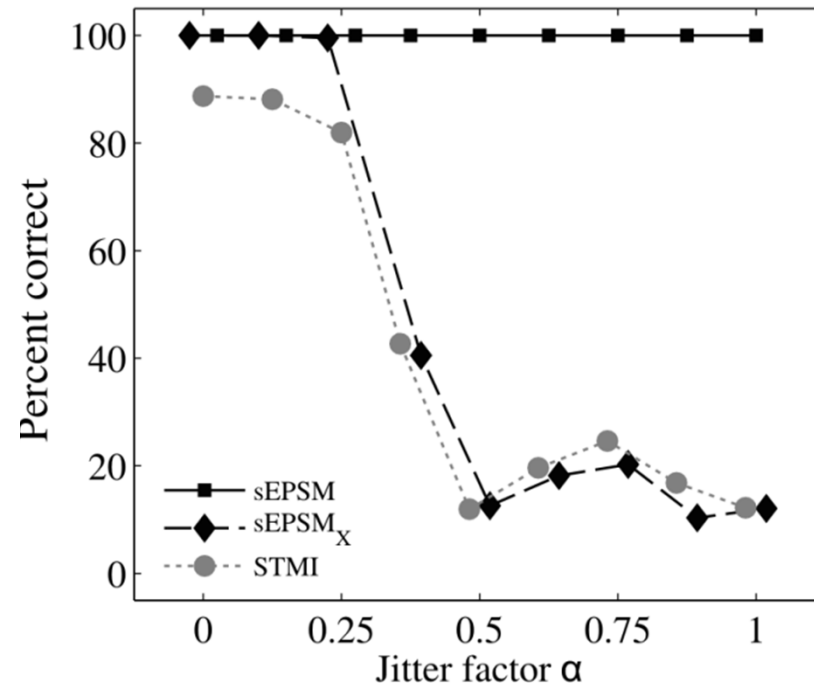




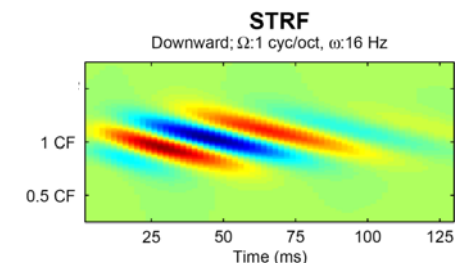
Across-frequency variance

Weighing of SNR_{env} by across-channel variance (Chabot-Leclerc *et al.*, 2015):

- ⇒ sEPSM_x predictions (incl. weighting) provide **good agreement** with measured data
- ⇒ **Similar** results as with **STMI** predictions by Elhilali *et al.* (2003)



- Conceptually **related to correlation** of neural activity **across sensory channels** that has been proposed in connection to auditory **streaming** (Elhilali *et al.*, 2009) and **CMR** (Piechowiak *et al.*, 2007).
- **Different from STRF** concept on which STMI is based.





Recent focus points



Current focus:

- Expansion towards two ears: Prediction of **spatial release from masking** due to "true" binaural unmasking vs "better-ear" listening (Chabot-Leclerc *et al.*, 2016).
- Combination of modulation-based preprocessing with **correlation-based decision metric** (Iborra *et al.*, 2017). (Back to the template-matching approach)?
- Prediction of consequences of **hearing loss** on speech intelligibility (e.g., consequences of **IHC** vs. **OHC** loss).
- Analysis of "**distortion vs attenuation**" component of a hearing loss (Plomp, 1986) in a modeling framework.
- ...

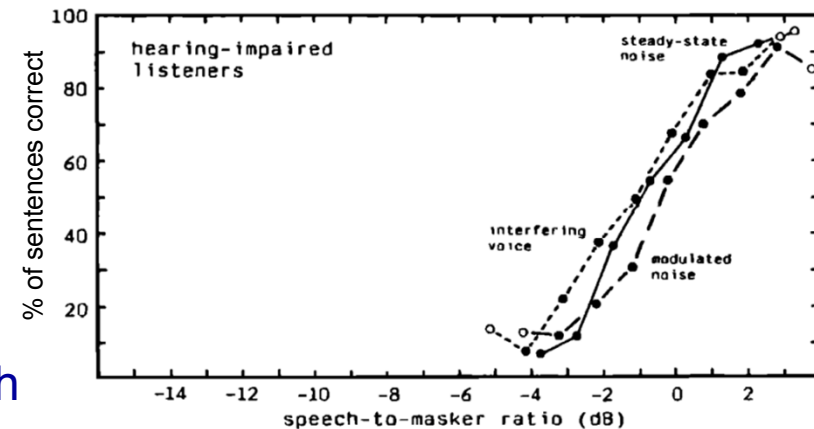


Implications and applications

Hearing-impaired listeners often show **highly reduced** speech masking release.

Fast envelope fluctuations may be inaudible or distorted.

Interesting input for **models of impaired speech perception** and the **evaluation** of hearing aids.



Festen and Plomp (1993)

The model is based on the concept of **modulation masking**. It even accounts for conditions with **interfering** talkers – often associated with “informational masking”.

However, the **model fails** if it does not have *a priori* **information** about the signal and the masker. It **cannot** provide stream segregation.

Unfortunately, **stream segregation** is one of the major challenges of **hearing-impaired** people.



HEARING SYSTEMS

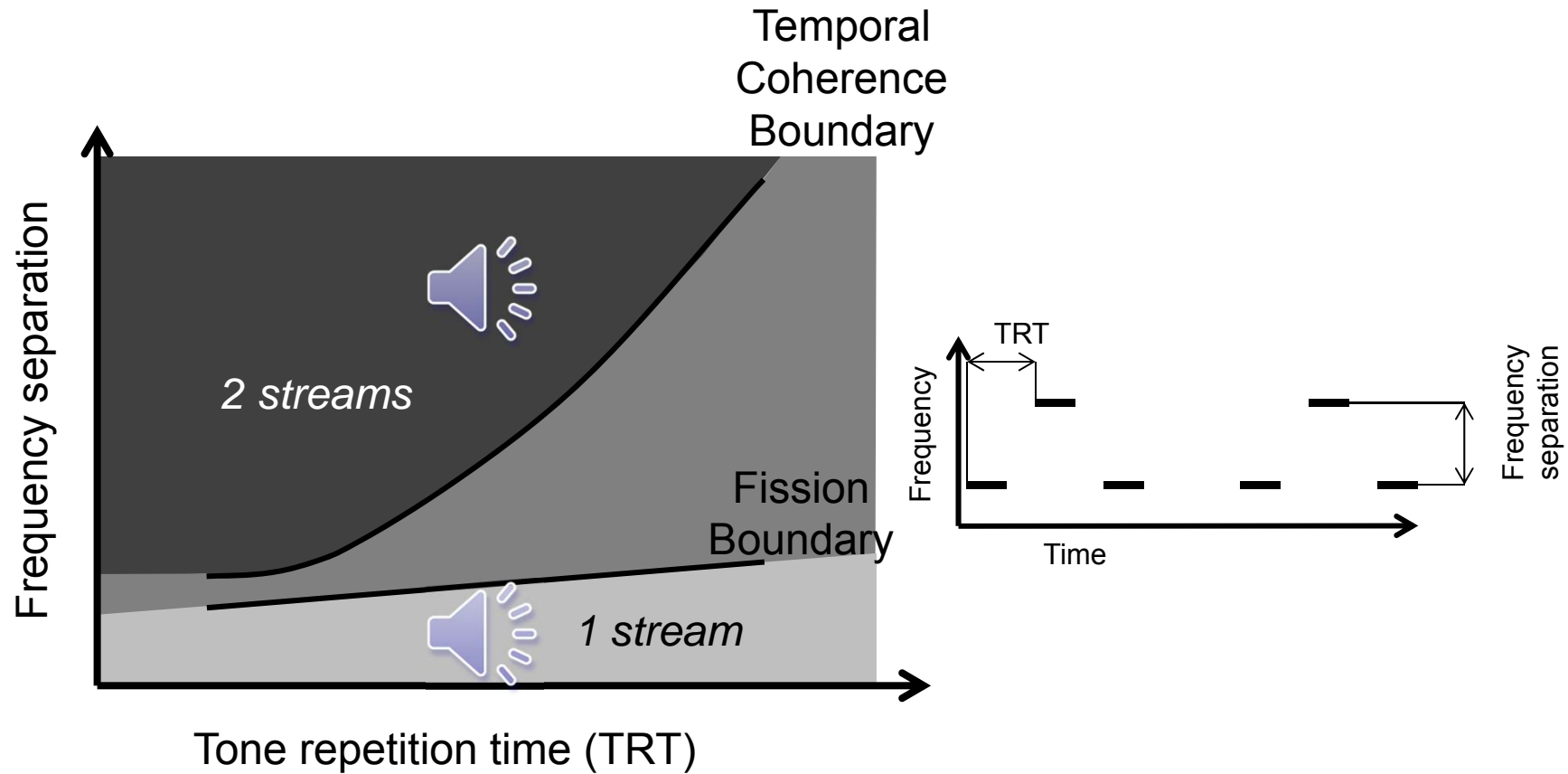
Towards a model of stream segregation





HEARING SYSTEMS

Example of stream segregation due to frequency separation



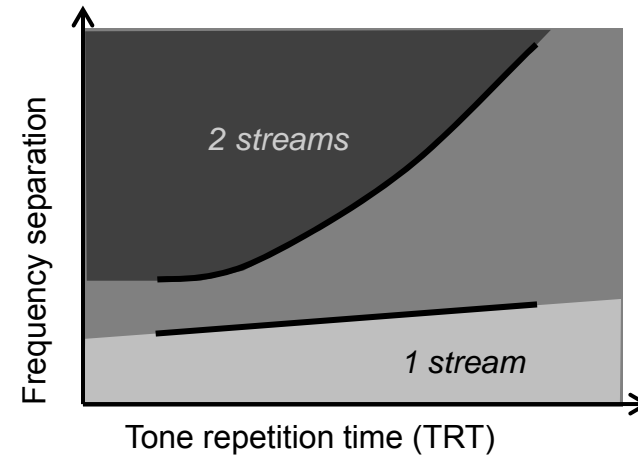
(van Noorden, 1975)



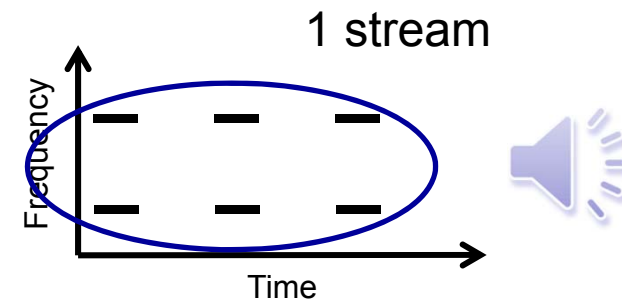
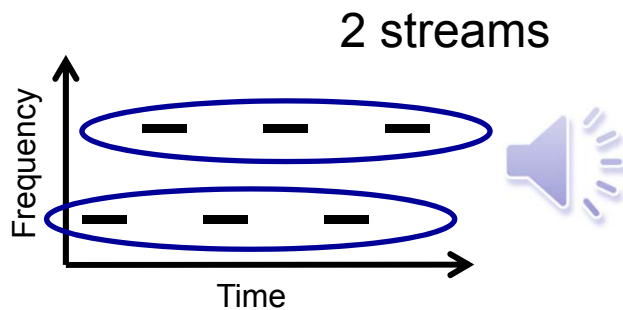
Grouping due to synchrony



- Tones with a sufficiently large frequency separation **always** split into **separate streams** (van Noorden, 1975).
- Unless the tones are **synchronized!** Then they merge into a **single stream** despite tonotopic separation (Bregman, 1990; Elhilali *et al.*, 2009).



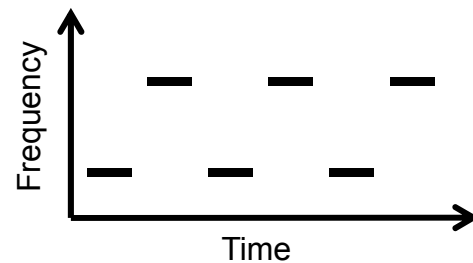
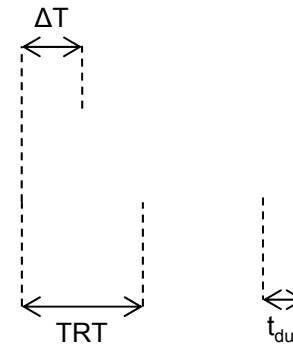
(van Noorden, 1975)





Grouping due to synchrony

- How strict is the "synchrony" grouping mechanism?
- Can the tones be slightly asynchronous ($\Delta T \neq 0$) and still be fused?
- Experiment investigating the influence of:
 - Tone repetition time (TRT)
 - Tone duration (t_{dur})

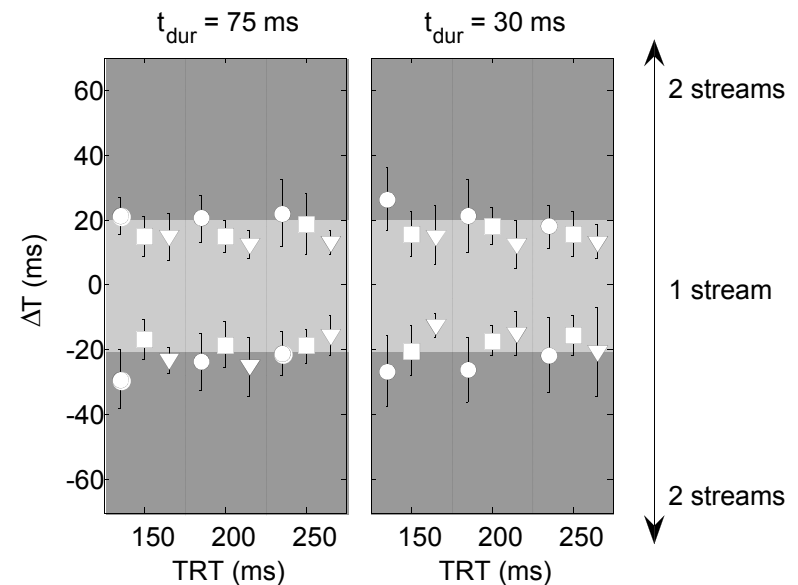
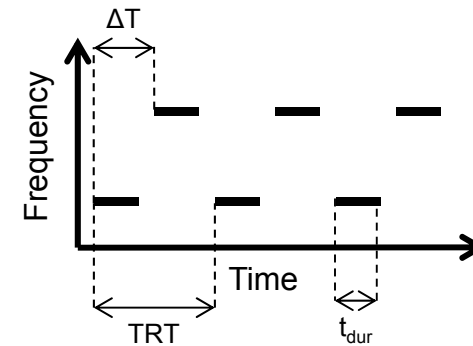




Grouping due to synchrony

Results:

- The tones *can* fuse together without perfect synchrony ($\Delta T = 0$).
- Fusion occurs if the asynchrony is less than ~ 20 ms.
- No significant effect of TRT and t_{dur} .



(Christiansen *et al.*, 2014; JASA)

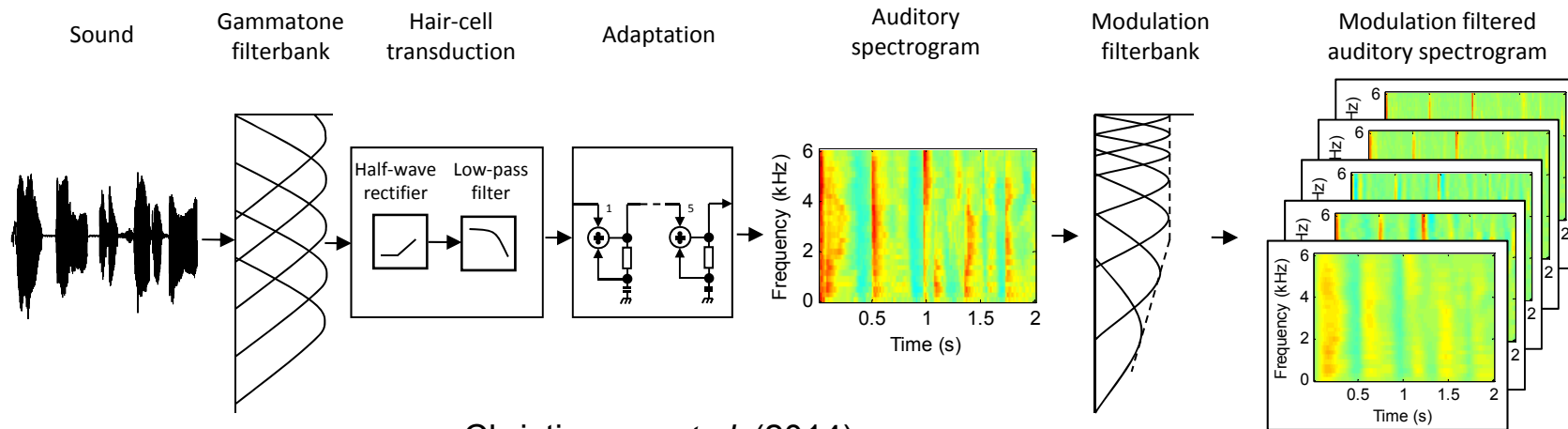


Modelling auditory stream segregation



Step 1: **Decomposition** of acoustic stimuli into a collection of **sensory elements** (following the concepts of Bregman, 1990):

- Using a physiologically inspired model of the auditory periphery, **CASP** (e.g., Dau *et al.*, 1997).



Christiansen *et al.* (2014)

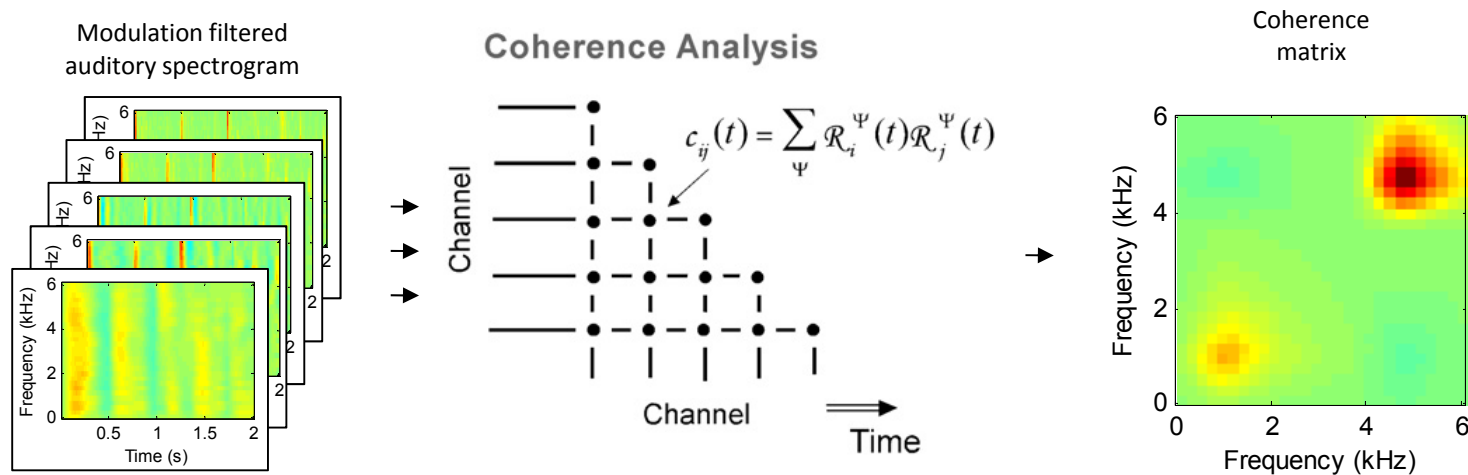
- The model has earlier been evaluated in various conditions of **spectro-temporal masking** in the auditory system.



Modelling auditory stream segregation

Step 2: Grouping of sensory elements:

- Based on **synchrony of neural activity** (including conditions with distant spectral components).
- Utilizing a correlation process **across tonotopic channels**, e.g., a **"temporal coherence analysis"** similar to Elhilali *et al.* (2009).



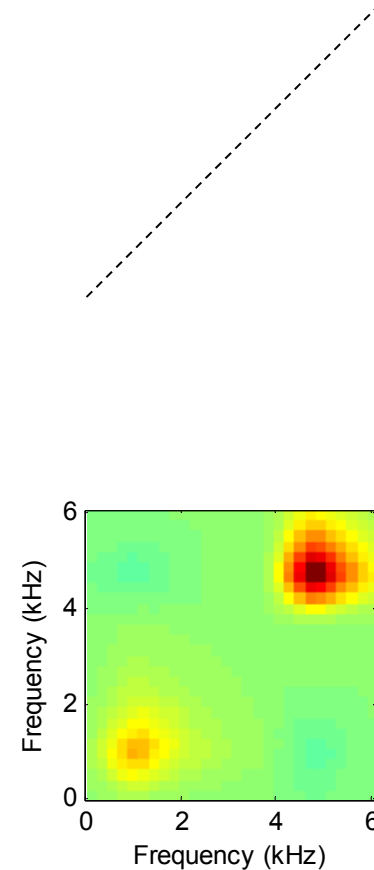
- Correlation between **each pair** of frequency channels \Rightarrow **Dynamic coherence matrix C** that evolves over time.



Analysis of model output



- **Diagonal entries** of the matrix shows the correlation of a given peripheral channel with itself.
- **Off-diagonal entries** reflect correlation across separate channels.
- To quantify the coherence matrix, **an eigenvalue decomposition** is performed.
- The ratio of the second largest to the largest eigenvalue (λ_2/λ_1) shows the **strength of the "two-stream percept"**.

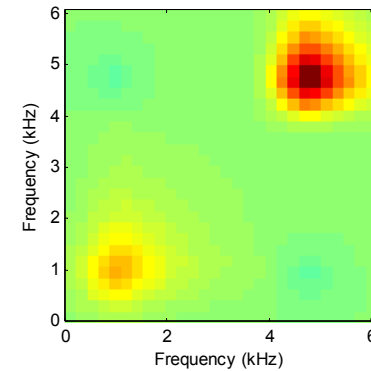
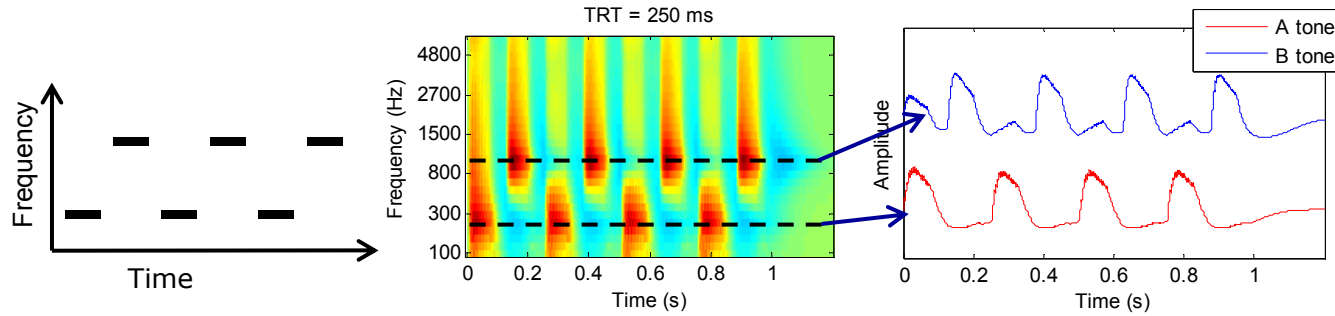


$$\frac{\lambda_2}{\lambda_1} \approx 0 \quad \Rightarrow \text{Only } 1 \text{ stream}$$

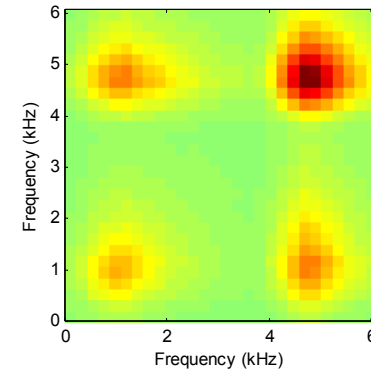
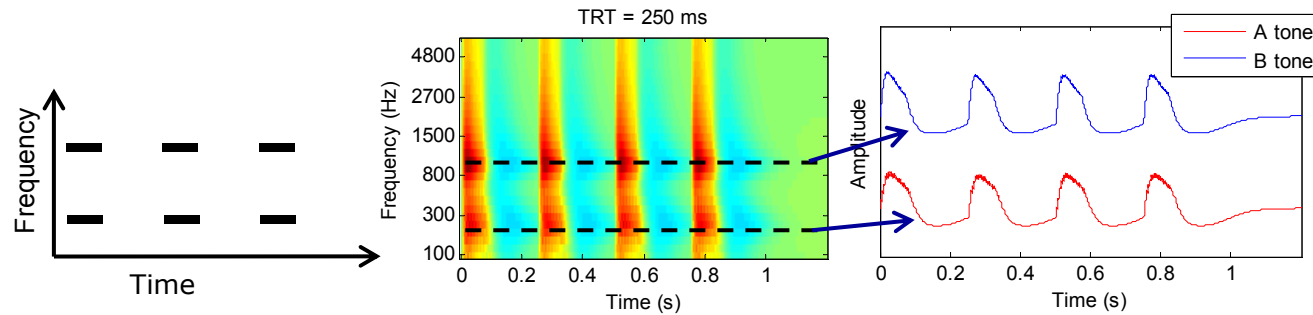
$$\frac{\lambda_2}{\lambda_1} \gg 0 \quad \Rightarrow \text{At least } 2 \text{ streams}$$



Synchrony simulation



$$\frac{\lambda_2}{\lambda_1} \approx 0.46 \gg 0 \quad \Rightarrow 2 \text{ streams}$$



$$\frac{\lambda_2}{\lambda_1} \approx 0.08 \approx 0 \quad \Rightarrow 1 \text{ stream}$$

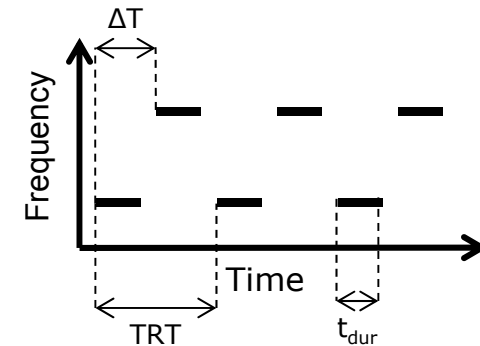


Synchrony simulation

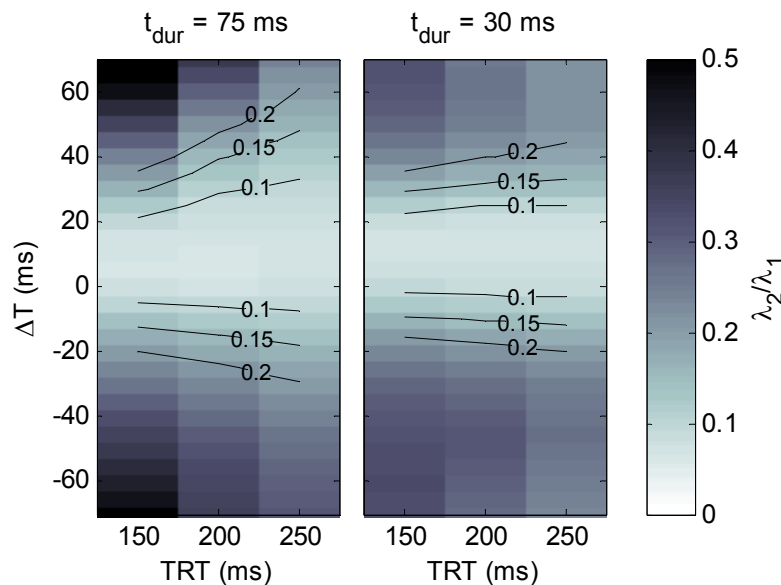


Applying the model on the same experimental setup as used in the psychoacoustic experiment:

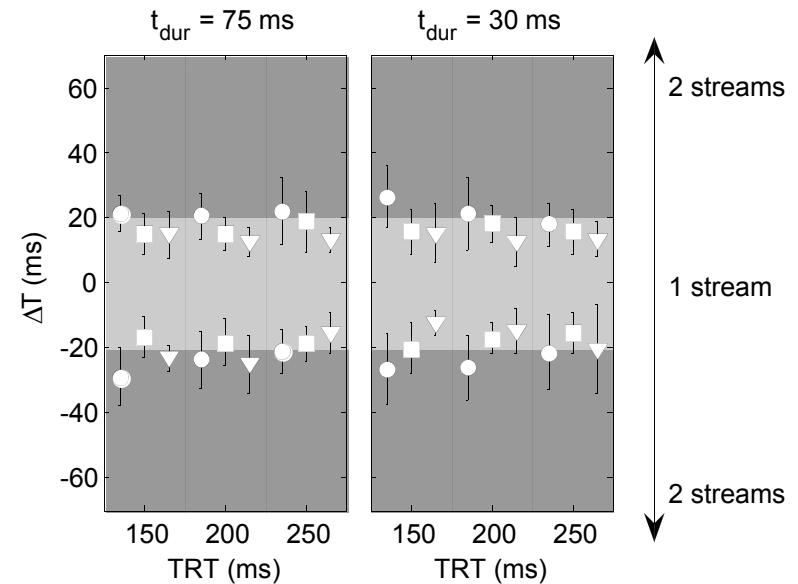
- Similar overall behaviour
- However, the model shows some dependency on TRT



Model



Data



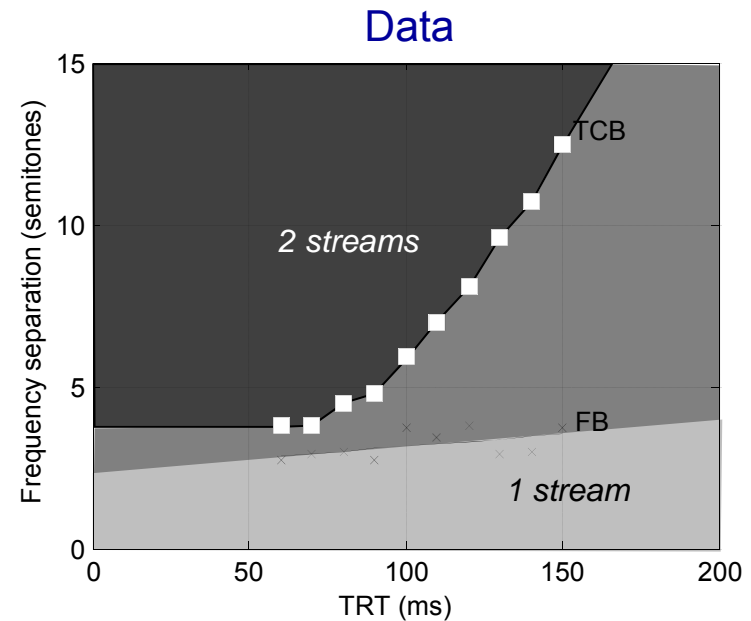
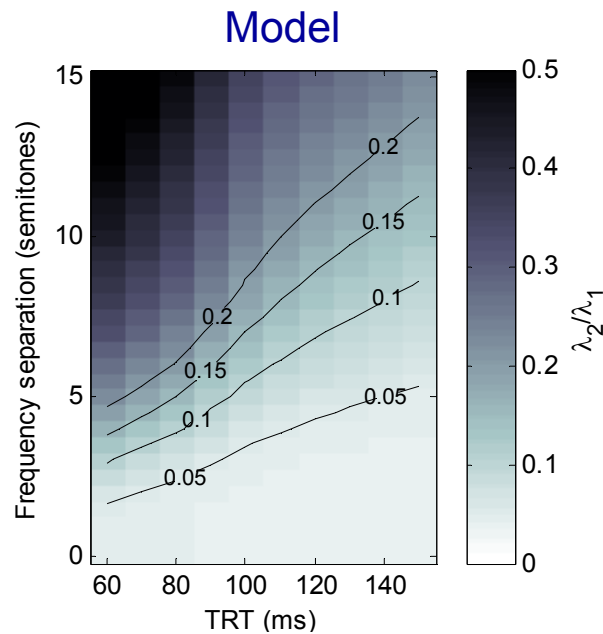
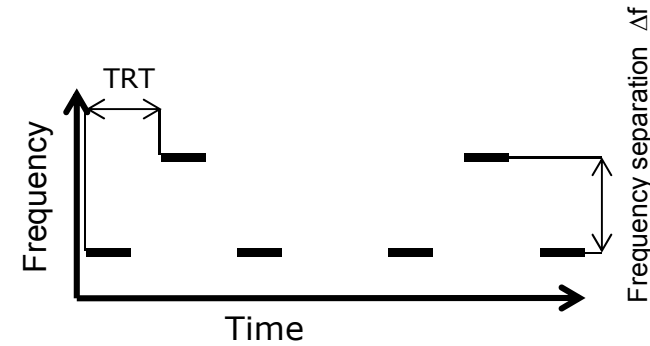


Van Noorden simulation



Applying the model to the **classical van Noorden stimuli**:

⇒ Model accounts for the dependency of segregation/fusion on TRT and Δf .



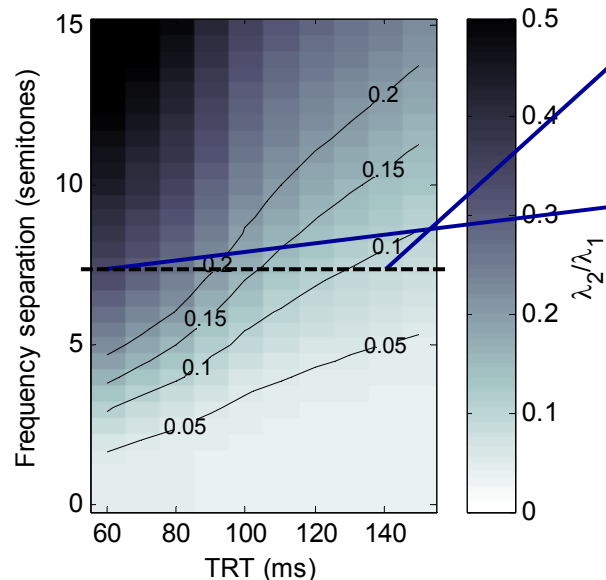
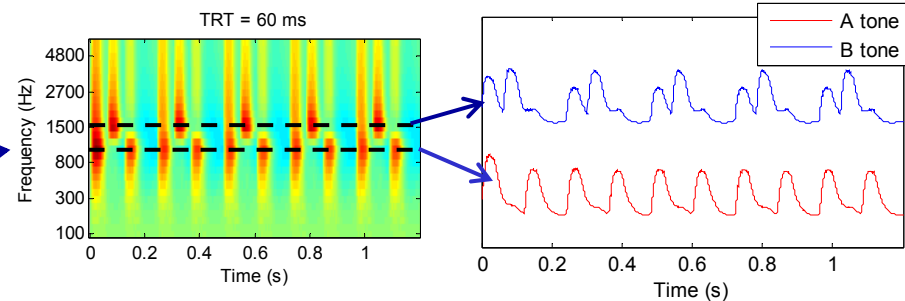
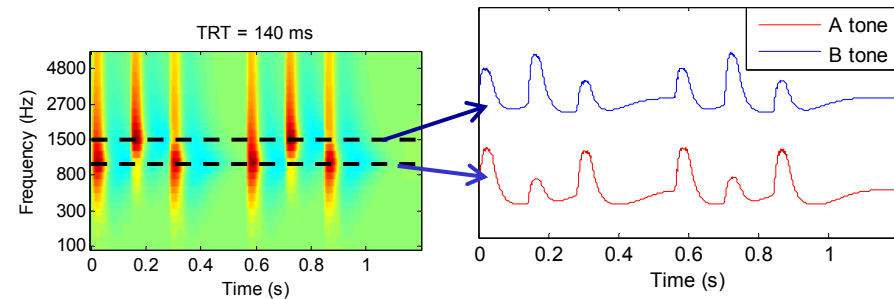
(Christiansen *et al.*, 2014; JASA)



Van Noorden simulation



- Spread of excitation causes a high cross-frequency correlation
- For short TRTs: forward masking reduces spread of excitation
 - reduced cross-frequency correlation



Consistent with physiological studies (e.g., Bee and Klump, 2005).



Implications and applications



- Temporal **coherence** may be the organizing principle behind primitive stream segregation.
- However, this requires an **appropriate preprocessing** (i.e., realistic **frequency-selective filtering** in the cochlea; an **adaptive** process accounting for forward masking and onset enhancement, and a **modulation filterbank**).
- The concept of coherence may be **generalizable to other sensory channels** (e.g., binaural processing).
- A **model** of auditory stream segregation might be useful for:
 - **Source separation** algorithms (ideally performing as well as NH listeners)
 - Classification of the **number of sources** in complex acoustic scenes
 - **Evaluation** of **hearing-aid** processing (e.g., does the processing “corrupt” acoustic cues necessary for stream segregation?)



Overall discussion



- Modeling can be helpful to **test specific hypotheses**. It allows to quantify the effects of individual components in the framework.
- The presented examples have highlighted several **features** that seem important for **robust auditory signal analysis**.
- Despite the different methods and "outcome measures" illustrated here, **similar features** and processes were found to be **essential**.
- Combination of approaches might be interesting; e.g. to model **target-interferer confusion** in stream segregation could help interpret the **speech-in-noise** problem for the hearing impaired.
- Some of the model insights might be useful for **applications**:
 - mostly regarding **objective evaluations** of the effects of hearing-instrument processing ("analysis approach").
 - and maybe less in terms of **applying** the **signal-processing** directly in compensation strategies