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Applying Intelligibility and Quality Metrics to Noisy Speech, Noise Suppression, and Hearing Aids

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Hearing-Aid Processing

- Typical hearing-aid design
  - Multichannel filterbank
  - Time-varying gain adjustments in each frequency band
  - Gain can improve audibility, but amplitude modulation introduces nonlinear distortion
- Metrics measure signal changes
  - Envelope important for speech intelligibility and quality
  - Determine degree to which envelope is modified
  - Can also add other signal features: TFS, spectral change
  - Want interaction of all hearing-aid signal processing algorithms
  - Context of the auditory periphery and hearing loss

Quantitative Metrics

- Intrusive
  - Compare degraded signal to clean reference
  - Any change in the degraded signal is considered detrimental
  - Degradation includes effects of processing and auditory threshold
- Non-intrusive
  - Uses degraded signal alone
  - Requires machine model of perception
- This presentation deals with intrusive metrics
  - Hearing Aid Speech Perception Index (HASPI): intelligibility
  - Hearing Aid Speech Quality Index (HASQI): speech quality

Metric Construction

- Components
  - Model of the auditory periphery
  - Speech feature extraction
  - Map features to human subject data
- Training data
  - Metric tied to the speech materials and signal degradations used to train it
  - Sentences different mapping than keywords correct
  - Low data-rate codecs differ from additive noise
  - Extrapolating beyond the training data may be inaccurate

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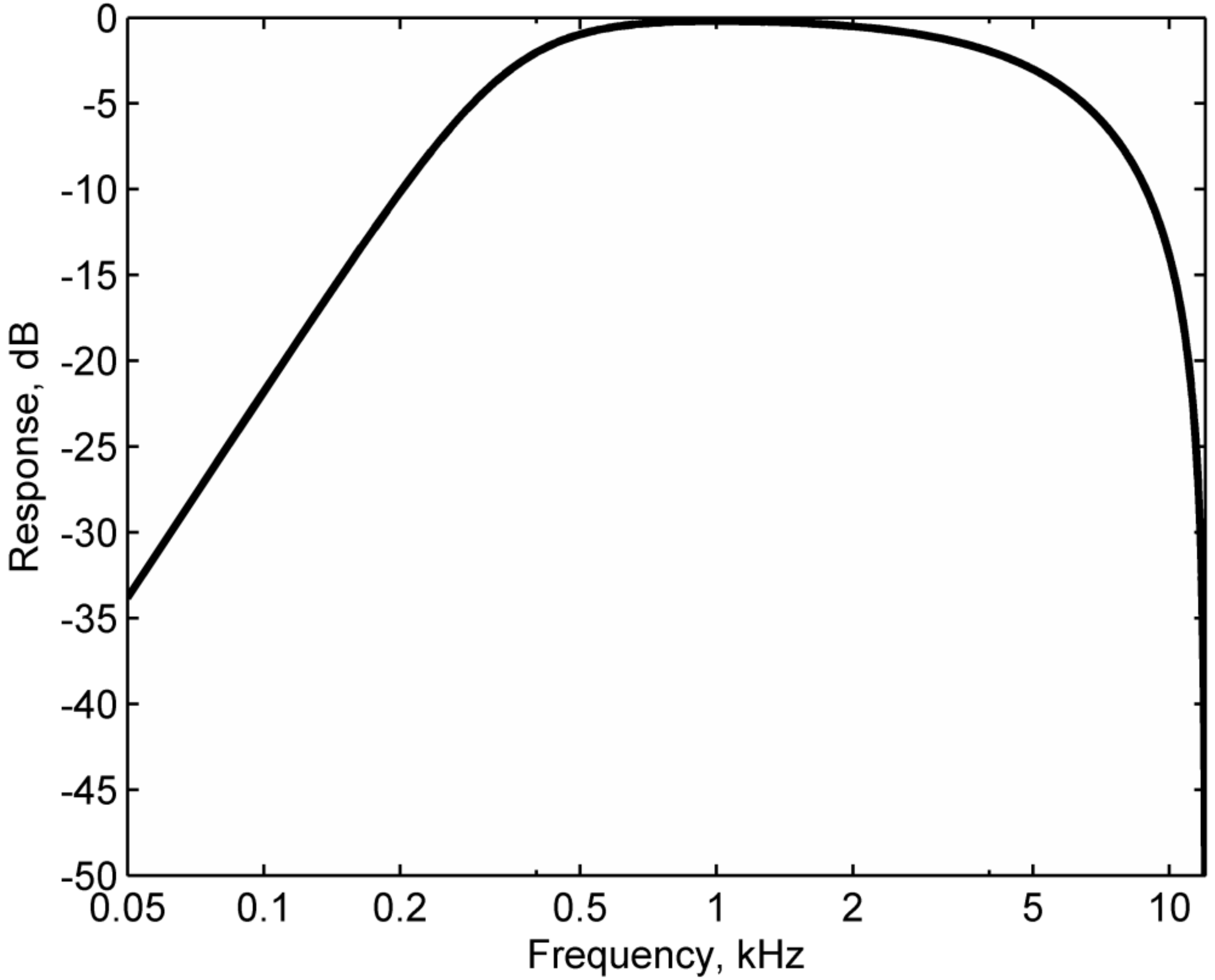
HASPI and HASQI Auditory Model

Model of the Auditory Periphery

- Resample signal at 24 kHz
- Middle ear bandpass filter 350 to 5000 Hz
- Auditory filterbank
  - 32 gammatone filters from 80 to 8000 Hz
  - Bandwidth depends on hearing loss and signal level
- Outer hair cell (OHC) dynamic-range compression
  - Compression ratio decreases with increasing OHC damage
  - Shift in auditory threshold
- Inner hair cell (IHC) neural firing rate adaptation
  - Rapid (2 ms) and short-term (60 ms) adaptation
  - IHC damage gives additional threshold shift

(Kates, 2013)

Middle Ear Filter



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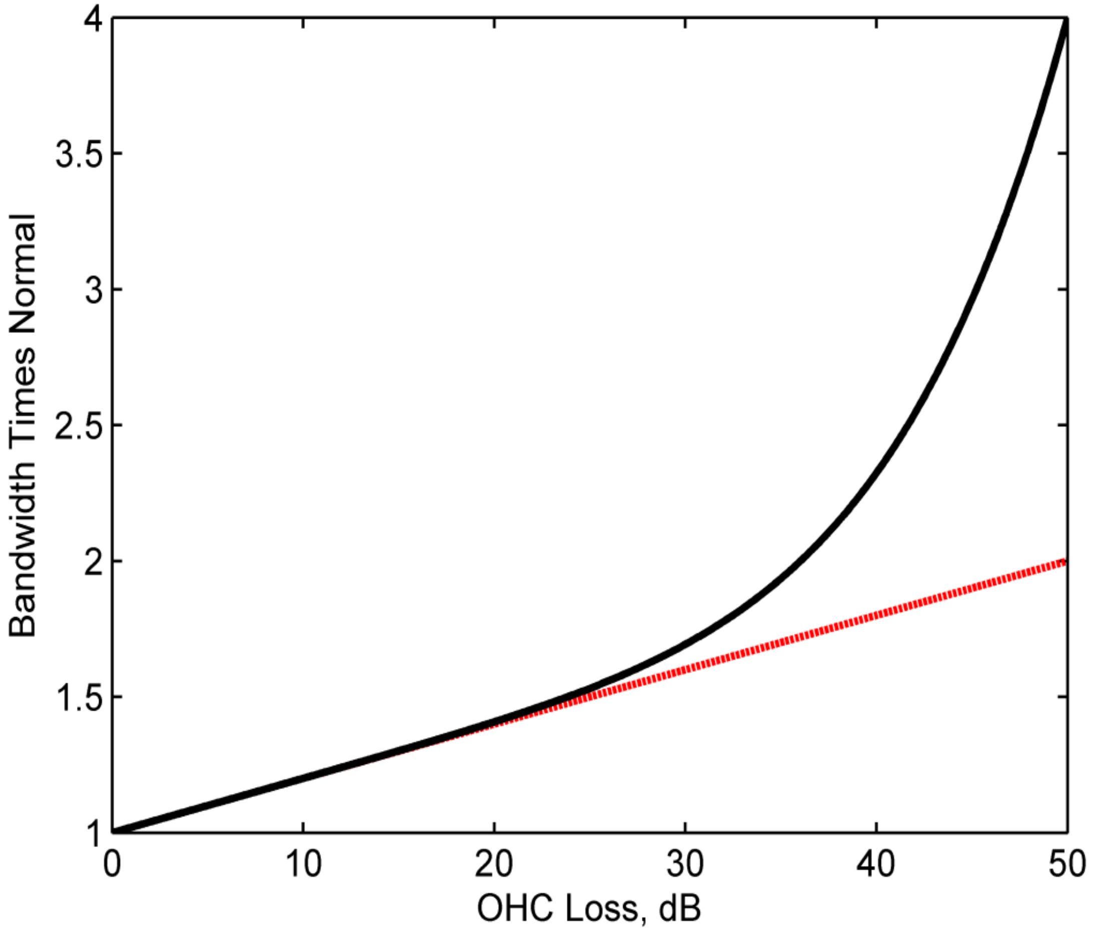
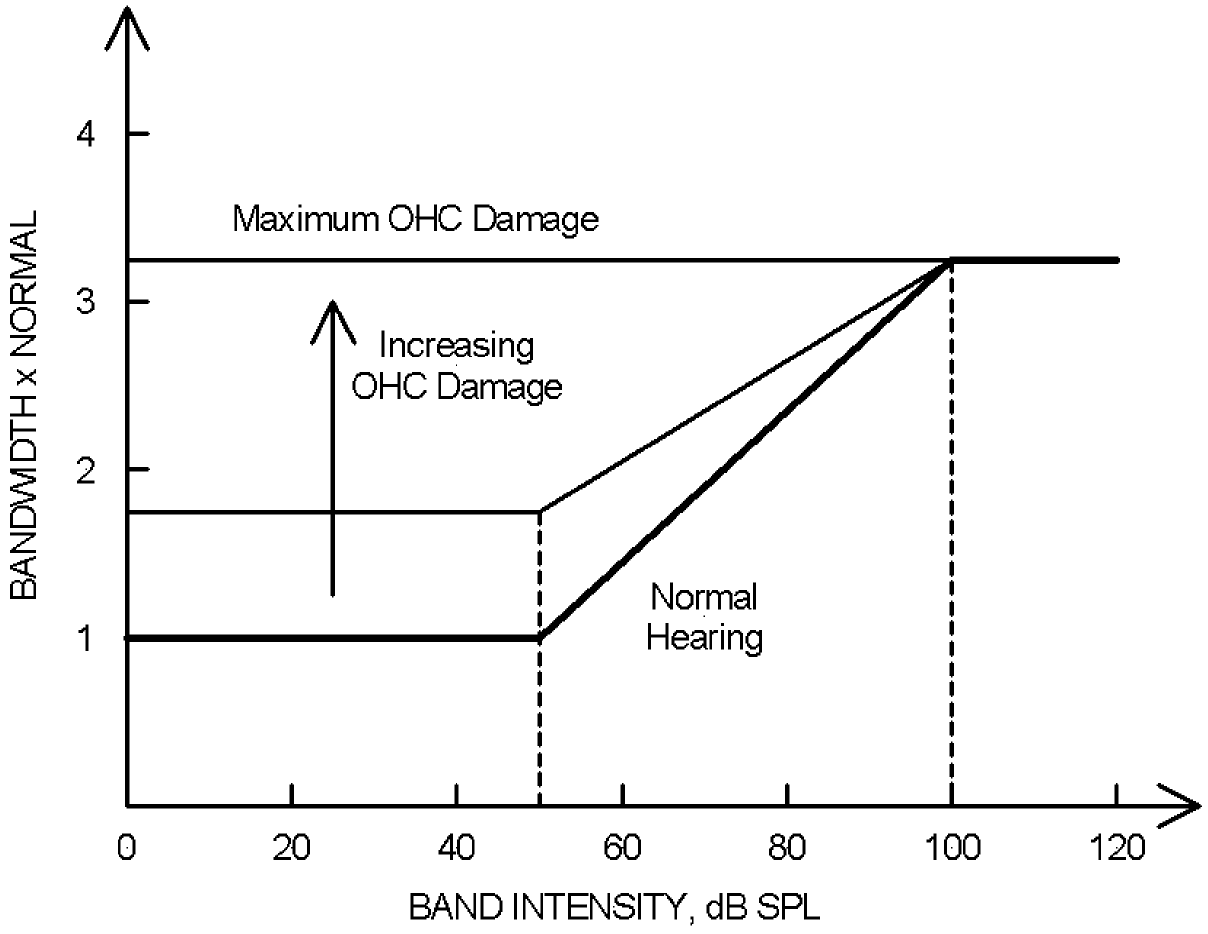
Auditory Filter Bandwidth



Signal Intensity



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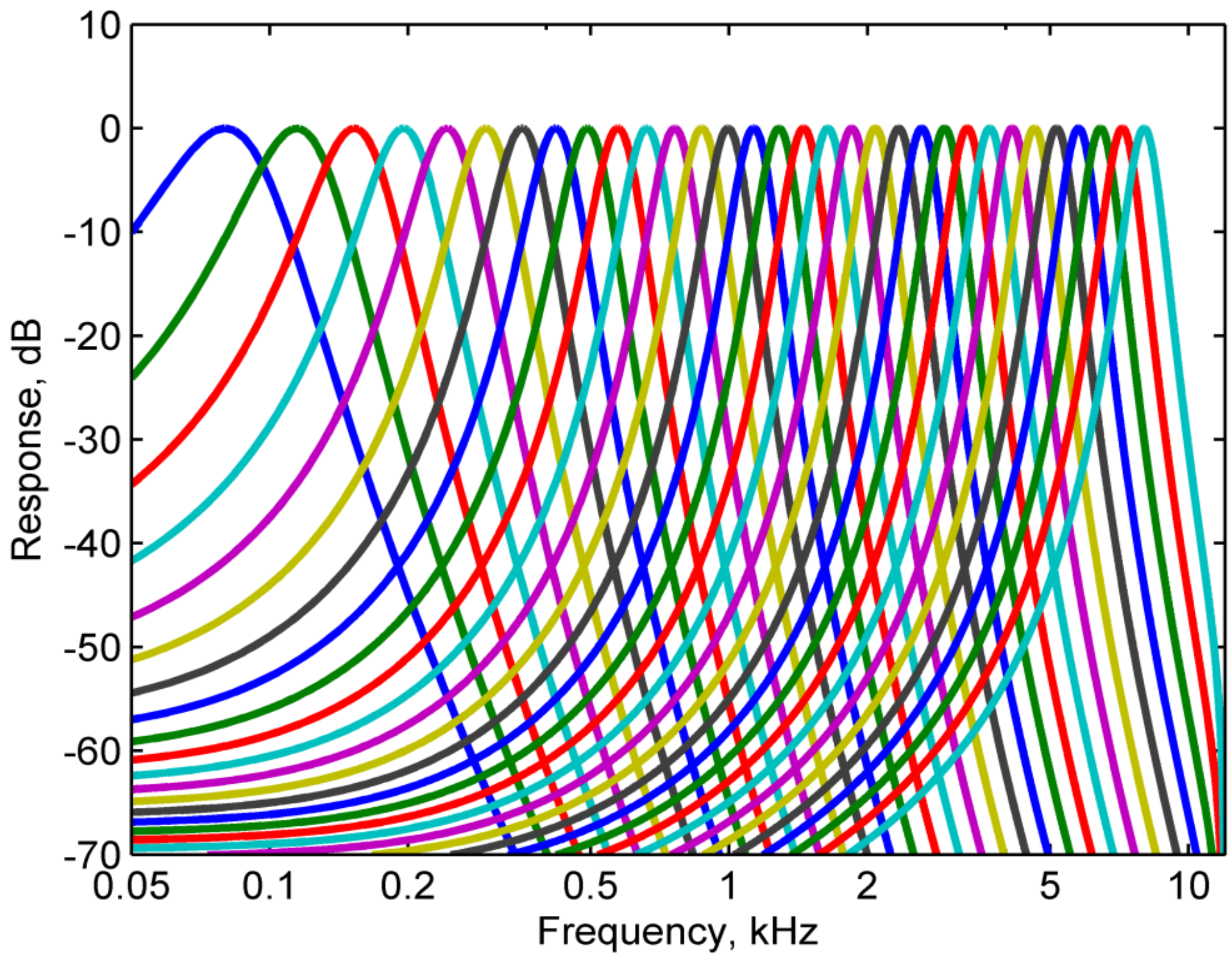
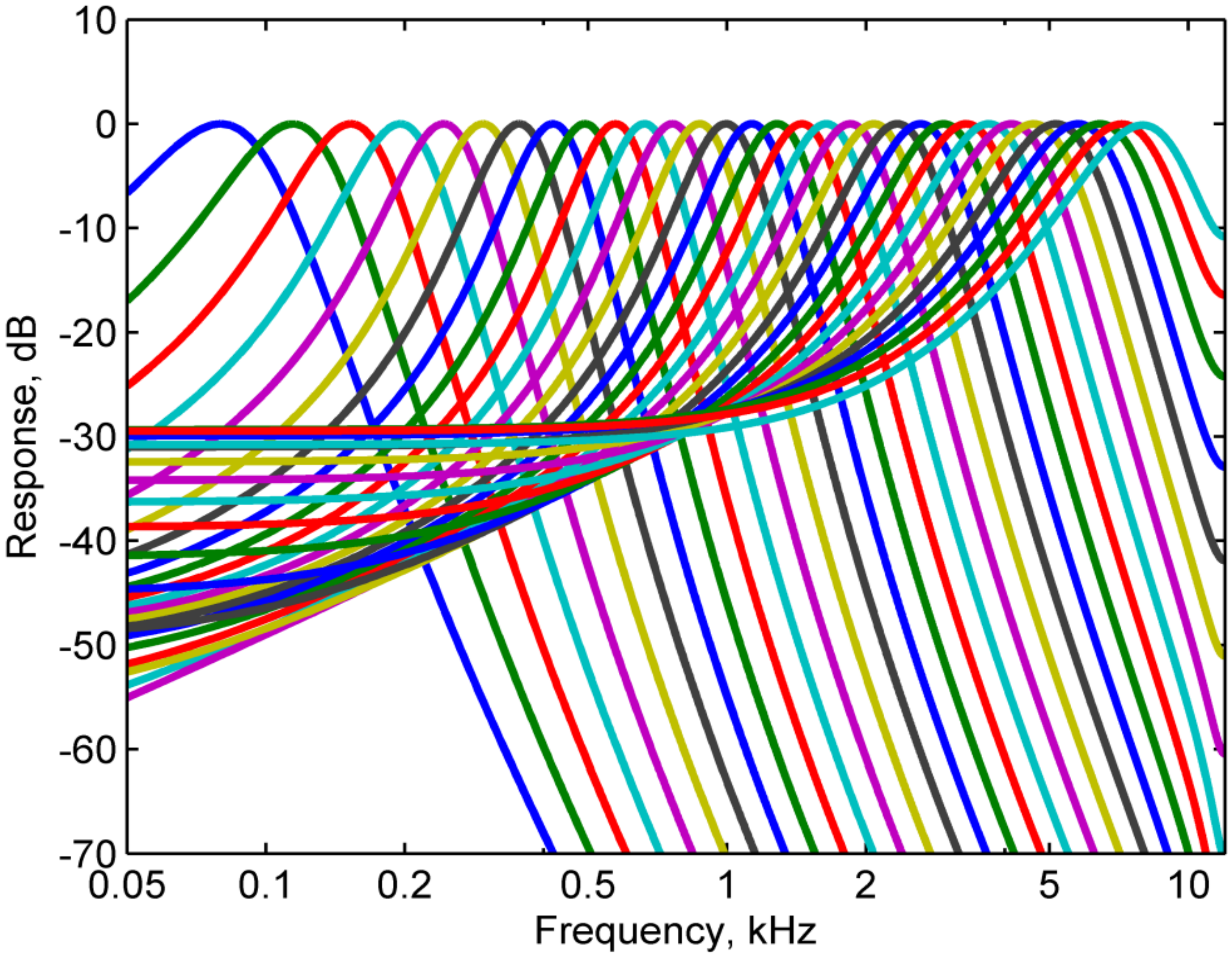
Gammatone Filters: Normal Hearing



Gammatone Filters: Max OHC Damage



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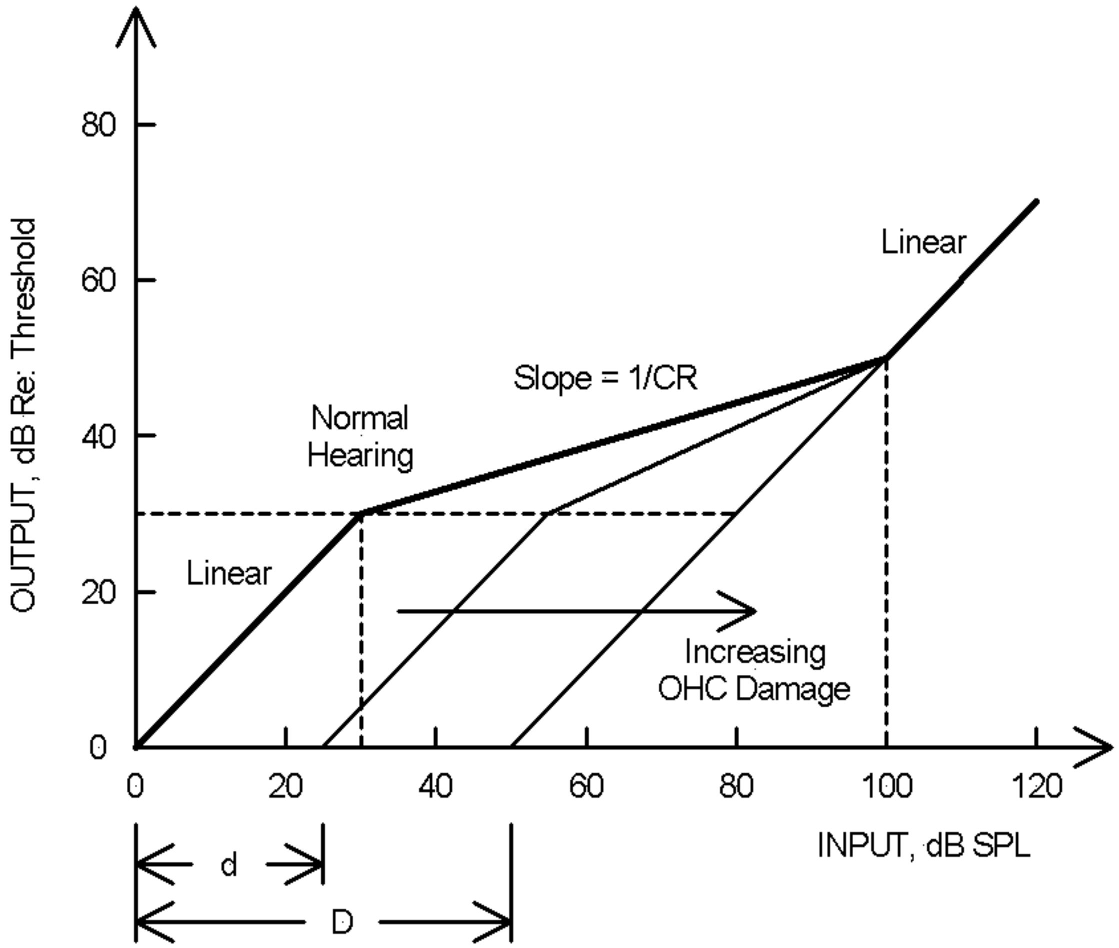
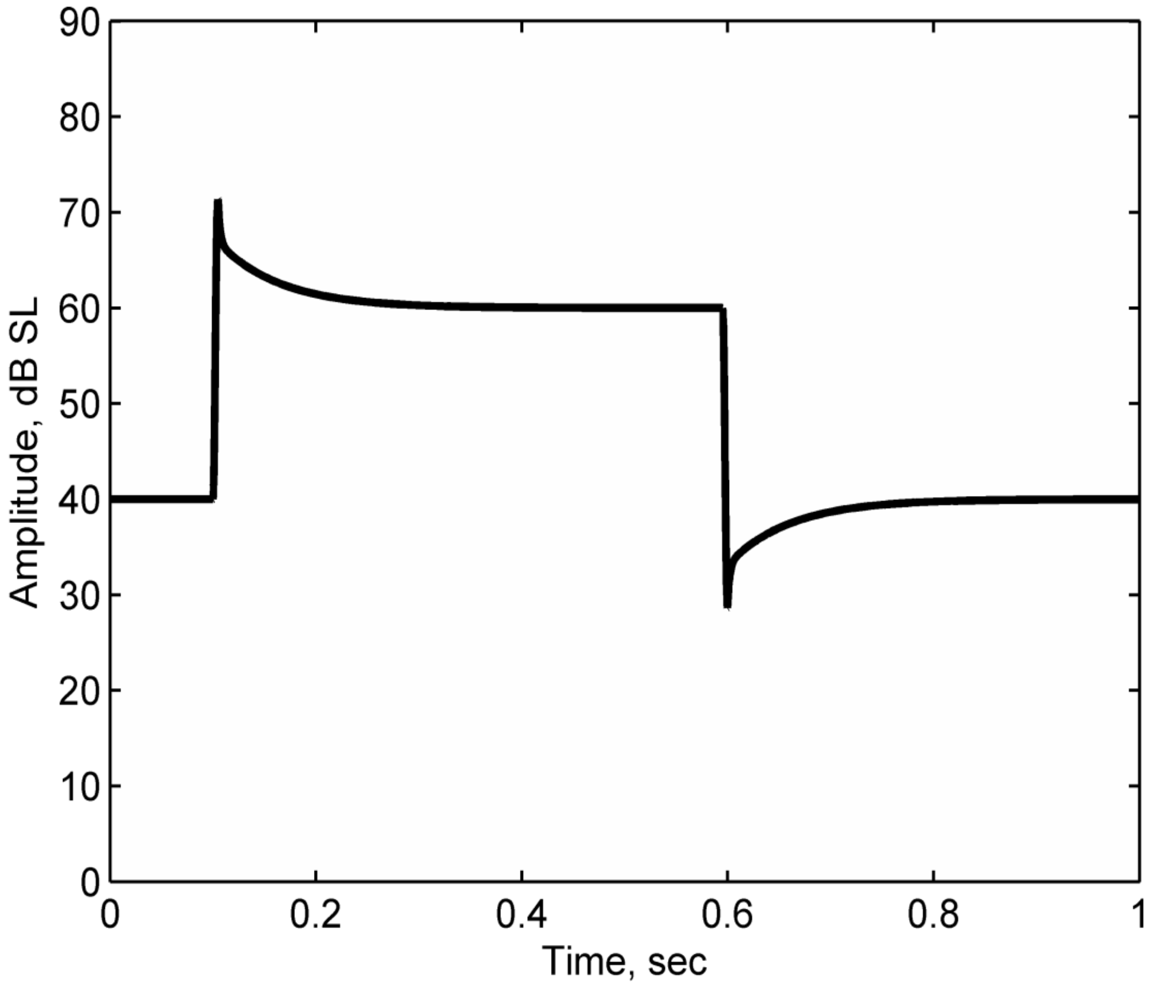
OHC Dynamic-Range Compression



IHC Adaptation



Auditory Model Summary

- One peripheral model for all applications
  - Intelligibility and quality
  - Normal and impaired hearing
- Representation of hearing loss based on audiogram
  - Elevated auditory threshold
  - Increased auditory filter bandwidth
  - Reduced OHC dynamic-range compression
  - Reduced amount of two-tone suppression
- Model outputs
  - Envelope: Modulated envelope in each band in dB re: threshold
  - BM Vibration: Modulated envelope in dB applied to bandpass signal, includes temporal fine structure in each band

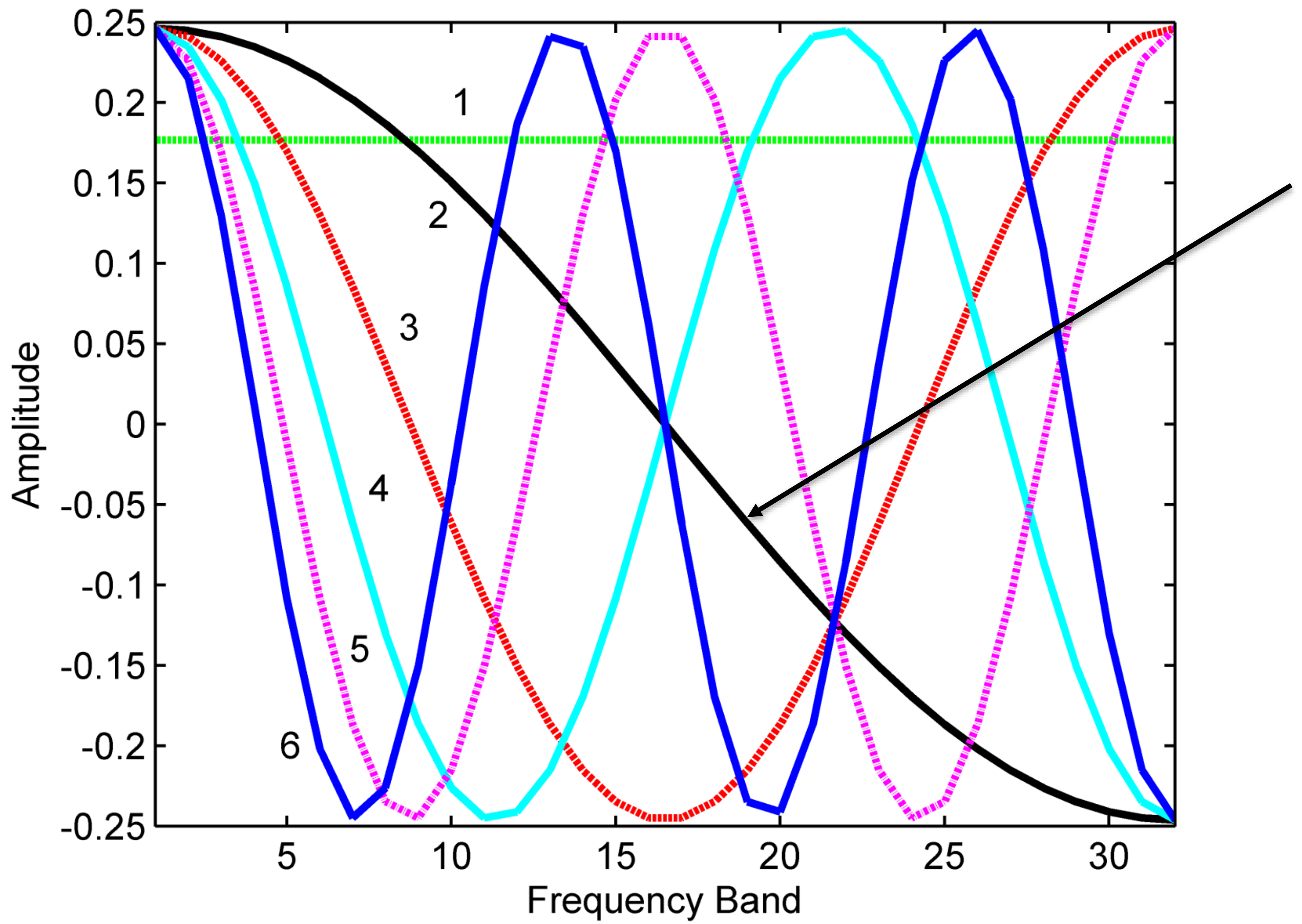
HASPI and HASQI Calculation

HASPI version 2

- Reference is clean speech, normal-hearing periphery
- Envelope time-frequency modulation analysis
  - Peripheral model envelope outputs in dB above threshold
  - Lowpass filter at 320 Hz, resample at 2560 Hz (8 x cutoff)
  - Remove samples identified as silences in reference
  - Fit short-time log spectra with 5 half-cosine basis functions from ½ to 2½ cycles per spectrum => mel-freq cepstral coefficients
  - Each coefficient sequence passed through modulation filterbank, 10 bands with center frequencies from 2 to 256 Hz
  - 5 basis functions vs time x 10 modulation filters = 50 sequences
  - Cross-correlate processed signal with reference for all 50
  - Average over 5 basis functions at each modulation rate to get 10 correlation values

(Kates and Arehart, 2014b; Kates and Arehart, 2015; Kates and Arehart, 2021)

Log Spectrum Basis Functions



Basis function 2 applied to the short-time spectra gives spectral tilt as a function of time.

HASPI v2 Neural Network

- Fit to HINT or IEEE sentences correct (all 5 keywords)
- Conditions: Noise and 6-talker babble, noise suppression, WDRC, frequency lowering, reverberation and reverb processing
- Neural network structure
  - Inputs are the 10 averaged modulation rate values
  - Single hidden layer, 4 neurons
  - Output layer with 1 neuron
  - Sigmoid activation function
- Ensemble of 10 networks: Bootstrap aggregation (“bagging”)
  - Networks fit to 63% of data randomly selected with replacement
  - Average outputs of the 10 networks
  - Reduced error variance and improved immunity to overfitting

HASQI version 2

- Reference is clean speech NAL-R, impaired-hearing periphery
- Fit to HINT pair (1 M + 1 F) in noise and babble, linear, nonlinear proc
- Nonlinear term
  - Envelope modulation
    - Low-pass filter dB envelope in each band
    - Measures time-frequency envelope fidelity
    - Cepstral correlation
  - Temporal fine structure
    - Short-time normalized cross-correlation
    - Loss of neural firing rate synchronization at high frequencies
    - Vibration correlation
- Linear term: differences in long-term spectrum and slope

(Kates and Arehart, 2014a)

HASQI Cepstral Correlation

- Input is envelope in dB
- Segment 16-ms windows, 50% overlap => lowpass filter
- Remove segments identified as silences in reference
- Fit each remaining segment with half-cosine basis functions
- Sequences for amplitude of each basis function over time
- Cross-correlation of processed with clean reference sequences
- c = average over basis functions 2 - 6

HASQI Vibration Correlation

- Vibration correlation v
  - Input is BM vibration
  - Segment 16-ms windows, 50% overlap
  - Remove silent segments found in reference
  - Short-time correlations of processed with reference segments
  - Loss of IHC synchronization 5-pole LP at 3.5 kHz
  - Weighting reduces importance of TFS at high frequencies
  - Normalize, weight with loss of synchronization, and average over segments and frequency bands
- Nonlinear term $Q_{Nonlin} = c^2 v$

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HASQI Linear Term

- RMS average envelope outputs in each frequency band
- Sum over bands and adjust overall levels to remove loudness difference between reference and processed signals
- Standard deviation of the spectral differences σ_1
- Spectral slope from 1st differences of adjacent bands
- Standard deviation of the spectral slope differences σ_2
- Linear model $Q_{Linear} = 1 - 0.579\sigma_1 - 0.421\sigma_2$

HASQI v2 Model

- Product of nonlinear and linear terms

$$Q_{Combined} = Q_{Nonlin} \times Q_{Linear}$$

- Nonlinear term: Envelope dominates, but TFS also important
- Linear term: Spectrum and spectral slope both important
- Product: Change in either nonlinear or linear will reduce quality

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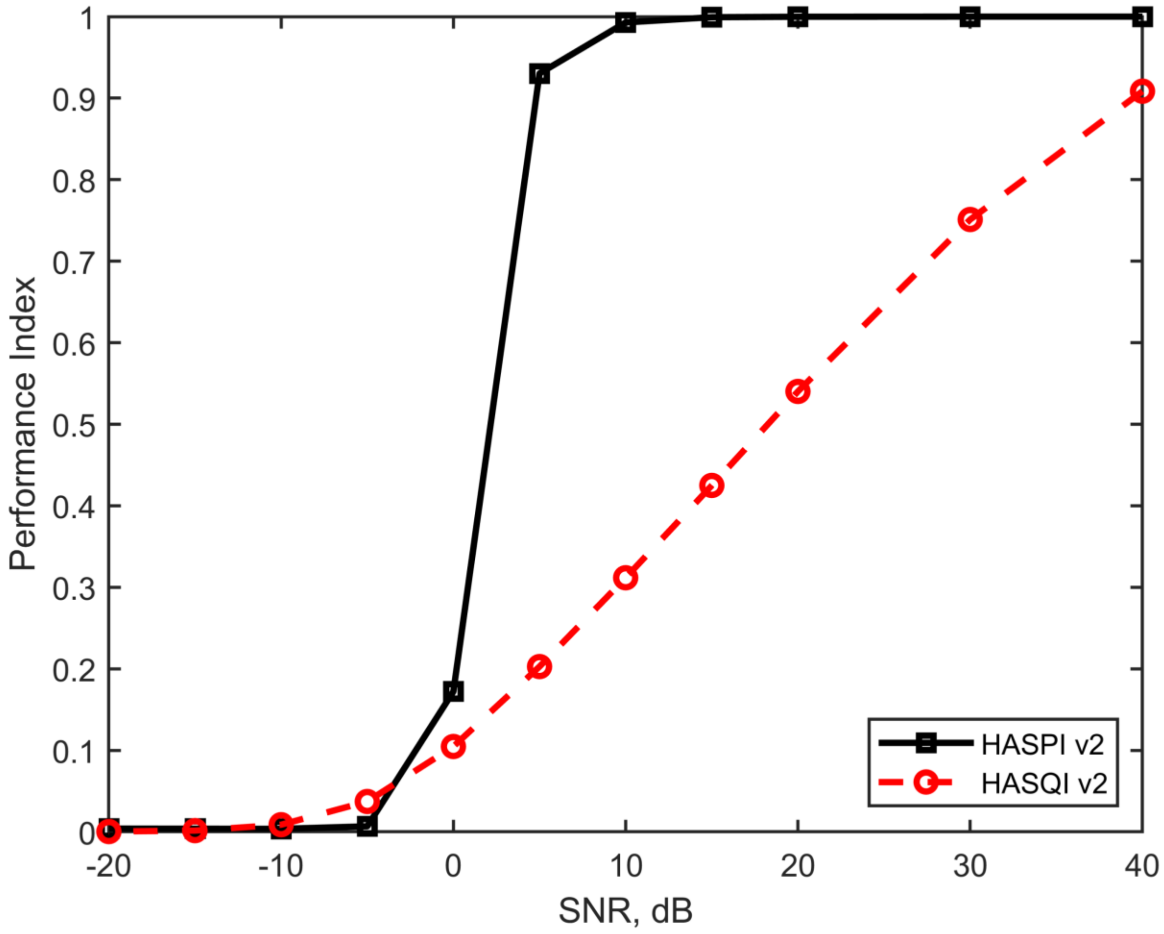
HASPI and HASQI for LTASS Noise, NH



Applications

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1. Quality Ratings for Noisy Speech

- Relationship between ratings and envelope modulation
- Ten older adult HI listeners, mild-moderate loss
- Five different noise types: 6-talker babble, 3-talker conversation, street traffic, kitchen, and fast-food restaurant
- Nine segments for each noise type
- Four SNRs: 3, 8, 12, and 20 dB
- Bilateral hearing-aid simulation: 2 settings x 2 vents per subject
- Quality ratings for HINT M + F sentence pair
  - 4 repetitions per processing condition with random noise segment
  - Rate 320 stimuli on scale from 0 – 10, converted to 0 – 100 for analysis

(Lundberg et al, 2020)

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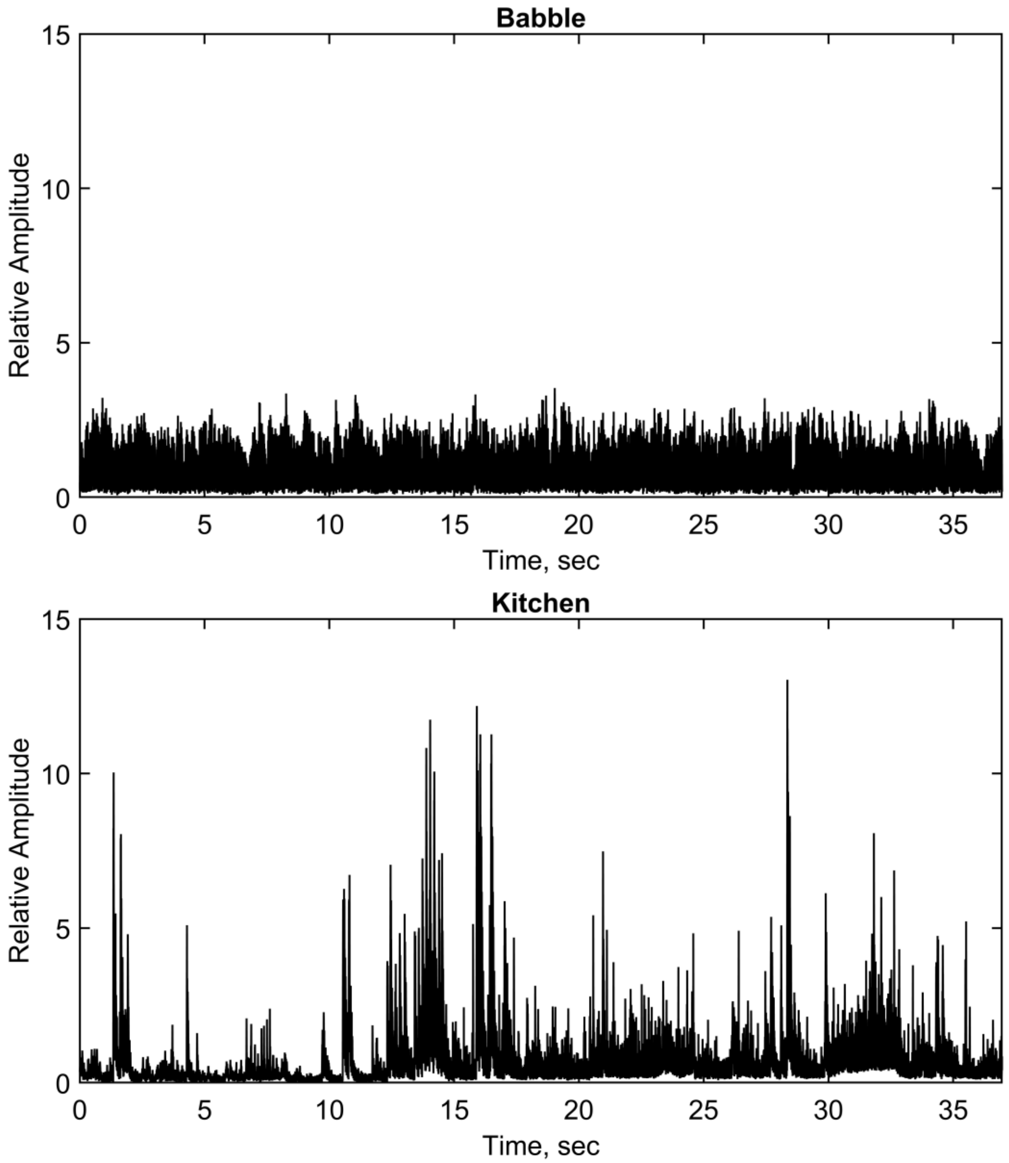
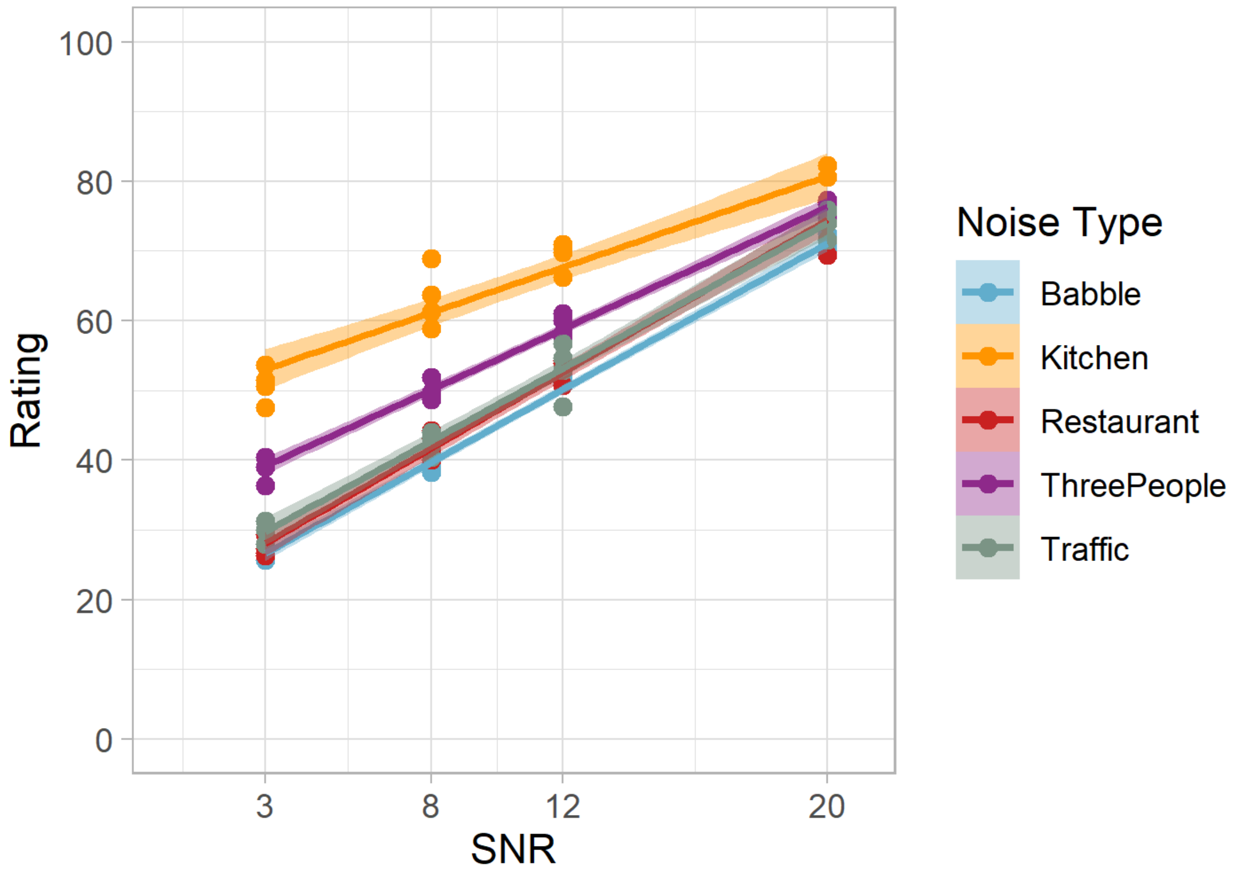
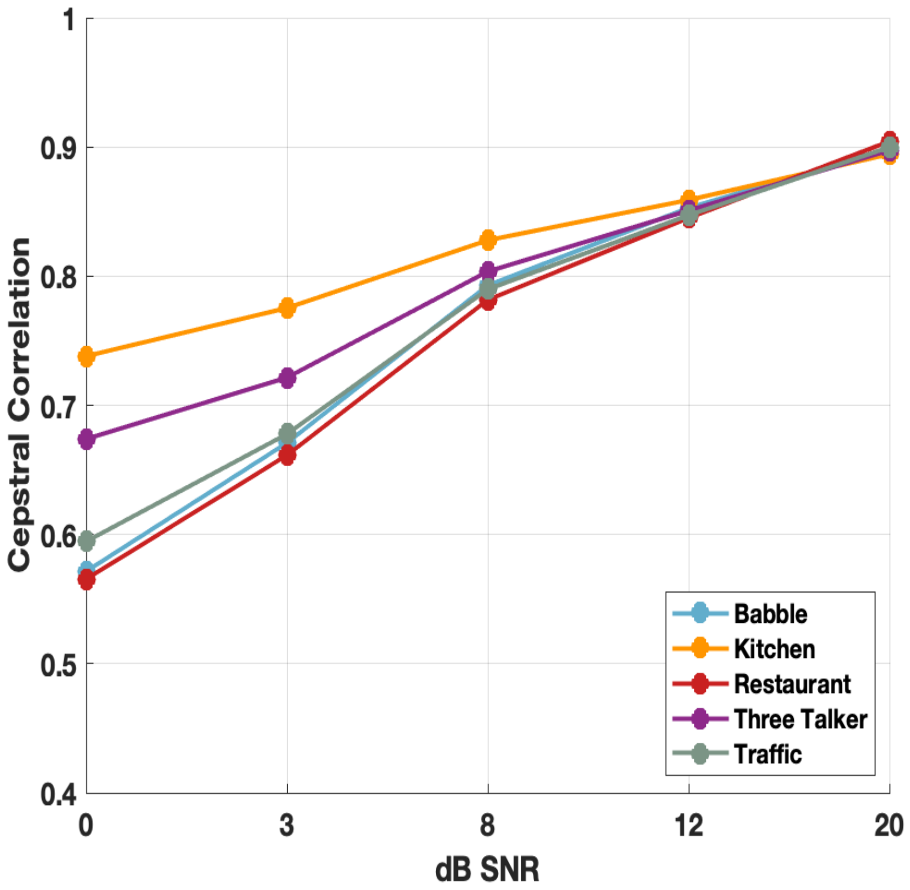
Noise Waveforms



Averaged Quality Ratings





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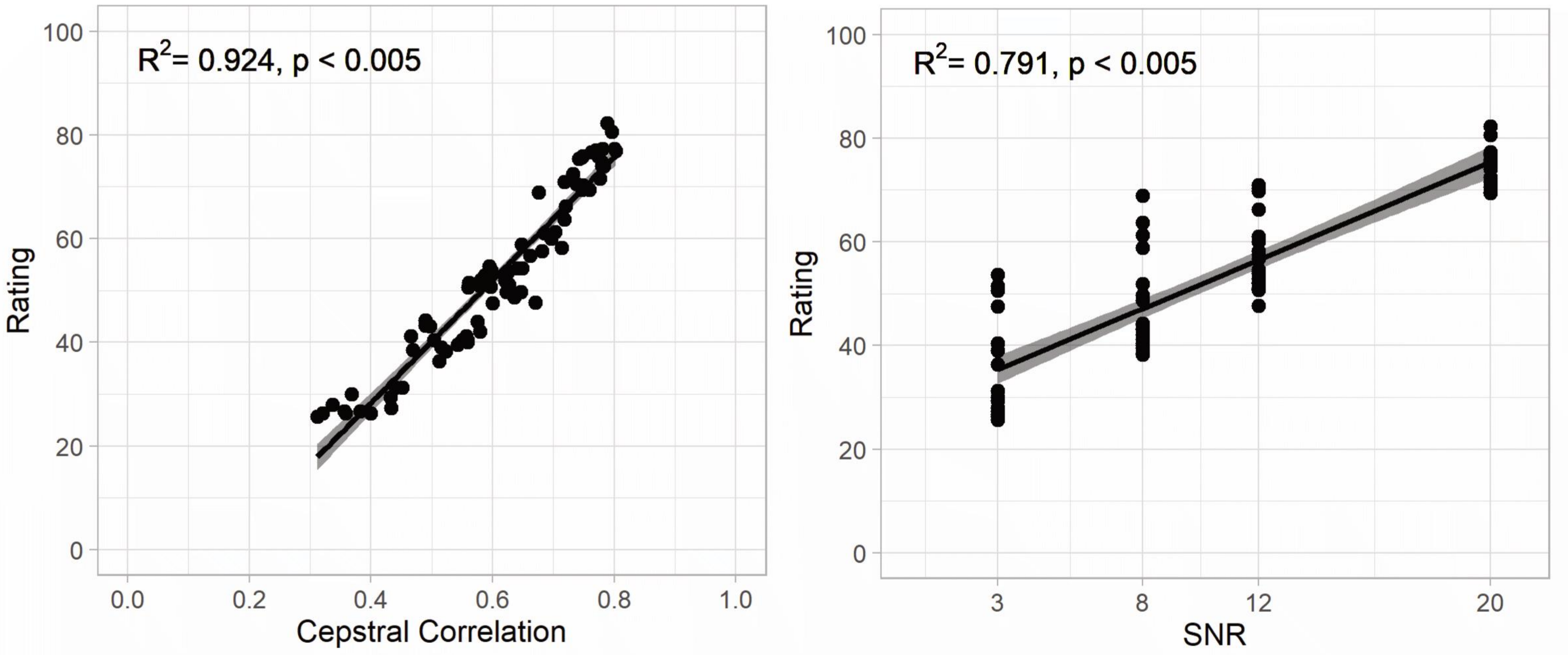
Accuracy of Envelope Modulation Model



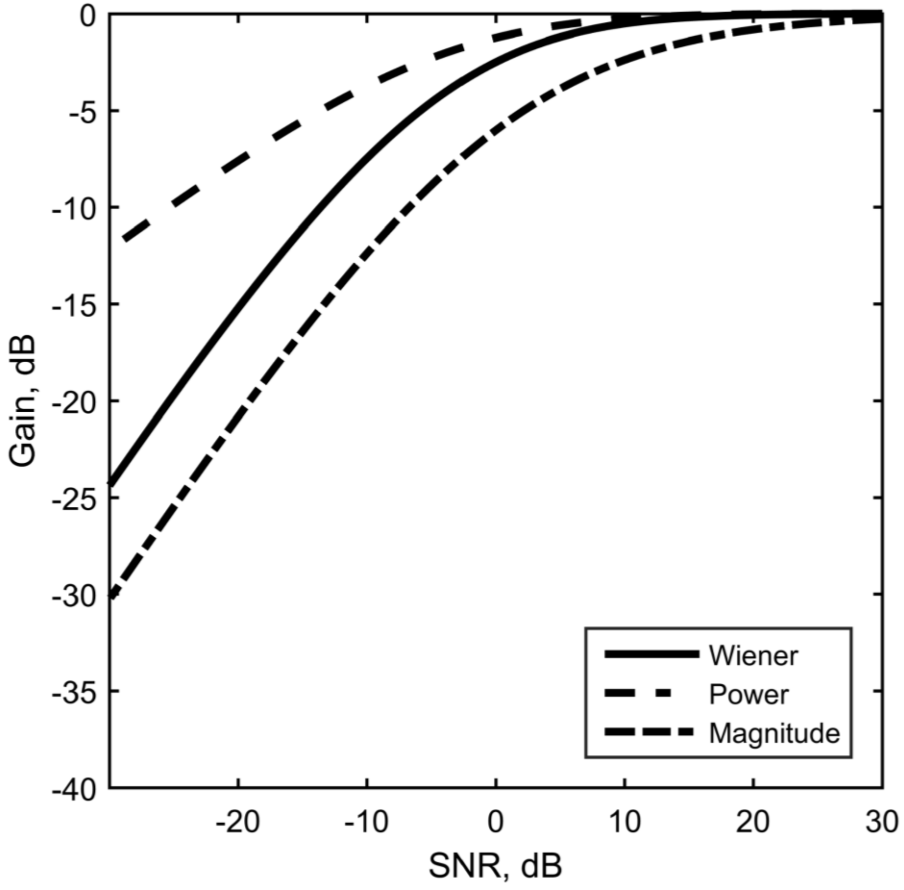
2. Single-Microphone Noise Suppression

- Use metrics to compare single-microphone algorithms
  - Spectral subtraction, 18 frequency bands
  - Spectral subtraction with upward spread of masking
  - Ideal binary mask (IBM)
  - Restore envelope of noisy speech to match that of clean speech
- Compare noise estimation procedures
  - Ideal knowledge of separate speech and noise RMS level fluctuations
  - Gives exact SNR in each time-frequency cell, 16-ms raised cos window
  - Or replace exact noise values with average over time in each band
- NH, N3 audiogram (moderate flat loss) with gain compensation
- Average over 20 IEEE sentences in 6-talker babble

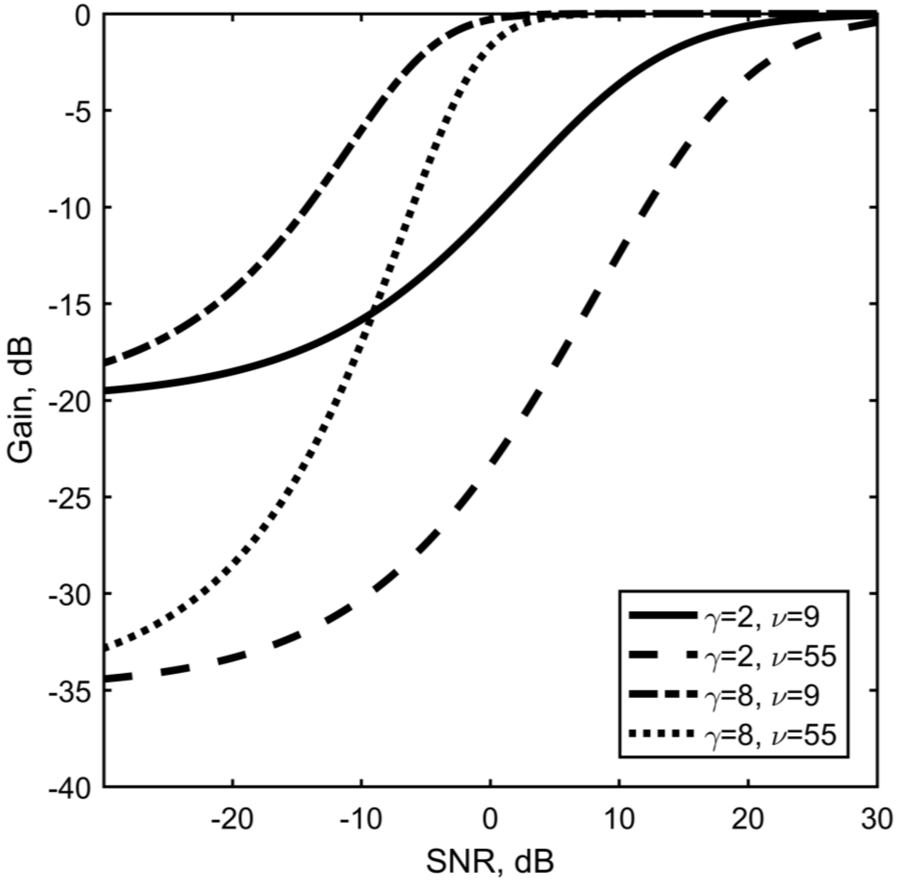
(Kates, 2017)

Gain vs SNR Rules

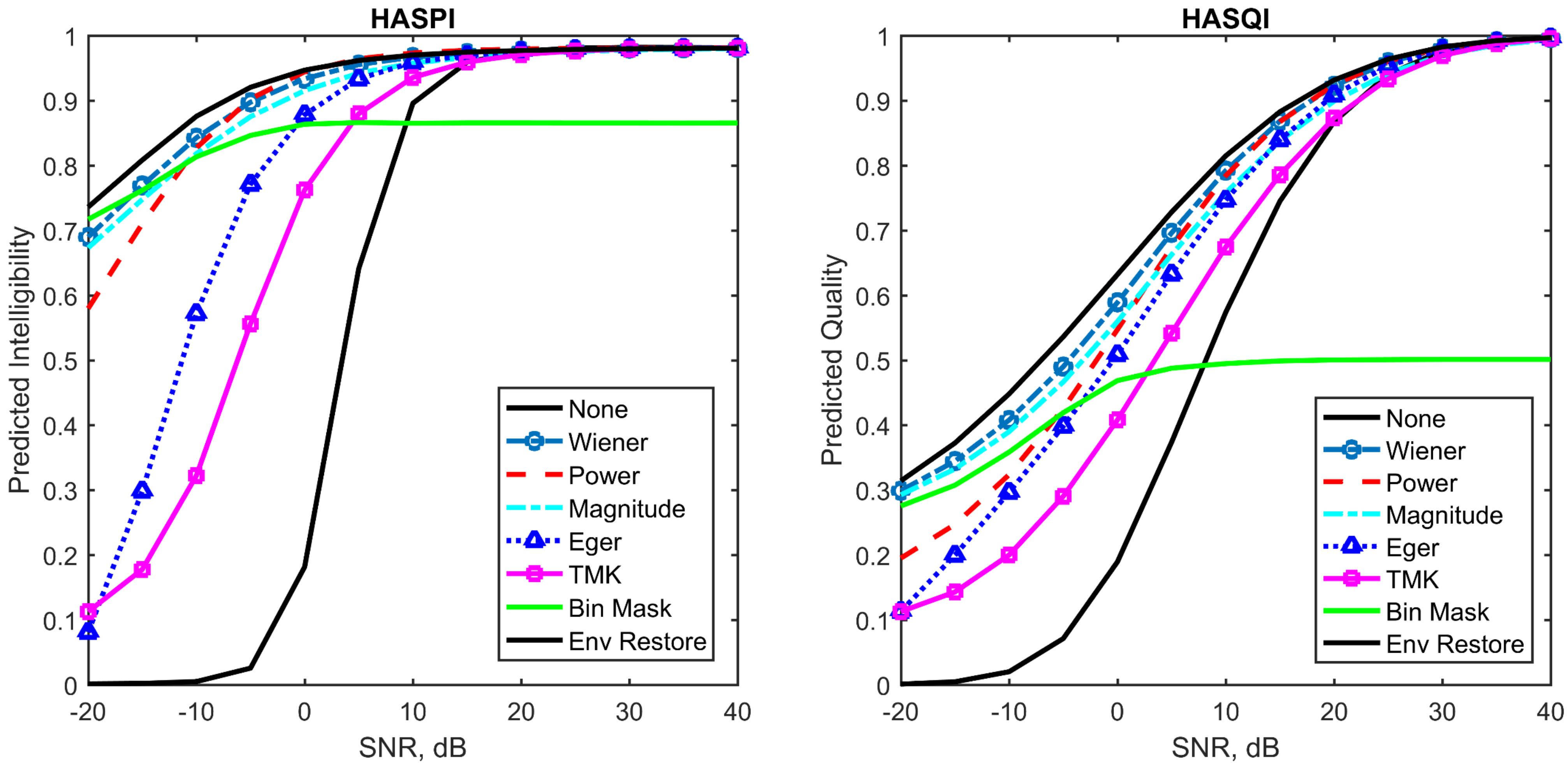
Spectral Subtraction



Eger



Ideal Processing, N3



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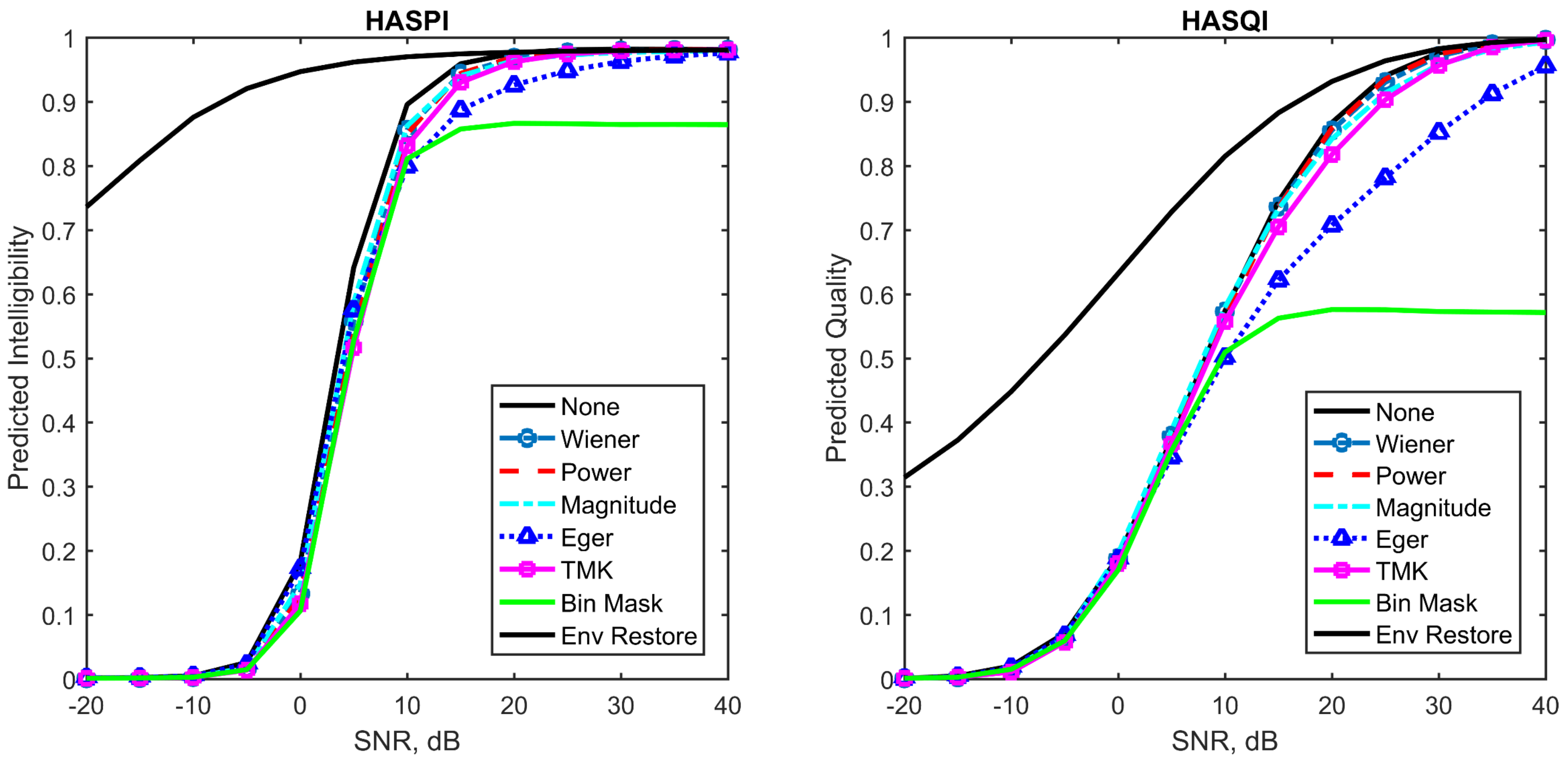
Average Noise Power, N3

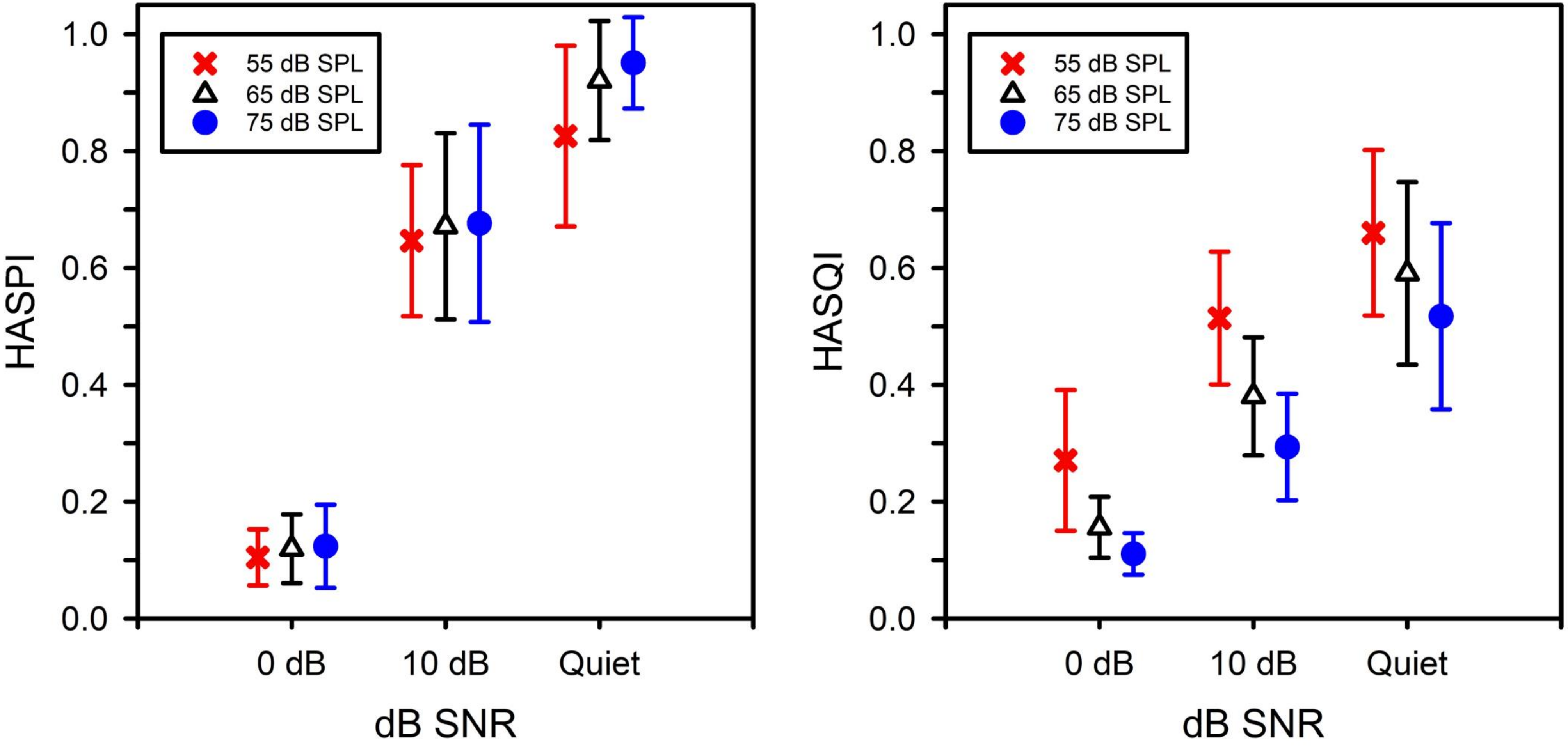


3. Commercial Hearing Aid Measurements

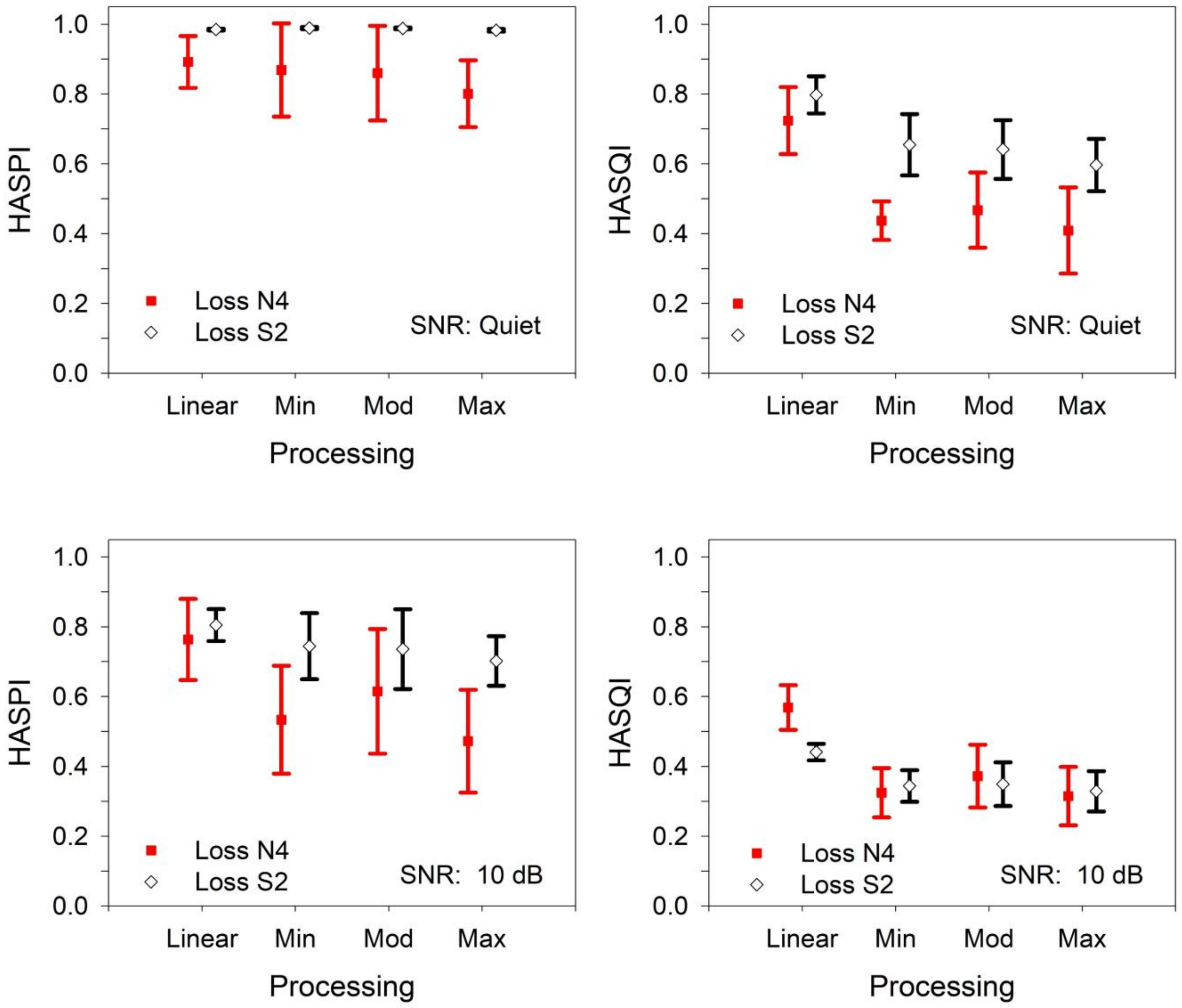
- Use metrics to distinguish between commercial devices
- Speech is HINT sentence pair
- Hearing aids
  – Three major manufacturers
  – Basic and premium model from each
  – WDRC, Noise suppression (NS), Frequency lowering (FL)
- Processing: NAL-R, Mild (no NS or FL), Moderate, Maximum
- Two audiograms: S2 (mild sloping), N4 (mod-severe flat)
- Vary SNR (6-talker babble), level of presentation
- Measurements use acoustic test box in sound booth

(Kates et al, 2018)

SNR, Multi-talker Babble



Processing Setting



Conclusions

- HASPI and HASQI accurate in predicting listener responses
  - Same peripheral model for both normal and impaired hearing
  - Measure nonlinear distortion, noise, linear response modifications
  - Envelope fidelity is important
  - Measures complete system, including processing interactions
  - Trade-off between audibility and nonlinear distortion
- Limitations
  - Derived for monaural headphone listening
  - Based on sentence test materials
  - Not validated for tonal languages
- MATLAB code free for the asking: *James.Kates@colorado.edu*

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