Cochlear modeling and its role in human speech recognition

Miller Nicely confusions and the articulation index

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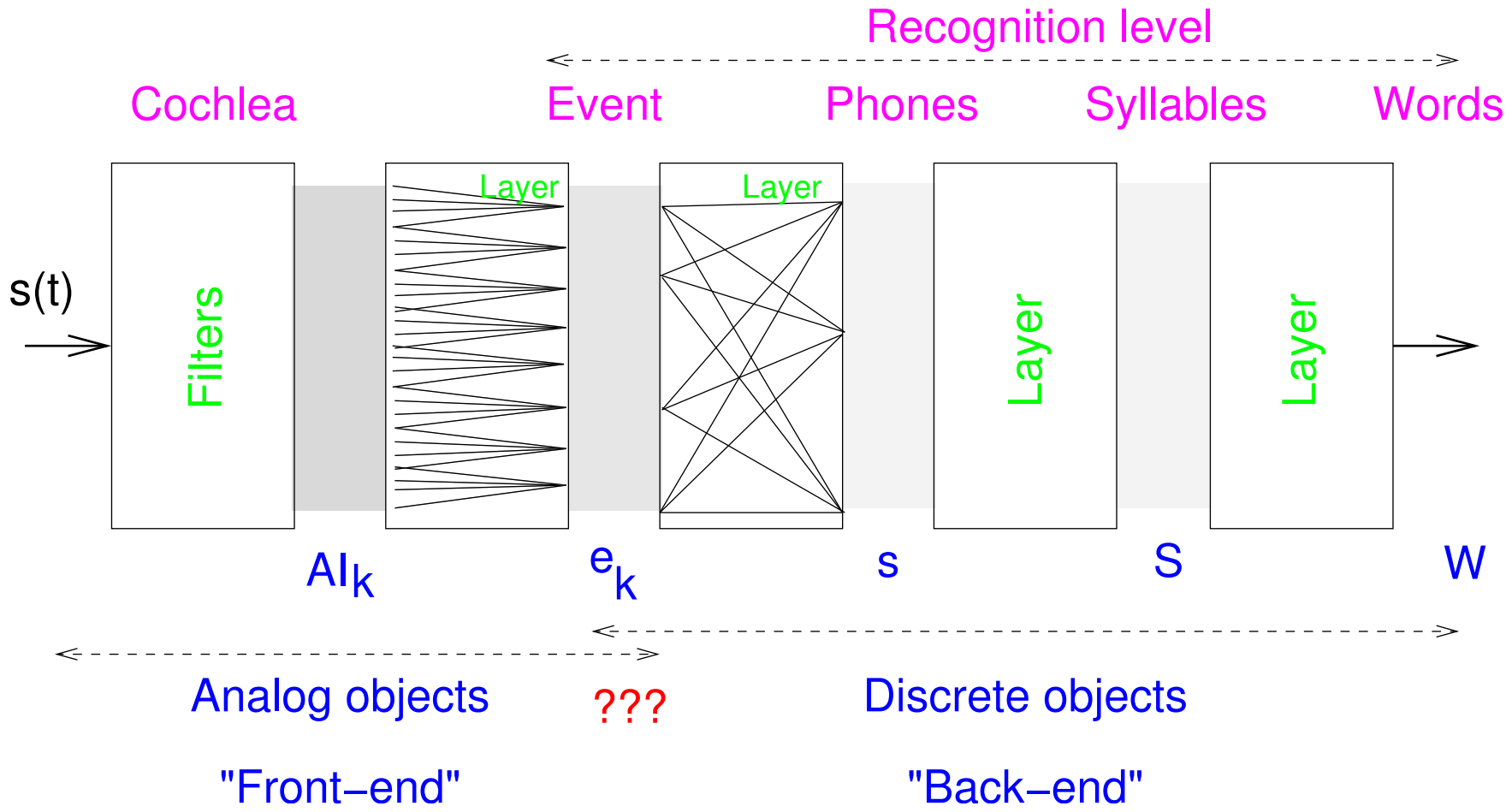
Model of human speech recognition (HSR

- The research goal is to identify *elemental HSR events*
  - An event is defined as a *perceptual feature*



Modeling MaxEnt HSR

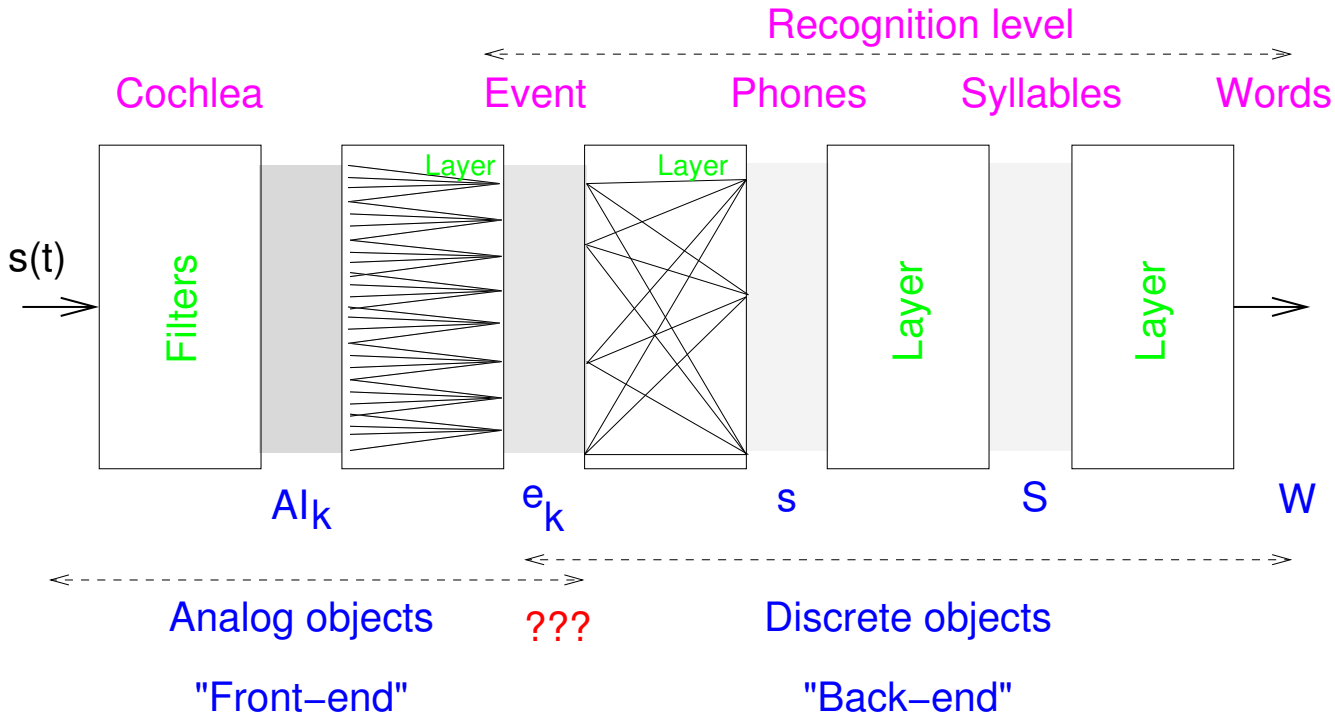
- Definition of MaxEnt (a.k.a. "nonsense") syllables:
  - A fixed set of { C,V } sounds are drawn from the language of interest
  - A uniform distribution for each C and V is required, to minimize syllable context ($\Rightarrow$ MaxEnt)
  - MaxEnt CV or CVC syllable score: $S_{cv} = s^2$, $S_{cvc} = s^3$
  - MaxEnt syllables first described in Fletcher, 1929
- A set of meaningful words is not MaxEnt
  - Modeling non-MaxEnt syllables require the context models of Boothroyd, 1968; Bronkhorst et al., 1993
- Fletcher's 1921 AI *band independence model*:

$$s(AI) \equiv 1 - e = 1 - e_1 e_2 e_3 \ldots e_{20} = 1 - e_{\min}^{AI} \qquad (1)$$

accurately models MaxEnt HSR (Allen, 1994)

Probabilistic measures of recognition

- Recognition measures (MaxEnt ≡ Maximum Entropy):
  - k^{th} band articulation index: $AI_k \propto \log(snr_k)$
  - Band recognition error: $e_k = e_{\min}^{AI_k/K}$ with $K = 20$
  - MaxEnt phone score: $s = 1 - e_1 e_2 \ldots e_K = 1 - e_{\min}^{\overline{AI_k}}$
  - MaxEnt syllable score: $S_{cv} = s^2$, $S_{cvc} = s^3$



What is an *elemental event*?

- Miller-Nicely's 1955 articulation matrix $\mathcal{A}$ measured at [-18, -12, -6 shown, 0, 6, 12] dB SNR

TABLE III. Confusion matrix for $S/N = -6$ db and frequency response of 200–6500 cps.

STIMULUS	p	t	k	f	θ	s	ʃ	b	d	g	v	ð	z	ʒ	m	n
p	80	43	64	17	14	6	2	1	1		1	1			2	
t	71	84	55	5	9	3	8	1				1	2		2	3
k	66	76	107	12	8	9	4					1			1	
f	18	12	9	175	48	11	1	7	2	1	2	2				
θ	19	17	16	104	64	32	7	5	4	5	6	4	5			
s	8	5	4	23	39	107	45	4	2	3	1	1	3	2		1
ʃ	1	6	3	4	6	29	195		3							1
b	1			5	4	4		136	10	9	47	16	6	1	5	4
d							8	5	80	45	11	20	20	26	1	
g					2			3	63	66	3	19	37	56		3
v				2		2		48	5	5	145	45	12		4	
ð					6			31	6	17	86	58	21	5	6	4
z					1	1	1	7	20	27	16	28	94	44		1
ʒ								1	26	18	3	8	45	129		2
m	1							4			4	1	3		177	46
n					4			1	5	2		7	1	6	47	163

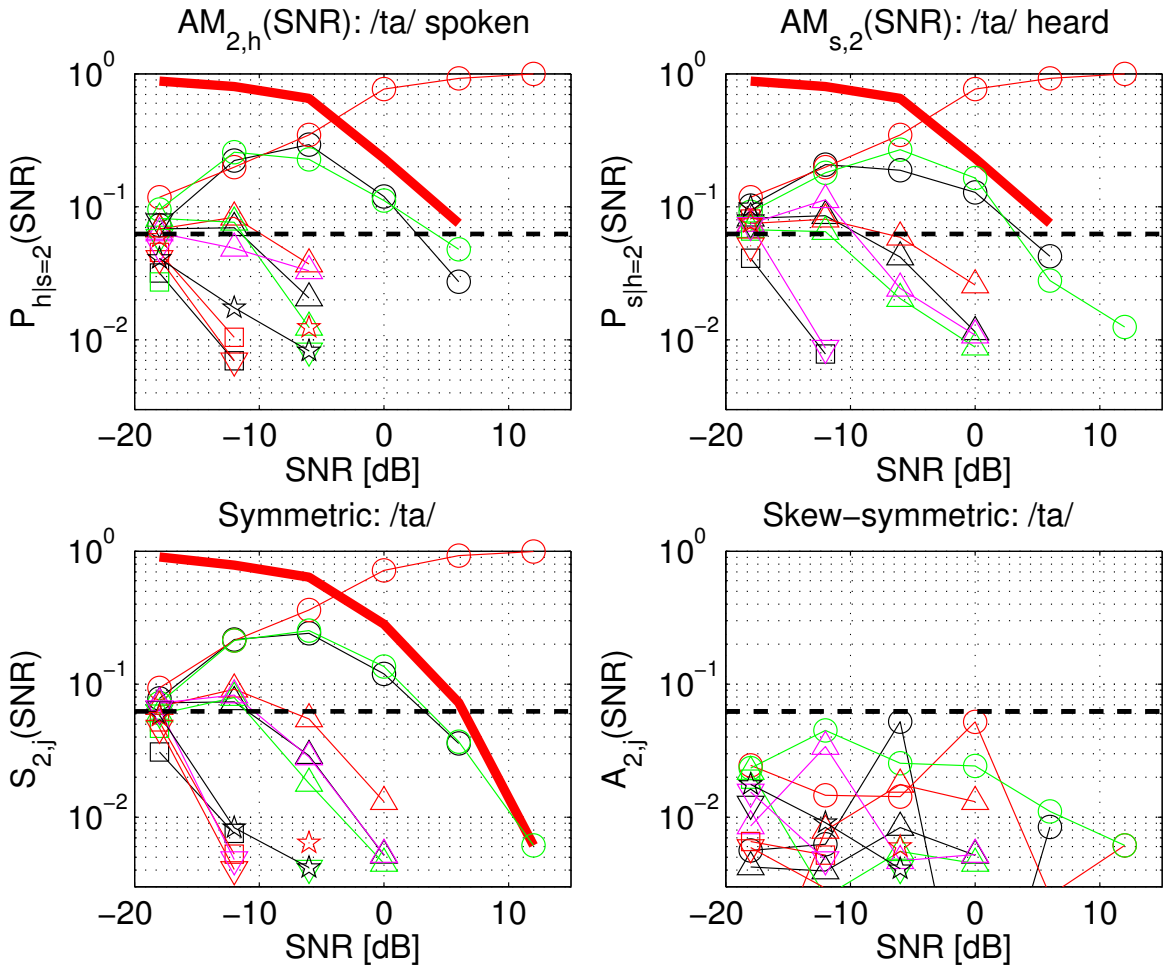
UNVOICED VOICED NASAL

RESPONSE

- Confusion groups formed in $\mathcal{A}(snr)$

Case of /pa/, /ta/, /ka/ with /ta/ spoken

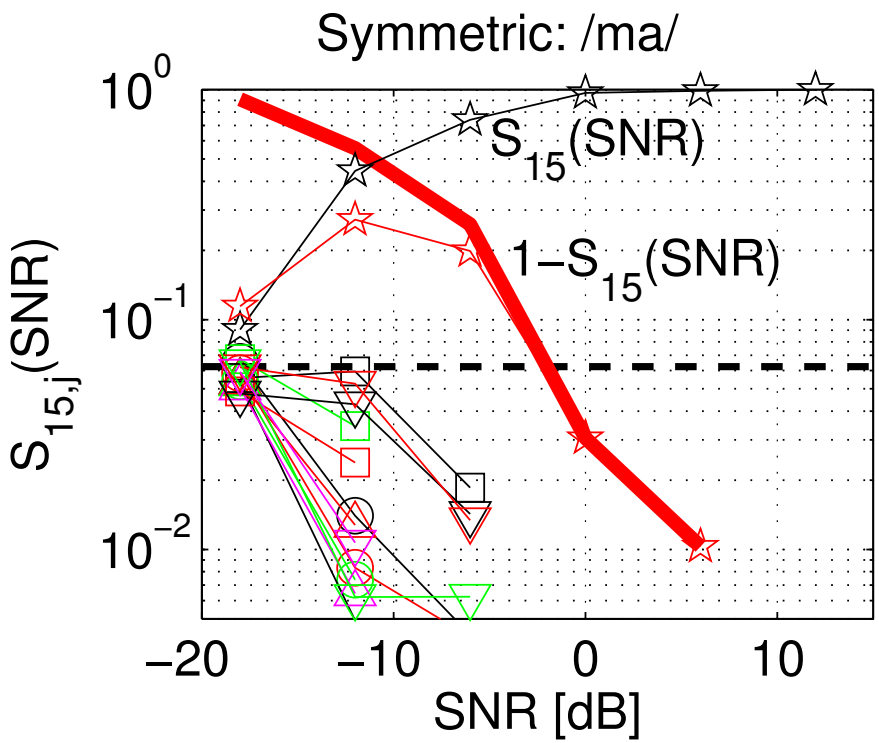
- Plot of $\mathcal{A}_{i,j}(snr)$ for row i =2 and column j =2

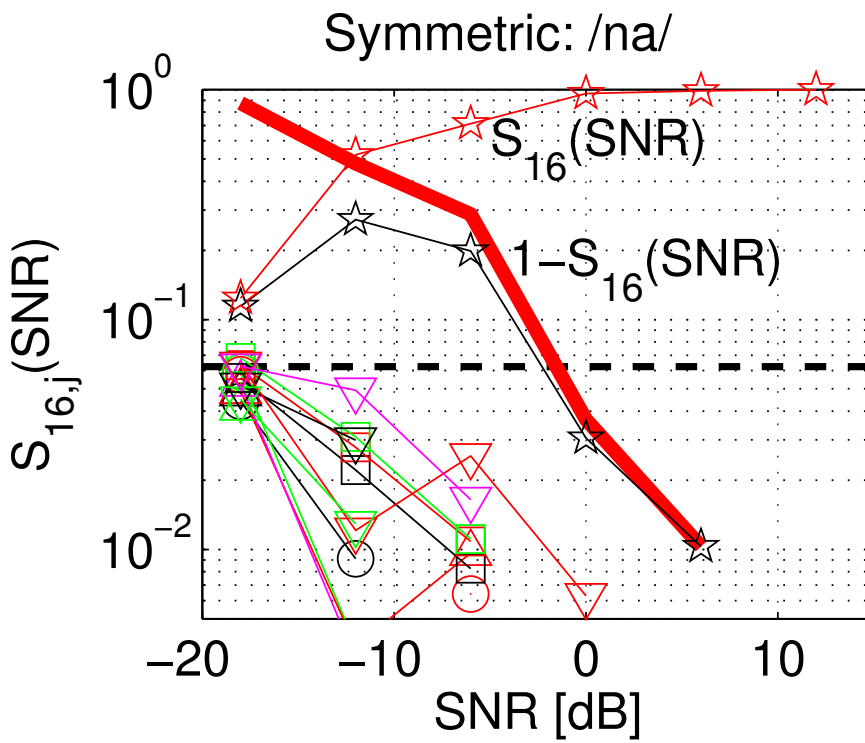


- Solid red curve is total error $e_2 \equiv 1 - \mathcal{A}_{2,2} = \sum_{j \neq 2} \mathcal{A}_{2,j}$

The case of /ma/ vs. /na/

- Plots of $S(\mathit{snr}) \equiv \frac{1}{2}(\mathcal{A} + \mathcal{A}^t)$, /ma/, /na/ spoken
- Solid red curve is total error $e_i \equiv 1 - S_{i,i} = \sum_{j \neq i} S_{i,j}$





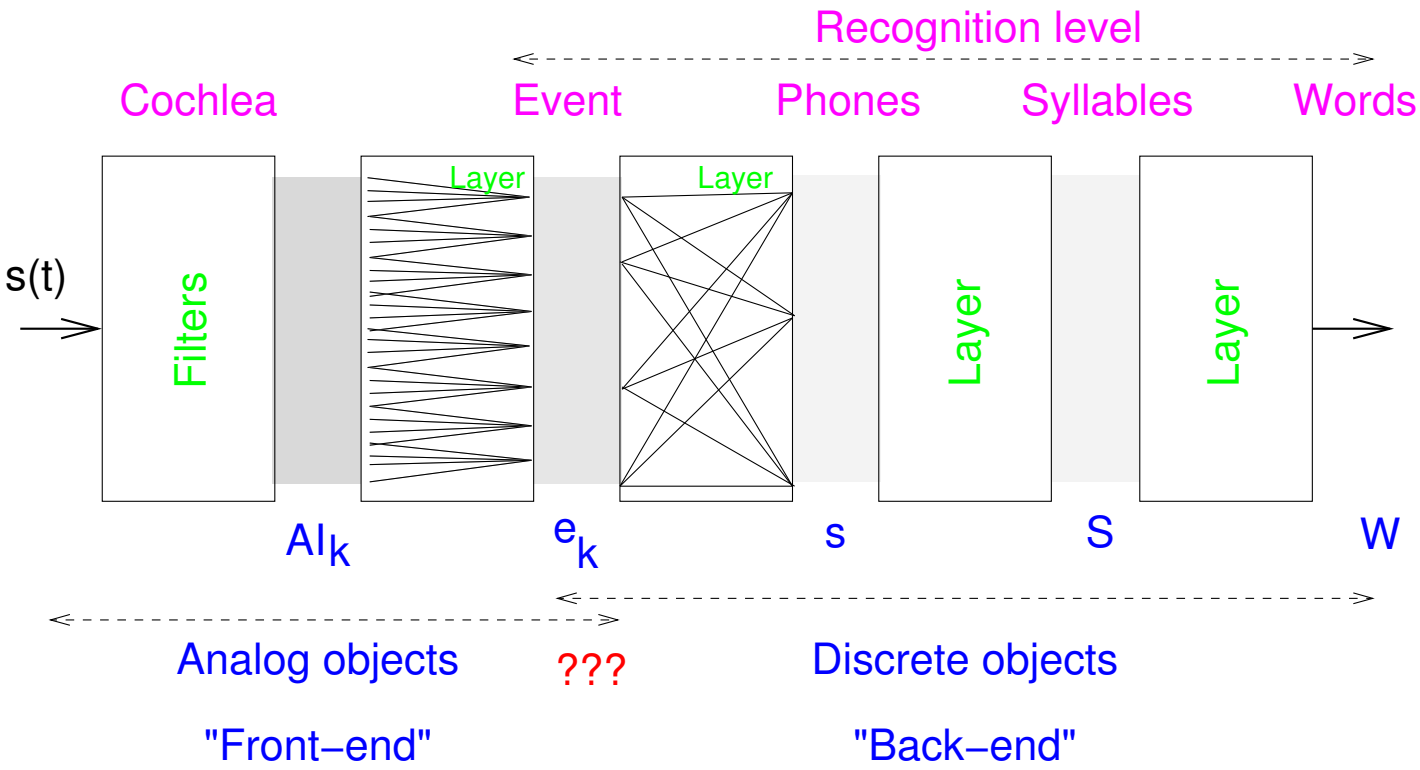
- This 2-group of sounds is closed since
  $S_{/ma/,/ma/}(\mathit{snr}) + S_{/ma/,/na/}(\mathit{snr}) \approx 1$

Definition of the *AI*

- Let AI_k be the k^{th} band cochlear channel capacity

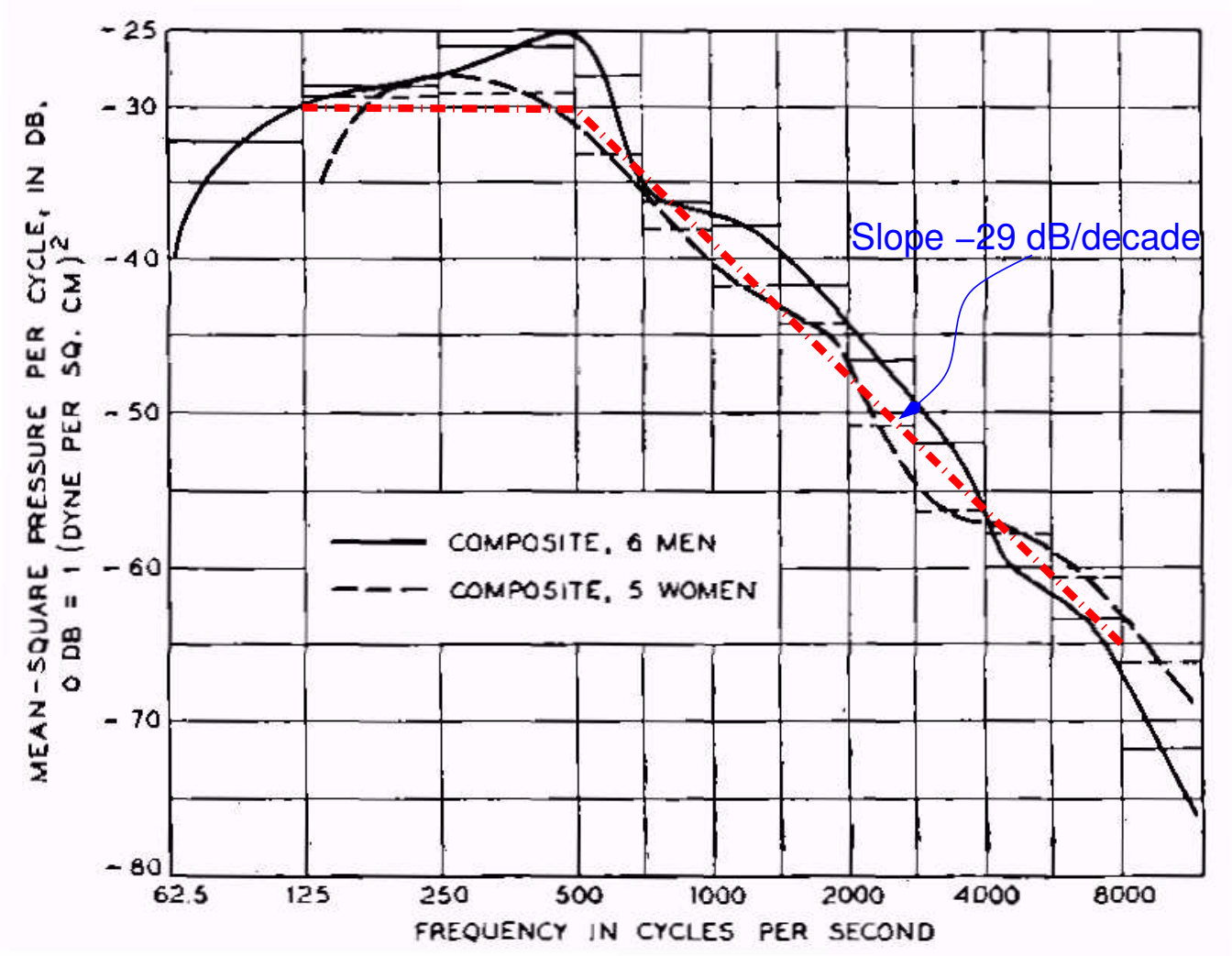
$$AI_k \equiv \frac{10}{30}\log_{10}(1 + c^2 snr_k^2), \text{ with } c = 2, AI_k \leq 1,$$

then $AI \equiv \frac{1}{K}\sum AI_k$ (Allen, 1994; Allen, 2004)



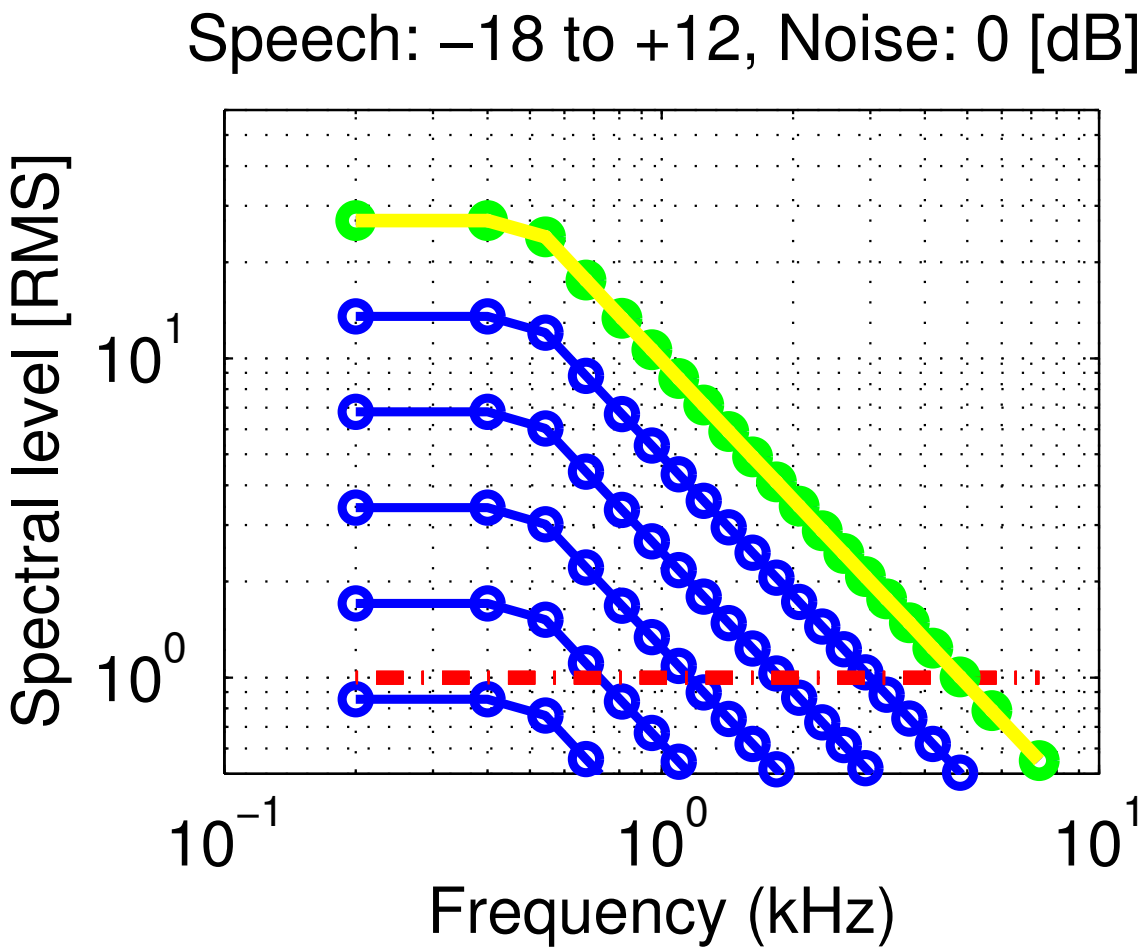
Long-term spectrum of female speech

- Speech spectrum for female speech Dunn and White
  - Dashed red line shows the approximation



Conversion from SNR to AI

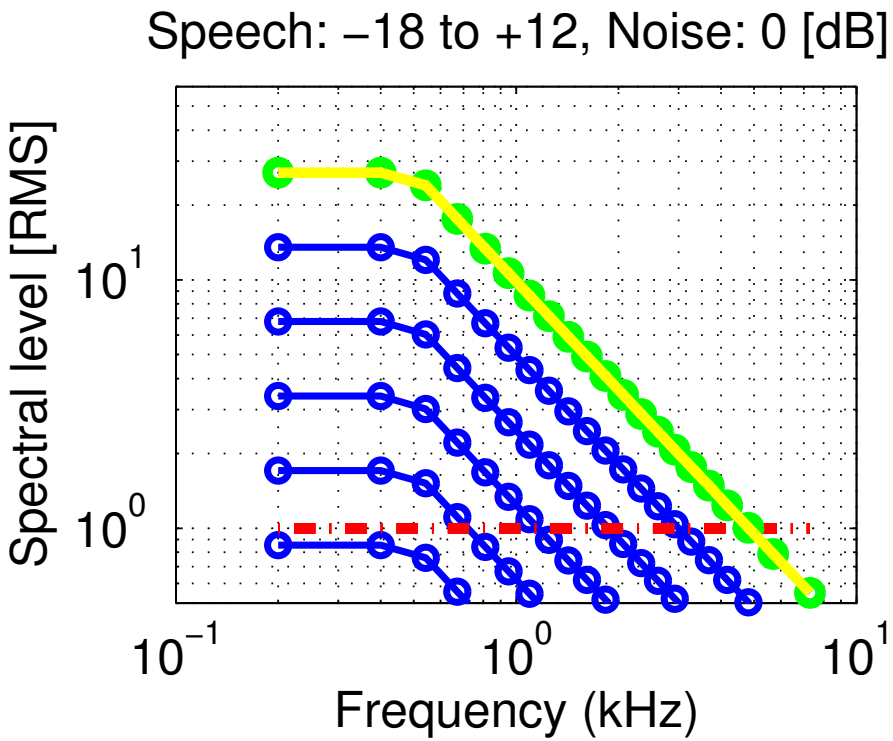
- Spectra for SNRs of [-18, -12, -6, 0, 6, 12] dB

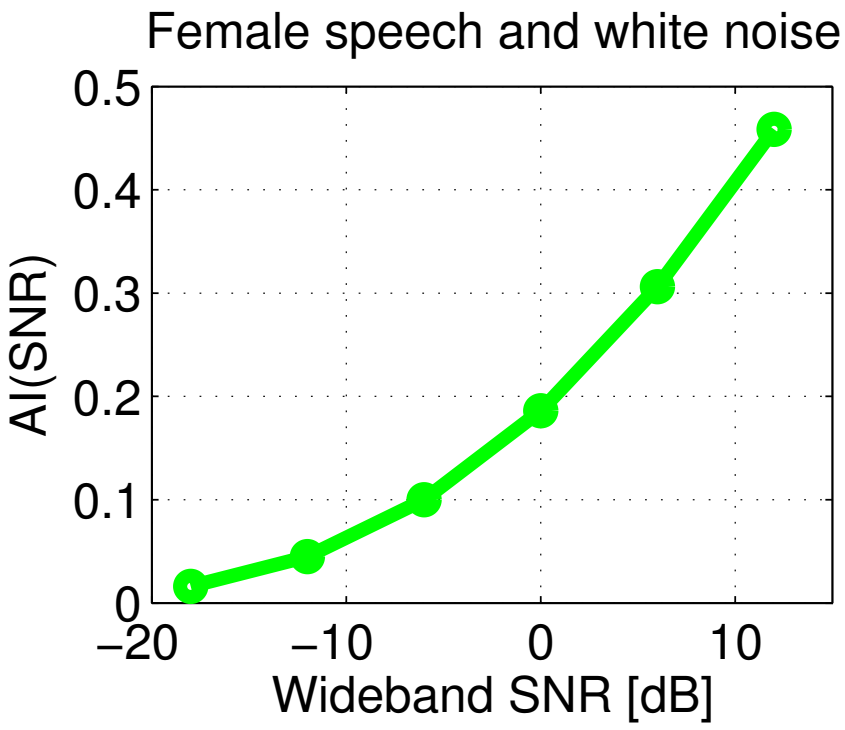


- snr_k is determined for $K = 20$ cochlear critical bands

AI(SNR) for Miller Nicely's data

- AI(SNR) computed from the Dunn and White spectrum



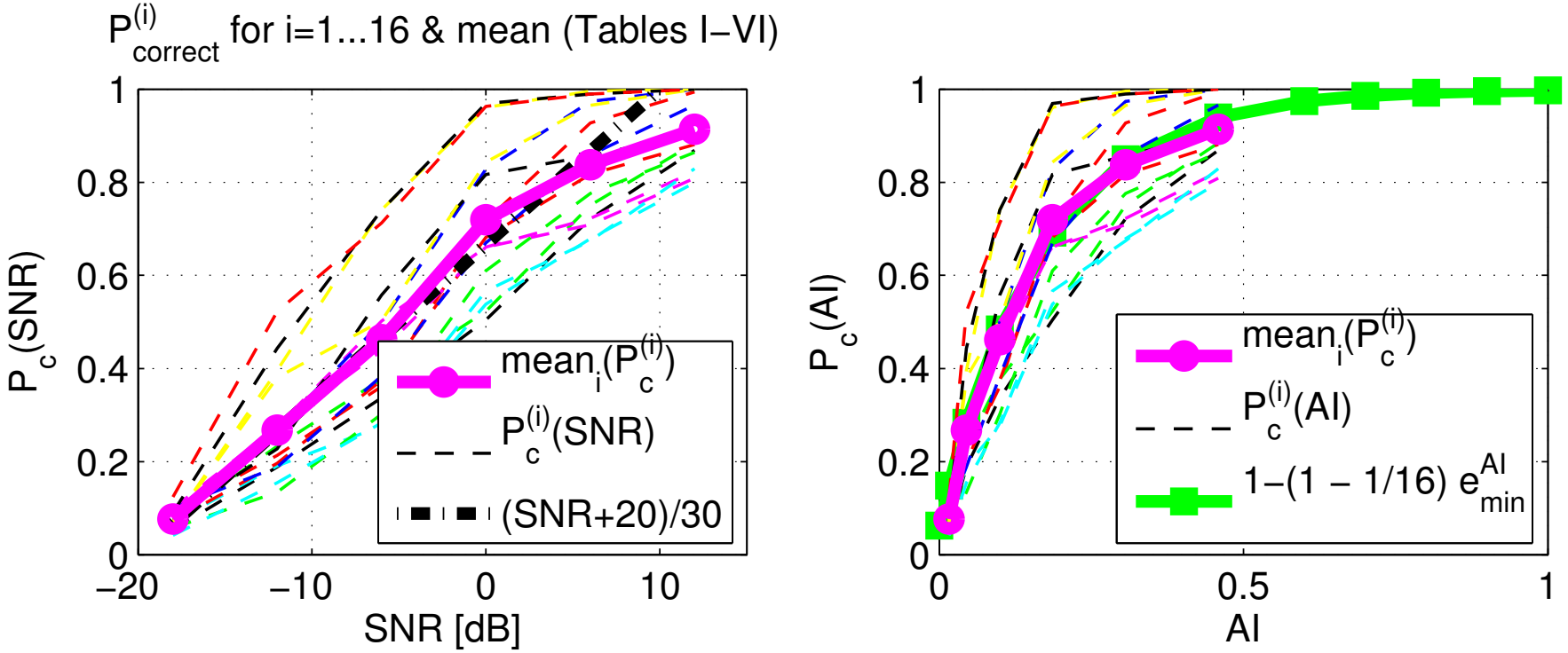


- Conversion from SNR_k to AI [Allen 2005, JASA]:

$$AI \equiv \overline{AI_k} = \frac{1}{60}\sum_{k=1}^{20}\log_{10}(1+c^2 snr_k^2), \quad c=2, AI_k \leq 1$$

MN16 and the AI model

- $P_c^{(i)}(AI)$ for the i^{th} consonant and $P_c(AI) \equiv \frac{1}{16}\sum_i P_c^{(i)}(AI)$
- $P_c(AI) = 1 - (1 - \frac{1}{16})e_{\min}^{AI}$ is the chance–corrected model



- Band independence seems a perfect fit to MN16 !!

Log-error probability

- Band-independence, corrected for chance,

$$P_e(AI, \mathcal{H} = 4) \equiv 1 - P_c(AI) = (1 - 2^{-\mathcal{H}}) e_{\min}^{AI}$$

- This suggests linear log-error plots vs. AI:
  - MN16 CVs $\log(P_e^{(i)}) = \log(1 - \frac{1}{16}) + \log(e_{\min})AI$
- This relation is of the form

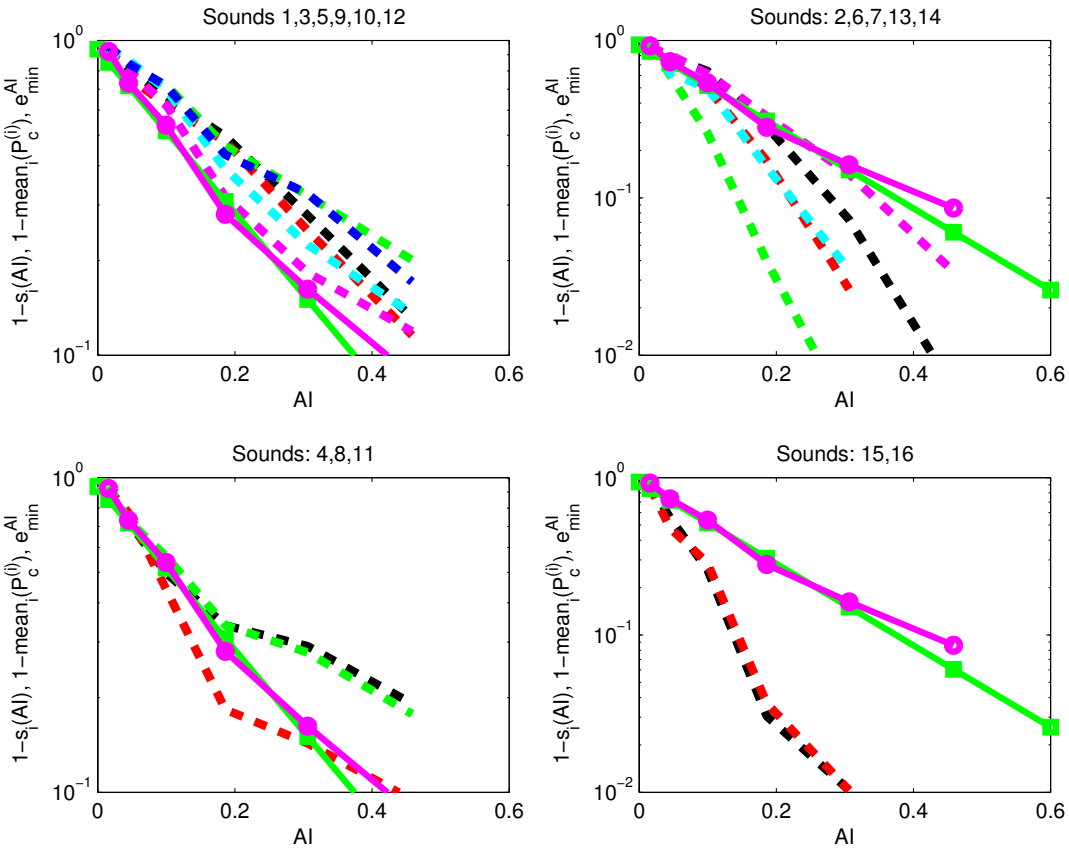
$$Y = a + bx$$

- Plots of $\log(P_e)(AI)$ vs. AI provide a nice test of Fletcher's "band independence" model
- Individual sounds $P_e^{(i)}(AI)$ from MN16 may be tested for band independence.

Testing the band-independence model

- CV log-error model:

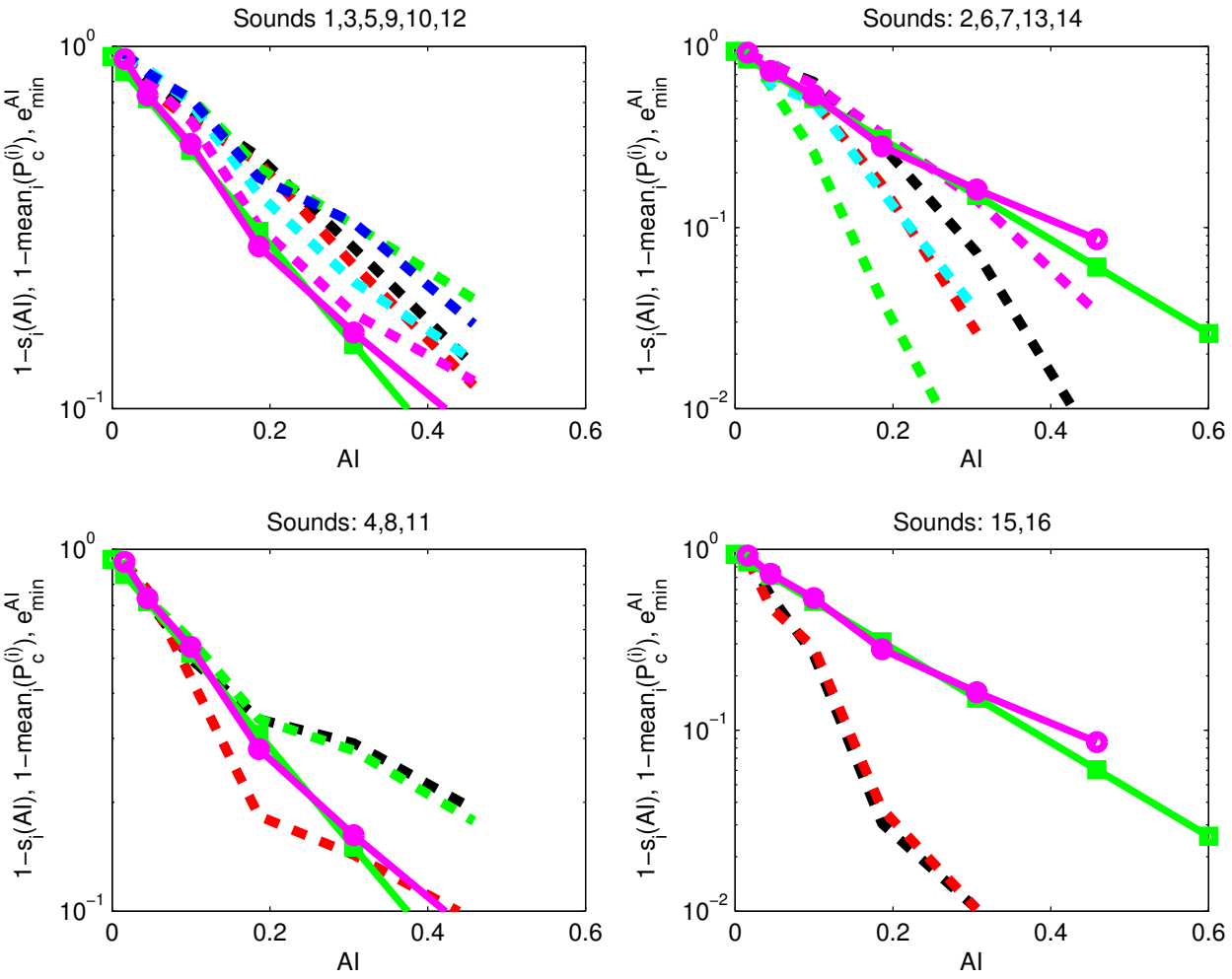
$$\log\left(P_e^{(i)}(AI)\right) = \log\left(1 - 2^{-4}\right) + \log\left(e_{\min}^{(i)}\right) AI$$



- AI Model; MN16 $P_c(AI)$; - - -, - - -: CV sounds

Testing the band-independence model

- Sounds: [1, 2, 3, 5, 8, 9, 10, 12, 13, 14] pass
- Sounds: [4, 8, 11, 15, 16] fail (nonlinear wrt *AI*)

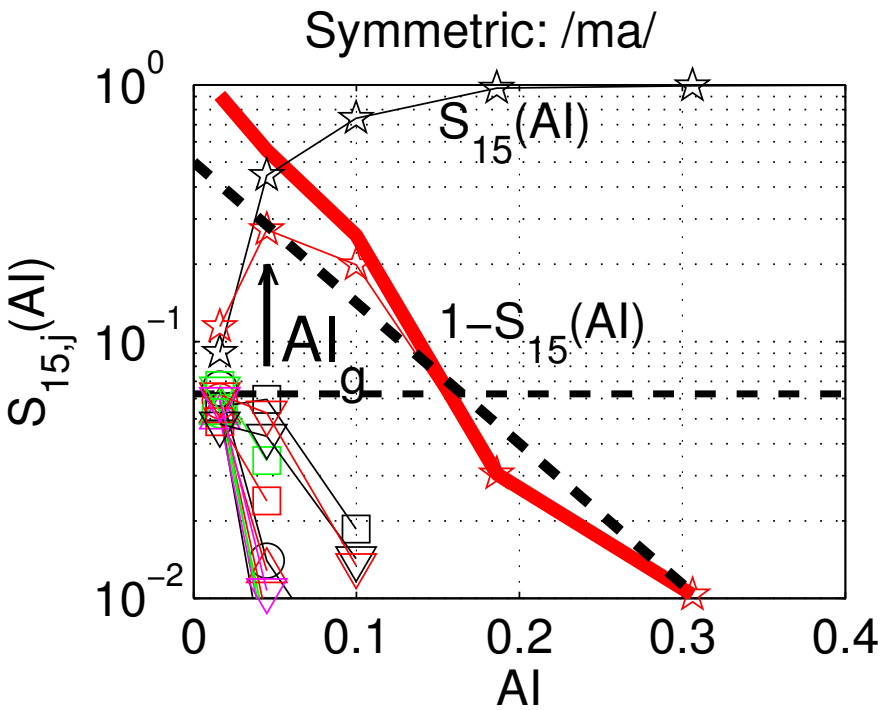


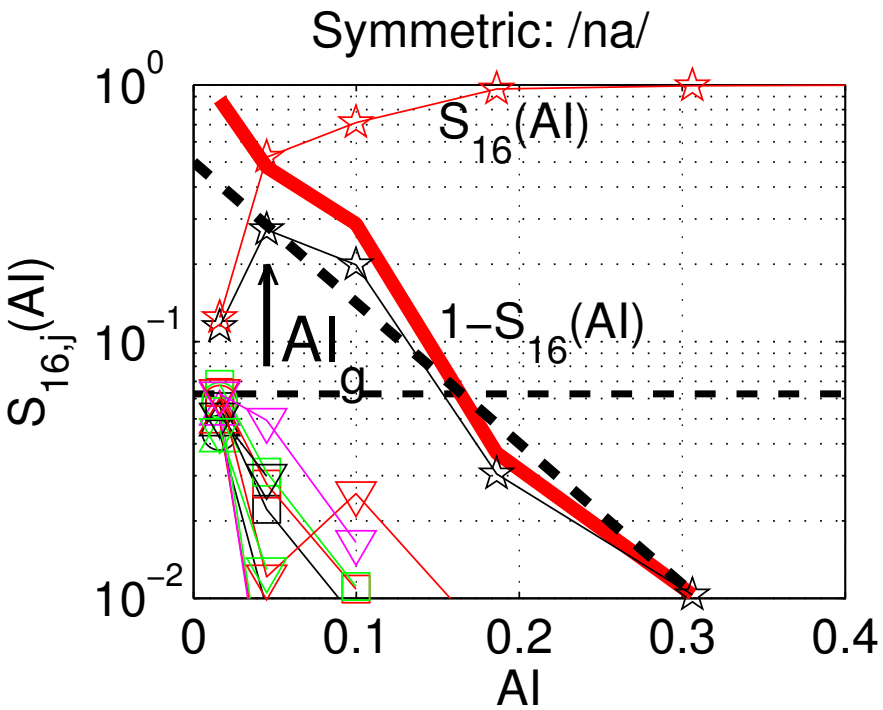
/ma/ and /na/ vs. AI

- The multichannel model is valid for the nasals

$$S_{i,j}(AI) \approx \delta_{i,j} + (-1)^{\delta_{i,j}} \left(1 - 2^{-\mathcal{H}_g}\right) \left(e_{\min}^{(i)}\right)^{AI} \quad \text{for } AI > AI_g$$

  - ${e_{\min}}^{(i)} \equiv 1 - S_{i,i}|_{AI=1}$
  - $\mathcal{H}_g = 1$ [bit] (i.e., a 2-group)

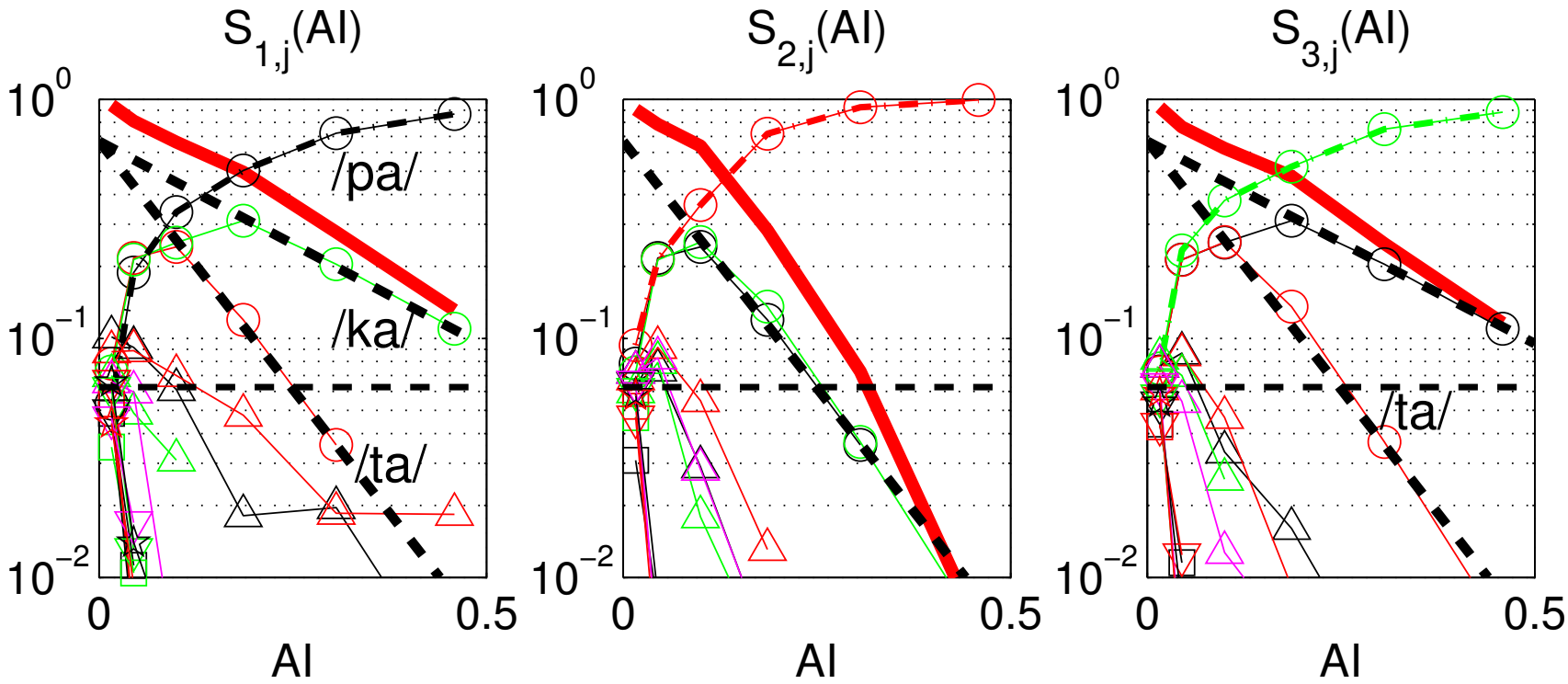




Case of /pa/, /ta/, /ka/ vs. AI

- Fletcher's multichannel model is valid for $i = 1, 2, 3$:

$$S_{i,j}(AI) \approx \delta_{i,j} + (-1)^{\delta_{i,j}} \left(1 - 2^{-\mathcal{H}_g}\right) \left(e_{\min}^{(i,j)}\right)^{AI} \quad \text{for } AI > AI_g$$



- Band independence holds for the [/pa/, /ta/, /ka/] group: $\mathcal{H}_g = \log_2(3)$, $AI_g = 0.15$ and $e_{\min}{}^{(i,j)}$ depends on i, j.

Conclusions I

- The AI predicts above chance performance near -20 dB
- HSR performance saturates near 0 dB SNR
- No overlap in ASR vs. HSR
  - ASR chance performance near 0 dB
  - ASR performance saturates near +20 dB SNR

Conclusions II

- Fletcher's AI theory is based on band independence

$$e(\mathit{snr}) = e_{\min}^{\frac{1}{K}\mathit{AI}_1} e_{\min}^{\frac{1}{K}\mathit{AI}_2} e_{\min}^{\frac{1}{K}\mathit{AI}_3} \ldots e_{\min}^{\frac{1}{K}\mathit{AI}_K} = e_{\min}^{\mathit{AI}} \qquad (2)$$

- Recognition of MaxEnt phones satisfy 2
- MaxEnt close set tests scores may be predicted by

$$P_c(\mathit{AI}, \mathcal{H}) = 1 - (1 - 2^{-\mathcal{H}}) {e_{\min}}^{\mathit{AI}}$$

- The first sign of $>$ chance performance is grouping
- The sound groups depend on the noise spectrum

Conclusions III

- The average over the 16 Miller Nicely consonant confusions $P_c^{(i)}(\mathit{snr})$ is accurately predicted by the Articulation Index:

$$\overline{P_c}(\mathit{snr}) \equiv \frac{1}{16}\sum_{i=1}^{16} P_c^{(i)}(\mathit{snr}) = 1 - \left(1 - \frac{1}{16}\right) e_{\min}^{AI}$$

- $P_c^{(i)}$ is the probability of correct identification of i^{th} CV
- $AI = \frac{10}{30}\sum_k \log_{10}(1 + 4\mathit{snr}_k^2)$ where k is the AI band index
- Chance error is given by $(1 - 1/16)$
- $e_{\min} \approx 0.005 \equiv \left.\frac{1-P_c(AI)}{(1-1/16)}\right|_{AI=1}$

Conclusions IV

- The *AI* model, corrected for 1/16 chance guessing, predicts the average Miller Nicely P_c quite well
- There are no free parameters in this model of $\overline{P_c}(snr)$
- For the MN experiment, the *AI* $\leq$ 0.5
- The *AI*(*snr*) is not linear in *snr*, due to the shape of the *snr(f)*
- The individual curves remain to be analyzed and modeled (if possible)
  - How can we explain the variance across sounds?

Conclusions V

- The MN data is very close to symmetric
- There are a few exceptions, but even for these, the asymmetric part is very small

Conclusions VI

- The off-diagonal PI(AI) functions linearly decompose error for i^{th} sound $P_c(i, AI)$, since $\sum_j P_{ij} = 1 \Rightarrow$

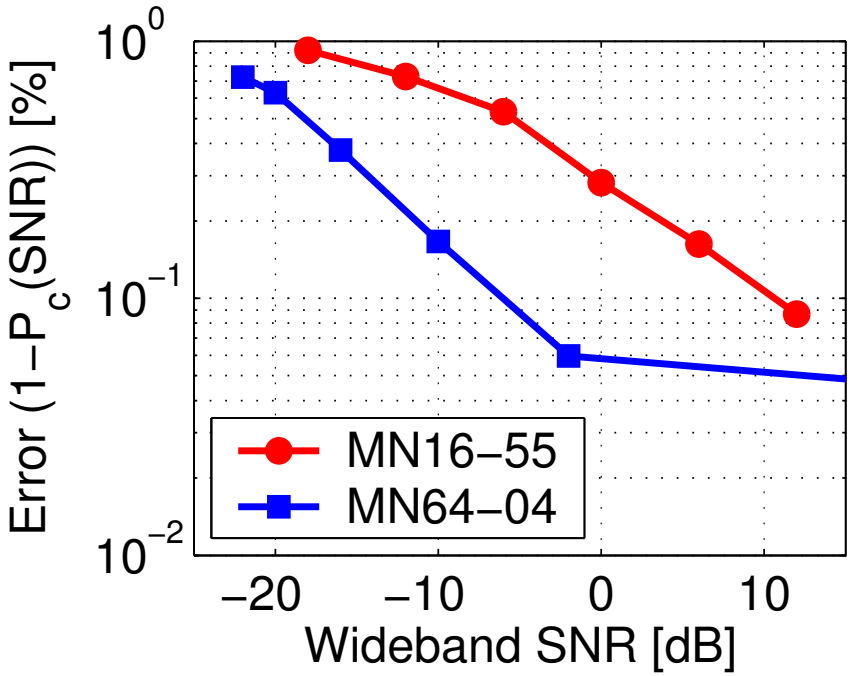
$$P_e(i, AI) \equiv 1 - P_{i,i}(AI) = \sum_{j \neq i} P(j|i, AI)$$

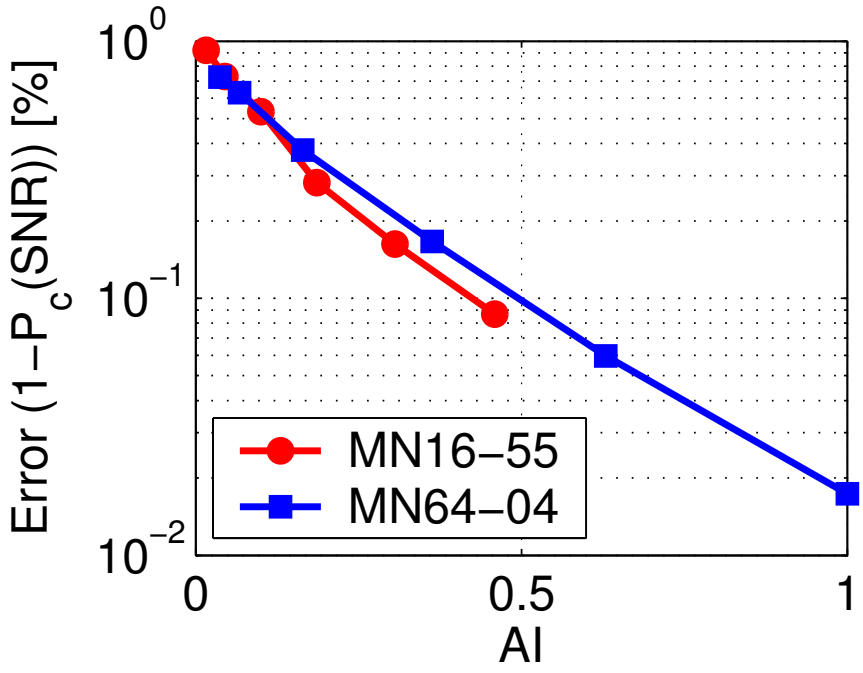
- In the previous figure the red curve is identically the sum of all the blue curves
- The green curve is the model

$$P_c(AI, \mathcal{H} = 4) = \left(1 - \frac{1}{16}\right) e_{\min}^{AI}$$

MN16 vs. MN64

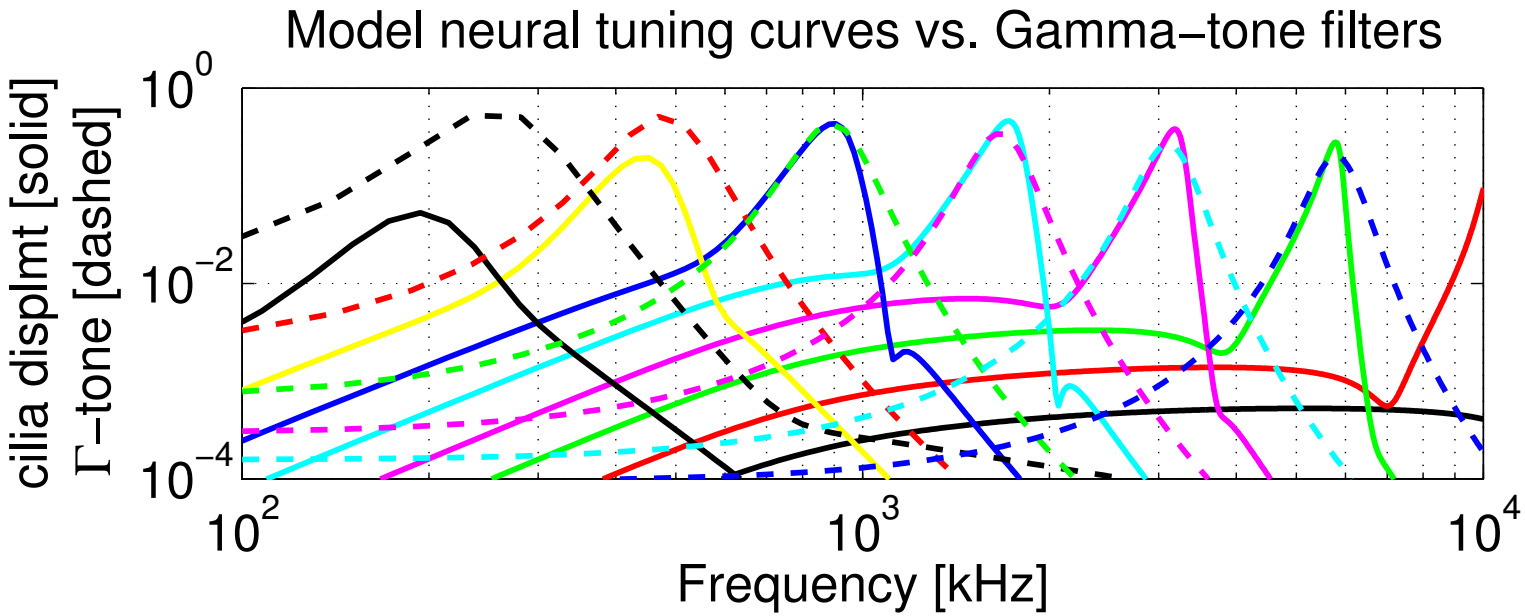
- Results of the MN16 and the MN64 CV experiments, plotted as a function of both the SNR and the AI.





Human vs. Γ-tone filters

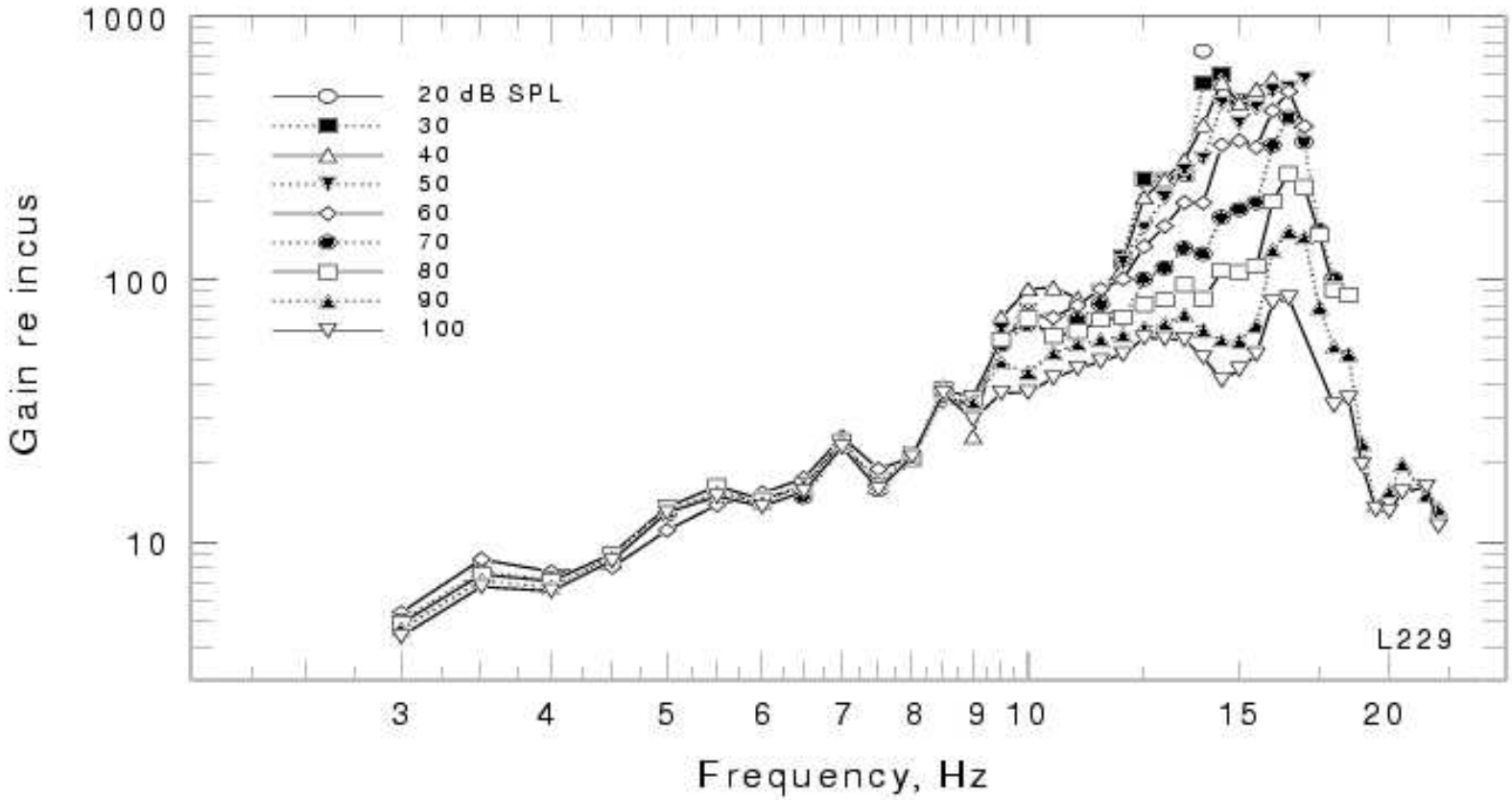
- $h(t, f_0) = t^3 e^{-2.22\,\pi\,\mathrm{ERB}(f_0)\,t}\cos(2\pi f_0 t)$ (Γ-tone filter)
- $\mathrm{ERB}(f_0) = 24.7(4.37 f_0/1000 + 1)$



- High frequency slope problem
- Low-frequency tails are wrong
- Wrong bandwidth at higher frequencies
- Missing middle ear high-pass response

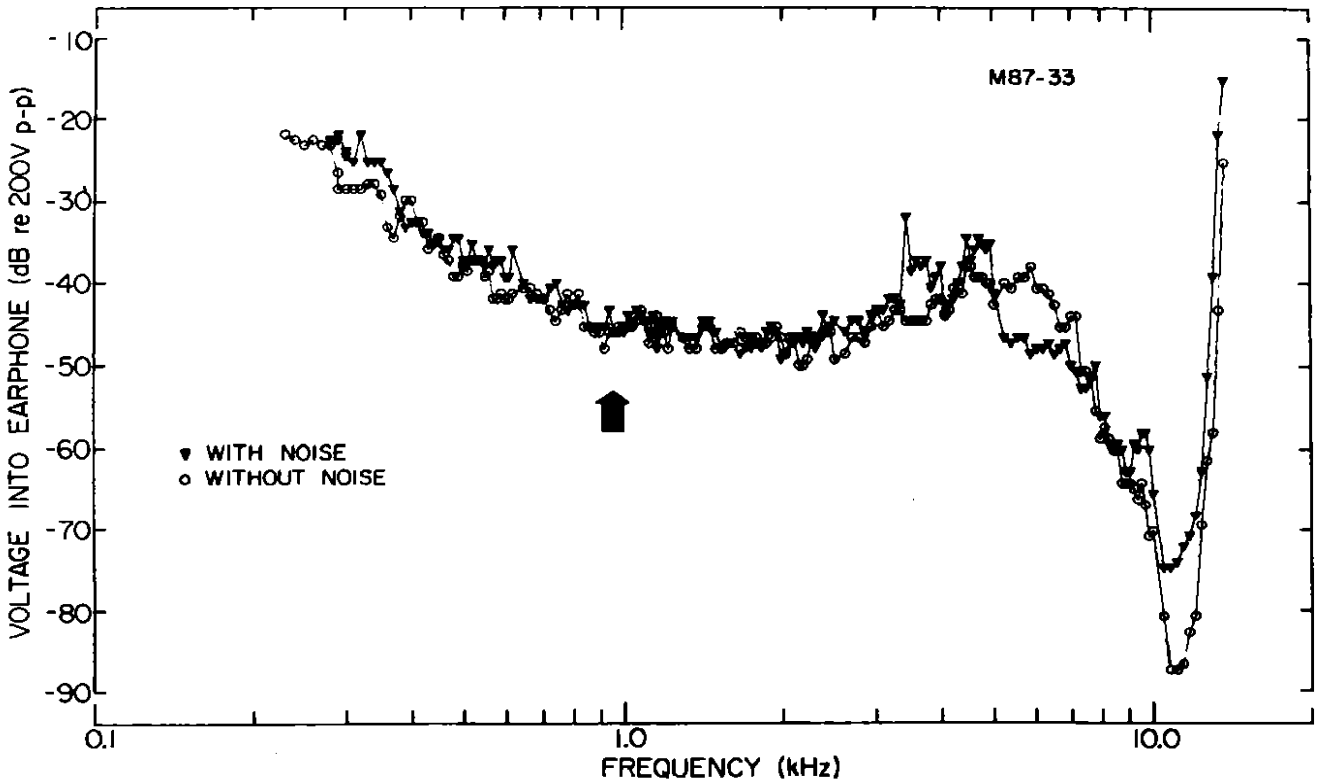
Narayan et al. data

- Narayan et al. 2000 (Gerbil)



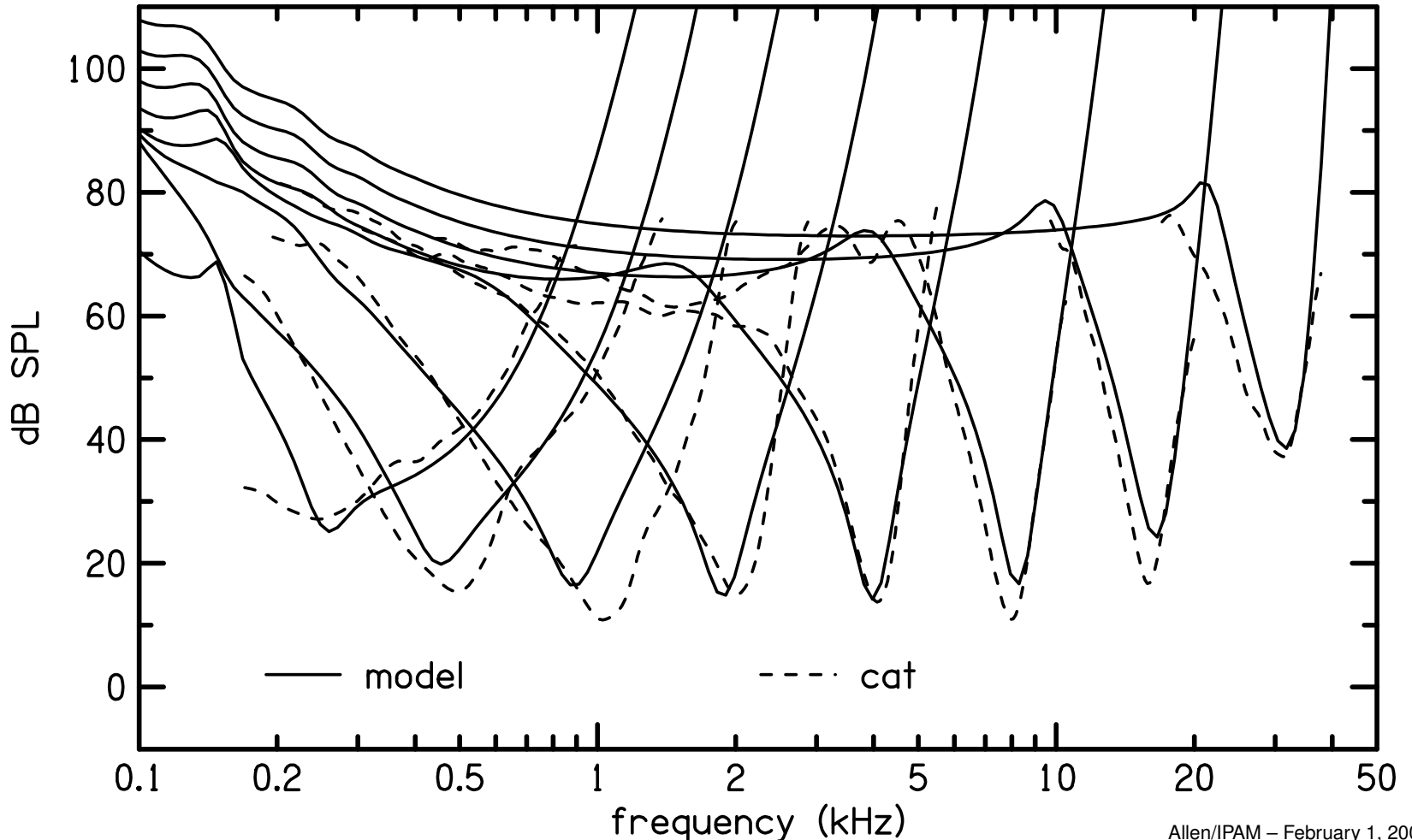
Kiang and Moxon 1979 cochlear USM

- Nonlinear upward spread of masking



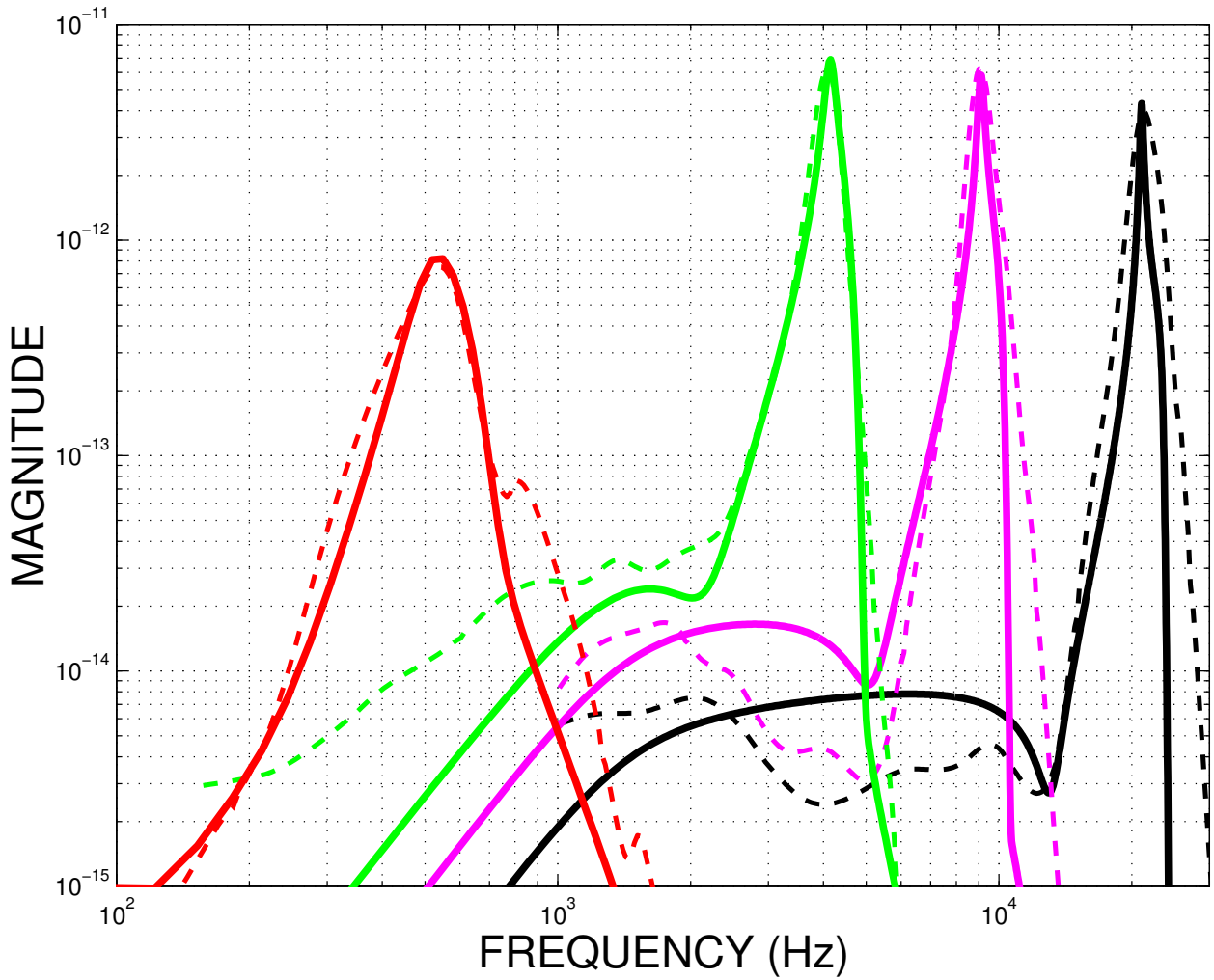
Neely model for Cat 1986

- Active model of the cochlea and cilia, based on the resonant TM model.
- Cat data from Liberman and Delgutte.

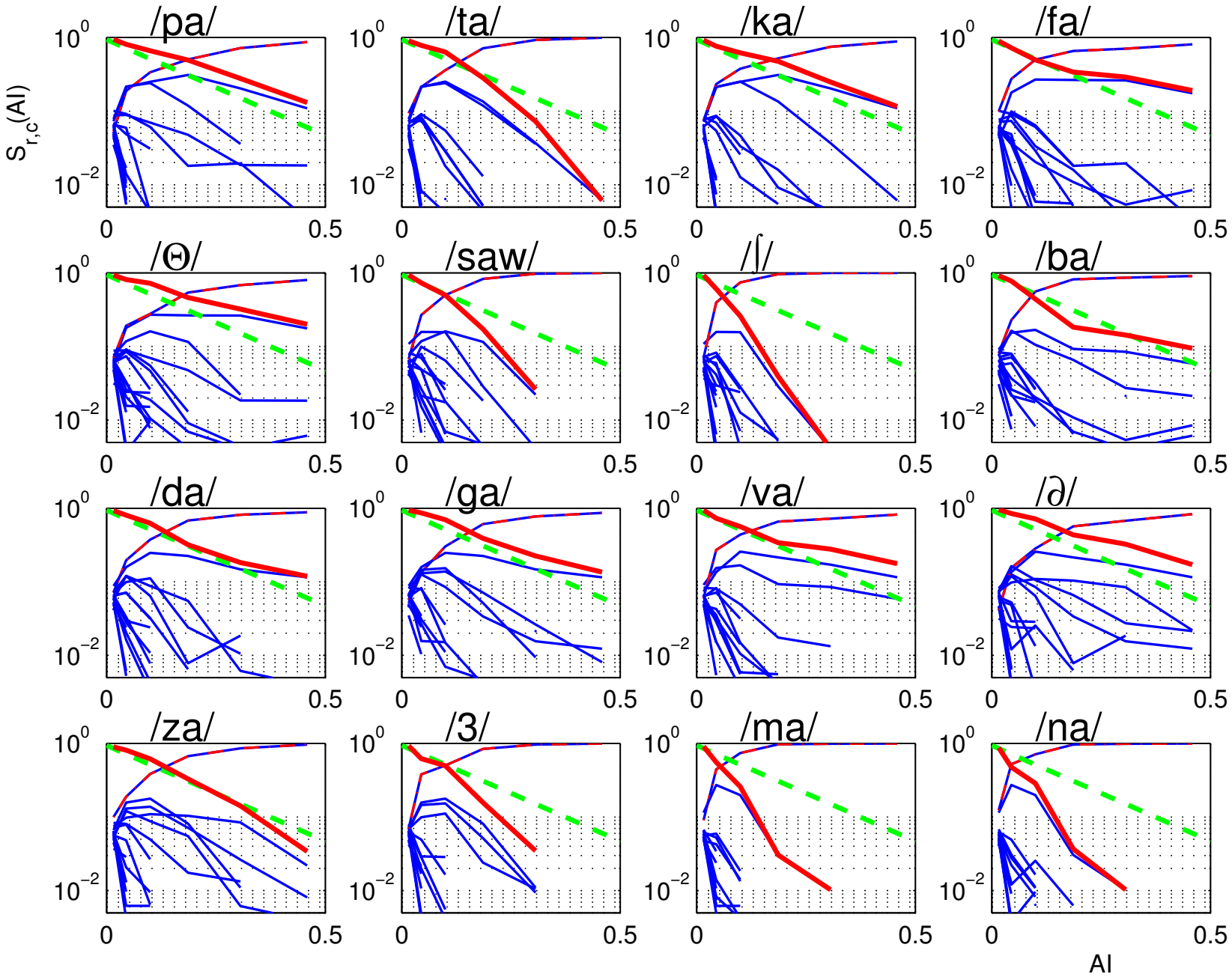


Allen model 1980

- Solid: Model; dashed Cat FTC (Liberman and Delgutte)



Symmetric form $S = (\mathcal{A} + \mathcal{A}^t)/2$



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