Cochlear nonlinearities and phoneme recognition

Finding the features in individual consonants.

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Notable quotes

We need to know more about human speech processing and and natural speech variation
–Sadaoki Furui (ASRU 2009)

This is so true!
–Jont Allen

Question your assumptions:

- Elephant in the room:
  Human CV speech is *not* variable.
- CV speech is *not* redundant.
- Why we don't know anything about the topic?
  $ spent on basic speech research $\rightarrow$0,

Outline of talk

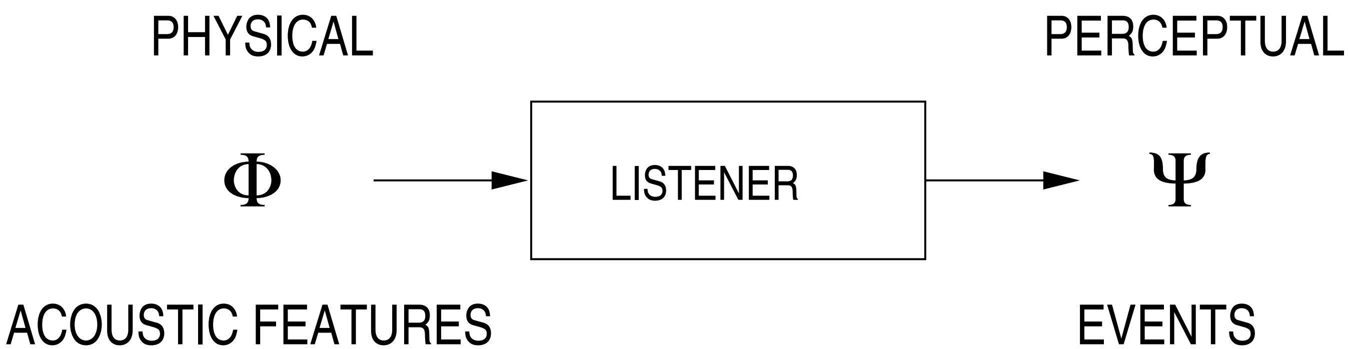
1. Intro + Objectives (5 mins)
   - The research goal is to
     - Identify the *elemental HSR events* in
     - Example consonants
2. Historical overview (5 mins $\Sigma 10$)
   - Rayleigh (1910) to Shannon (1948)
3. Methods (15 mins $\Sigma 25$)
   - -Information Theory; -Signal processing
   - -Psychophysics; -Articulation Index;
4. Results (30 mins $\Sigma 55$)
   - Confusions; Primes and Morphs;
   - Speech Modifications; Conflicting cues
5. Summary + Conclusions (5 mins $\Sigma 60$)

I – Introduction (5 mins)

- Statement of the problem:
  - A fundamental understand the Human Speech code
- Short-term Goal:
  - Identify the key features in individual CV utterances
    - -Plosives (e.g., /p, t, k/ and /b, d, g/)
    - -Fricatives (e.g., /θ, ʃ, ʧ, s, h, f/ and /z, ʒ, v, ð/)
    - -With vowels /o, ε, ı/
- Applications:
  - Reduce variability in ASR at frontend
  - Hearing Aids, Cochlear Implants
  - Smart Telcom products
  - TTS (Text to speech)
  - Intelligibility modifications (Robustness problem)
    - Speech enhancement in noise

Objective

- To develop rigorous procedures for analyzing and modifying speech in noise
- To identify perceptual features, denoted events



- Based on two basic measures:
  - AI-Gram (speech audibility measure)
  - Confusion matrix (CV discrimination measure)
- We will show that onset and durational timing cues form the consonant events

II – Historical HSR Studies (5 mins)

- Lord Rayleigh's 1908 and George Campbell 1910
  - First electronic articulation experiments
- Harvey Fletcher's 1921 Articulation Index AI
  - Accurate predictions of nonsense syllable scores
  - French and Steinberg 1947 first publish AI
- Shannon The thoeory of Information 1948+
  - G.A. Miller, Heise and Lichten Entropy $\mathcal{H}$ 1951
  - G.A. Miller & Nicely CM $P_{h|s}(SNR)$ 1955
- Context:
  - G.A. Miller 1951 *Language and communication*
  - G.A. Miller 1962 5-word Grammer $\equiv$ 4 dB of SNR
  - Boothroyd JASA 1968; Boothroyd & Nittrouer 1988
  - Bronkhorst et al. JASA 1993

Speech feature research

- 1910-1980: Bell Labs
- 1940-1960: Haskins Lab
- 1960-1990: MIT
- 1980-2010: ASR at AT&T, IBM, BBN, University research

Cochlear research

- 1910-1950: Bell Labs
- 1960-2010: MIT + Harvard HSTB
- 1980-2010: NIH funded University research

Speech feature research

- 1910-1980: Bell Labs
- 1940-1960: Haskins Lab Synthetic speech
- 1960-1990: MIT Consonant features unknown
- 1980-2010: ASR at AT&T, IBM, BBN, University research Not designed to be robustness to noise

Cochlear research

- 1910-1950: Bell Labs
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III – Methods (15 mins)

- Information Theory IT $\equiv$ Articulation index AI
  - Confusion matrix CM scores: $P_{h|s}(\mathit{SNR})$
  - AI to model mean phone errors $\sum_h P_{h|s}(\mathit{SNR})$
- Psychophysics
  - Real consonant-vowel CV speech
  - Several types of additive noise
  - Large number of trials
    - $>$20 talkers and $>$20 listeners
- Signal processing
  - AI-gram (crude cochlear model)
  - Frequency, time, intensity truncation 3^d-DS
  - Short-Time Fourier Transform STFT modifications

The CM and the *elemental–event*

- Miller-Nicely's 1955 articulation matrix $P_{h|s}(SNR)$, 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

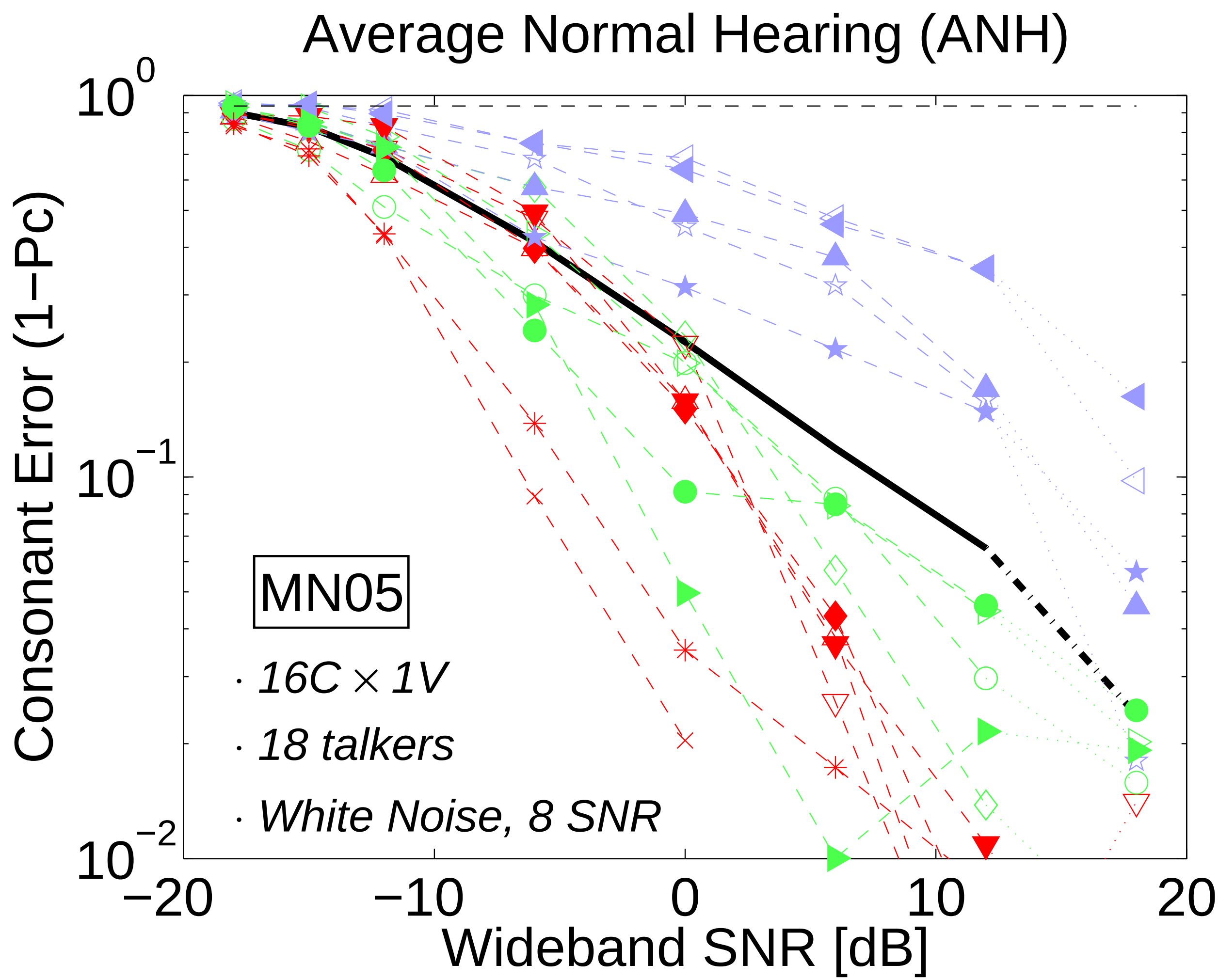
UNVOICED VOICED NASAL

RESPONSE

- Confusion groups $\equiv$ *inhomogeneous elemental-events*

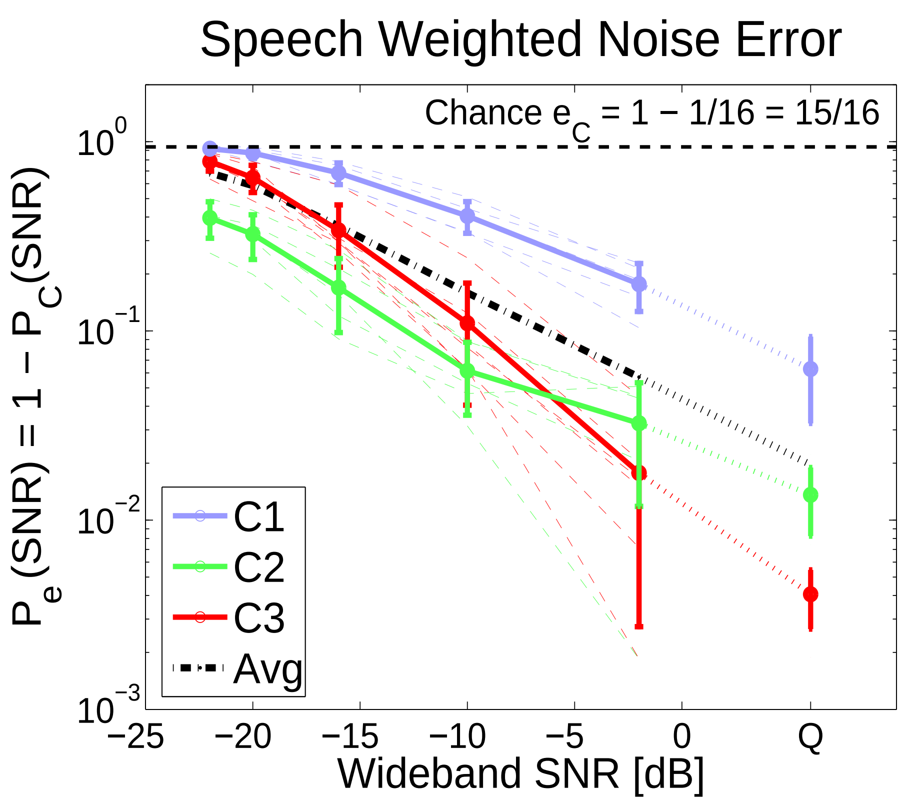
Average phone scores vs. SNR

- Consonant chance performance is -20 dB-SNR in white noise   Phatak Allen, 2007

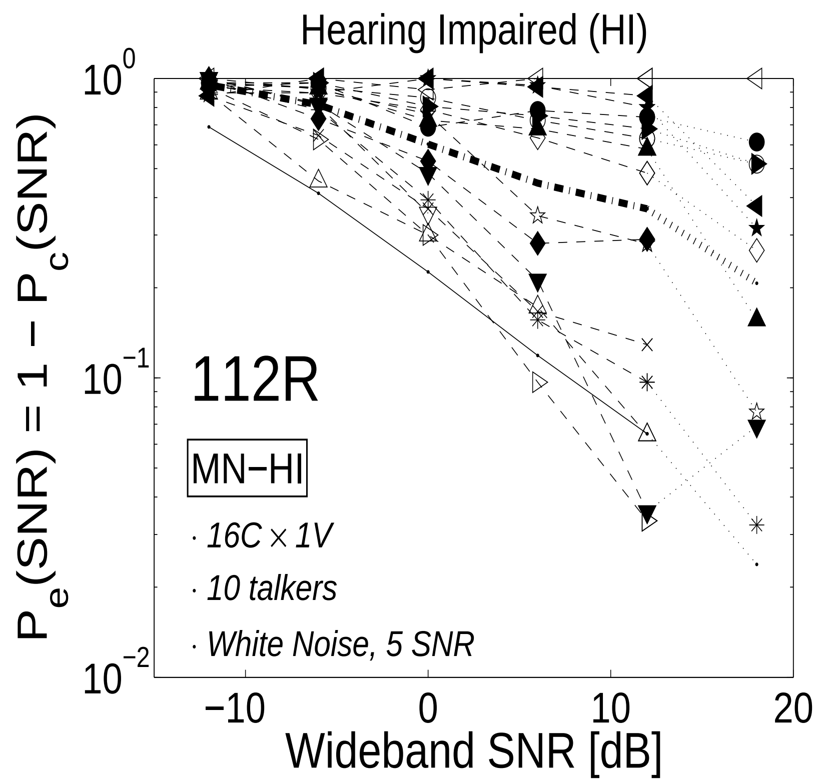


Consonant Variability

- Avg. Contant error $P_{h|s}(SNR)$ strongly hetrogeneous!
- NH listeners above chance at $<$ –25 dB SNR in SWN
  - HI $P_e(SNR) >> $ ANH $P_e(SNR)$



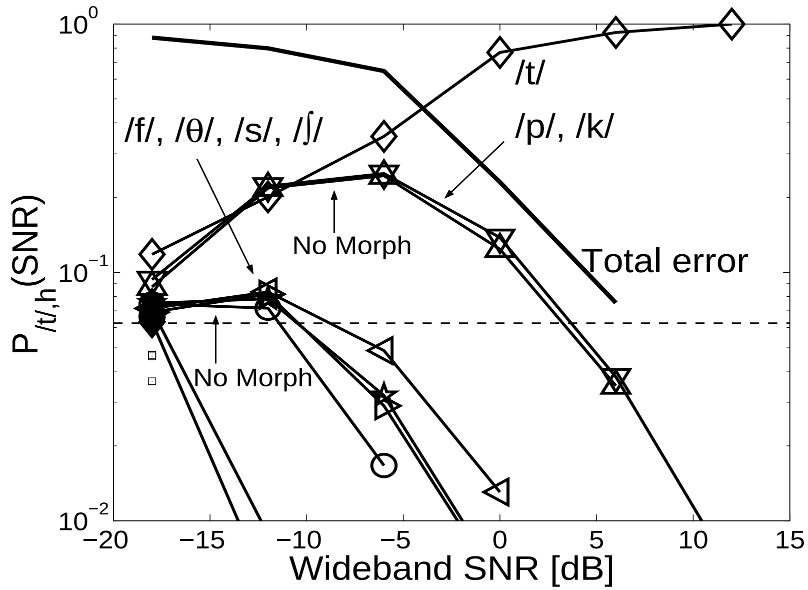
(a) Consonant errors ANH



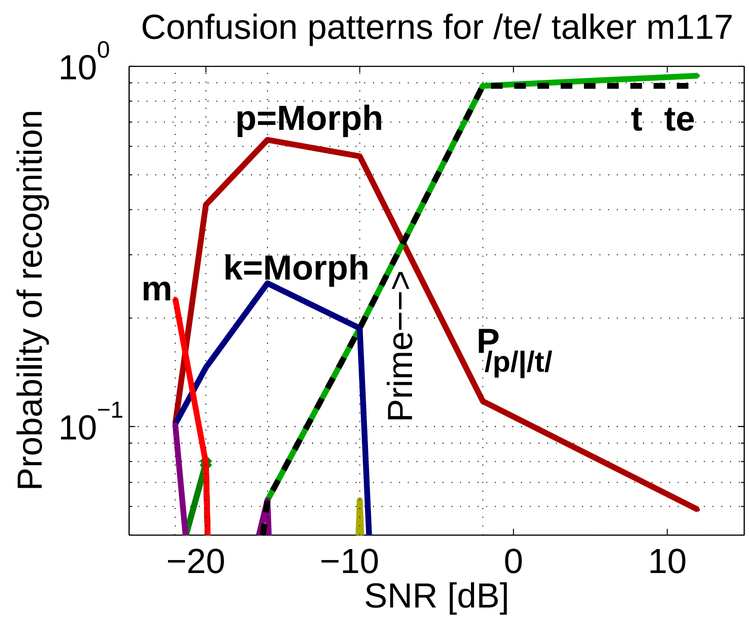
(b) Consonant errors HI

Row of CM $P_{h|/t/}$

- Utterance phone scores are hetrogeneous!



(c) Average over all /t/s.



(d) Talker m117 /te/ $P_{h|/ta/}(SNR)$

- Phone groups are due to shared sub-phonemic units
  - CV Morphs
  - Morphing sentences

Row of CM $P_{h|/t/}$

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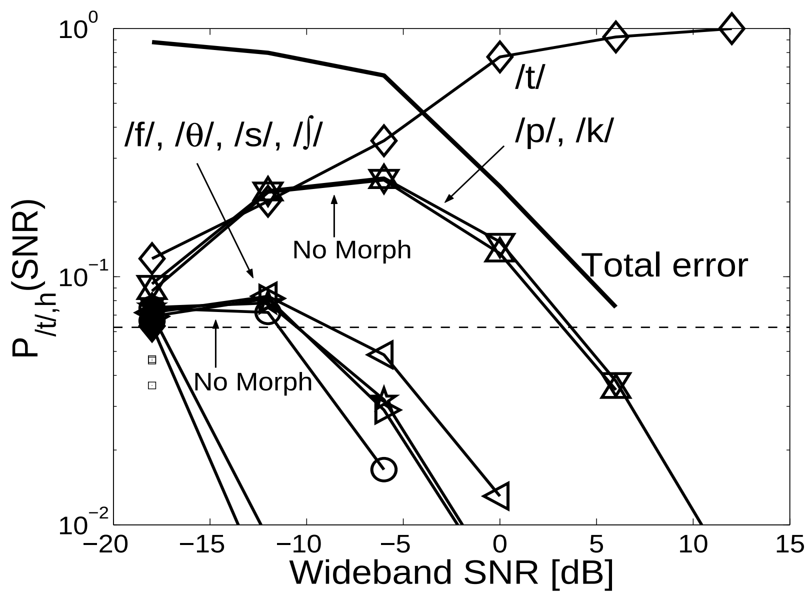
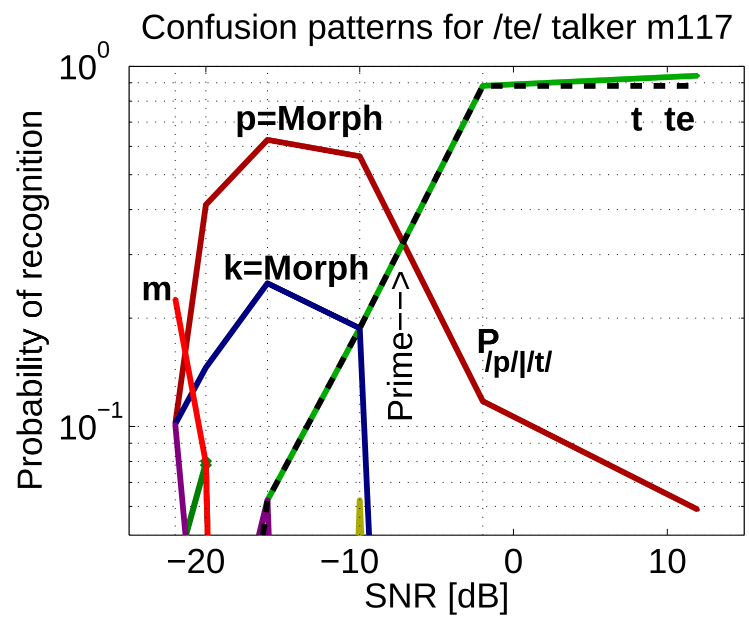


(e) Average over all /t/s.



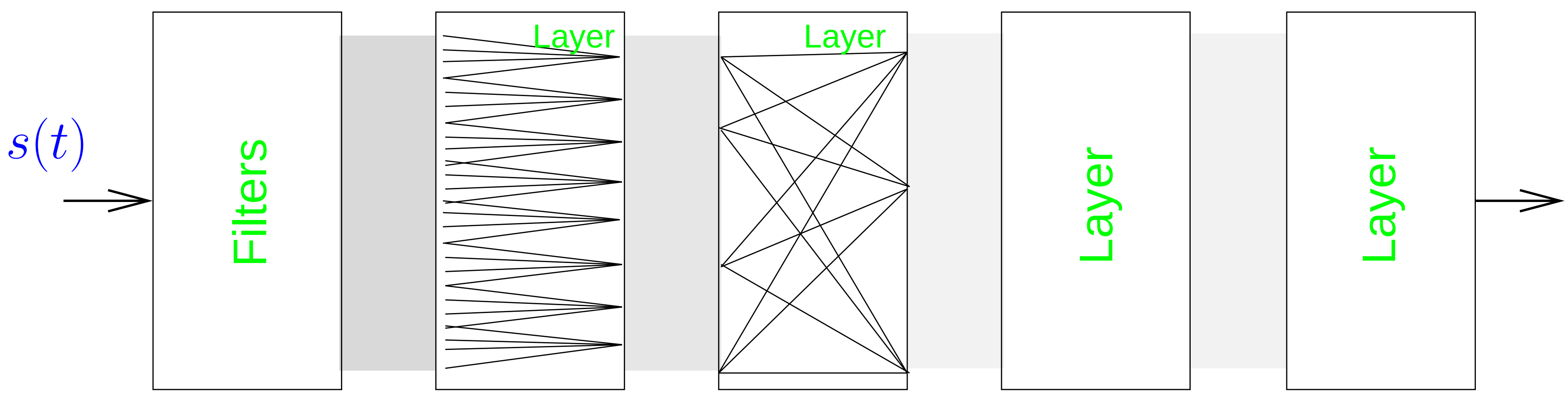
(f) Talker m117 /te/ $P_{h|/ta/}(SNR)$

- Phone groups are due to shared sub-phonemic units
  - CV Morphs DEMO
  - Morphing sentences DEMO

Model of human speech recognition HSR

- Research Goal:
  - Identify *elemental HSR events*
  - An event is defined as a *perceptual feature*
  - Event errors are measured by band errors e_k

Output:	Cochlea	Event	Phones	Syllables	Words	



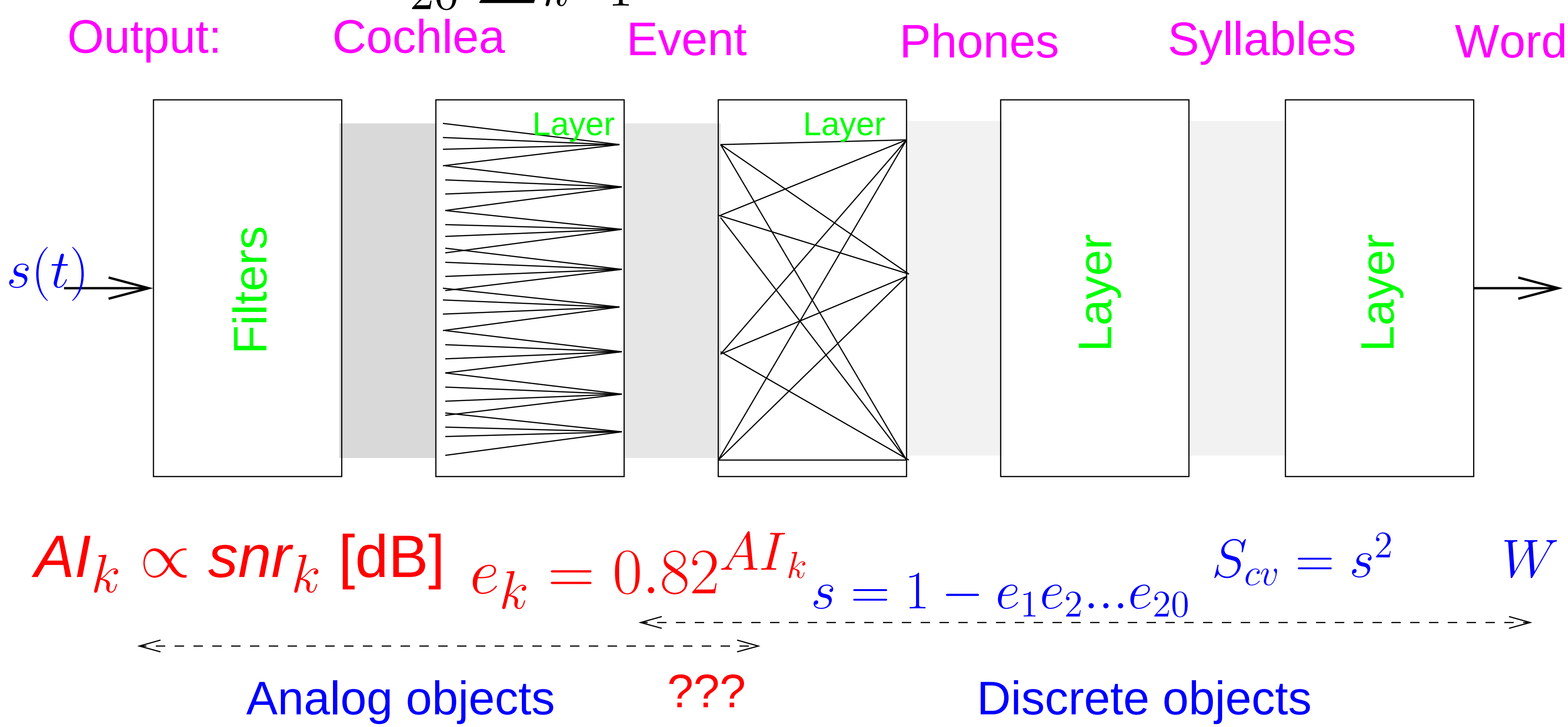
Measure:	AI_k	e_k	s	$S = s^3$	W
Formula:	$\propto$ *snr*$_k$ dB	$= 0.82^{AI_k}$	$= 1 - e_1 e_2 \ldots e_{20}$		

Analog objects ??? Discrete objects

Φ "Front-end" Ψ "Back-end"

Definition and use of the *AI*

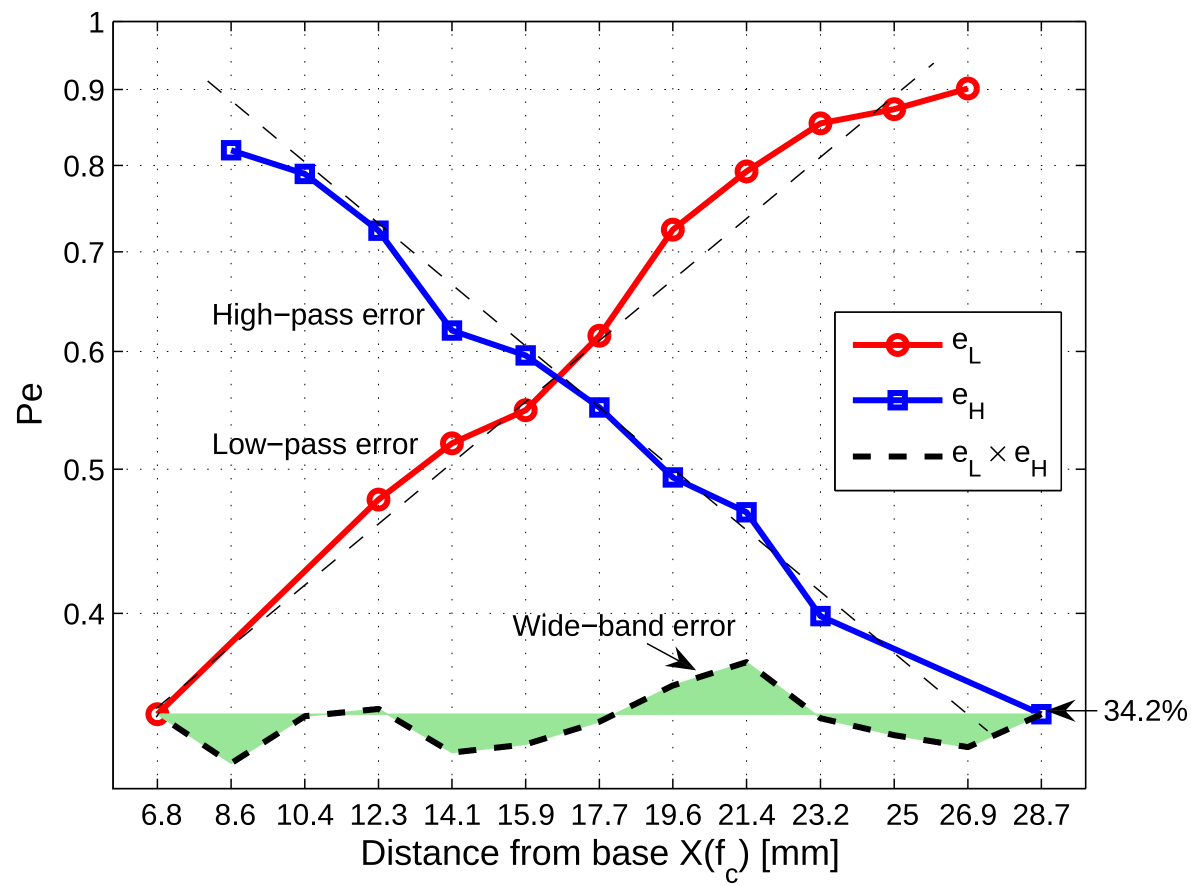
- The average error is: $P_e(\mathsf{SNR}) \equiv \prod_k e_k = 0.02^{\mathsf{AI}}$
  - $e_k = 0.822^{\mathsf{AI}_k(\mathsf{snr}_k)}$ cochlear k^{th} band-error
  - $AI_k = \log_{10}(1 + 4\mathsf{snr}_k^2)^{1/3}$ band channel-capacity
  - $\mathsf{AI} \equiv \overline{\mathsf{AI}_k} = \frac{1}{20}\sum_{k=1}^{20} AI_k,$



Fletcher's Lowpass/Highpass result

- The AI is based on the *band-error product formula*

$$P_e(\mathsf{snr}, \cancel{f_c}) \equiv e_{lp}(\mathsf{snr}, f_c) \times e_{hp}(\mathsf{snr}, f_c)$$

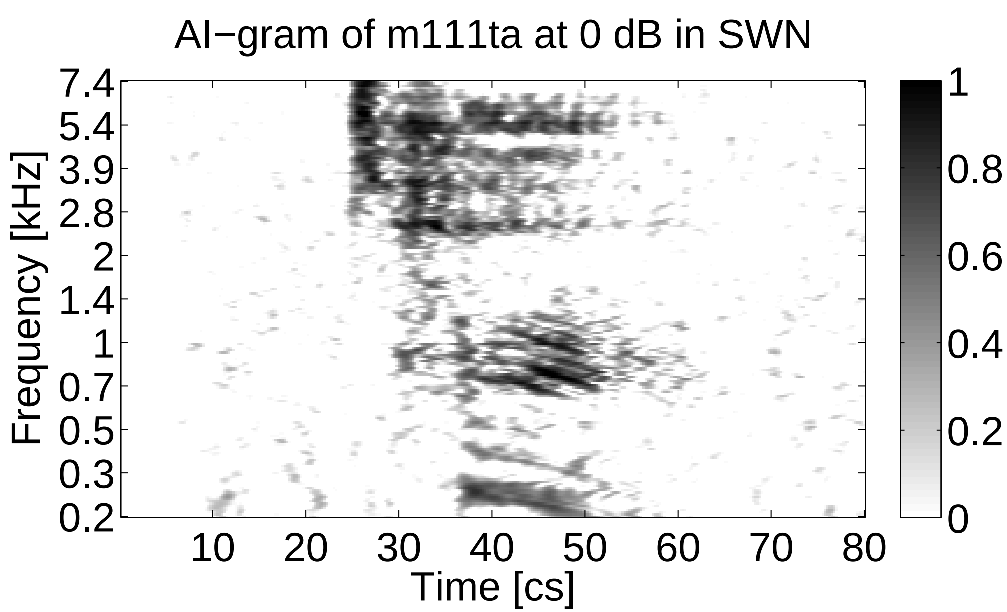


Human listeners as a Shannon Channel

- The Channel capacity theorem gives the maximum information rate as:

$$\mathcal{C} \equiv \int \log_2 \left(1 + snr^2(f)\right) df \qquad (1)$$

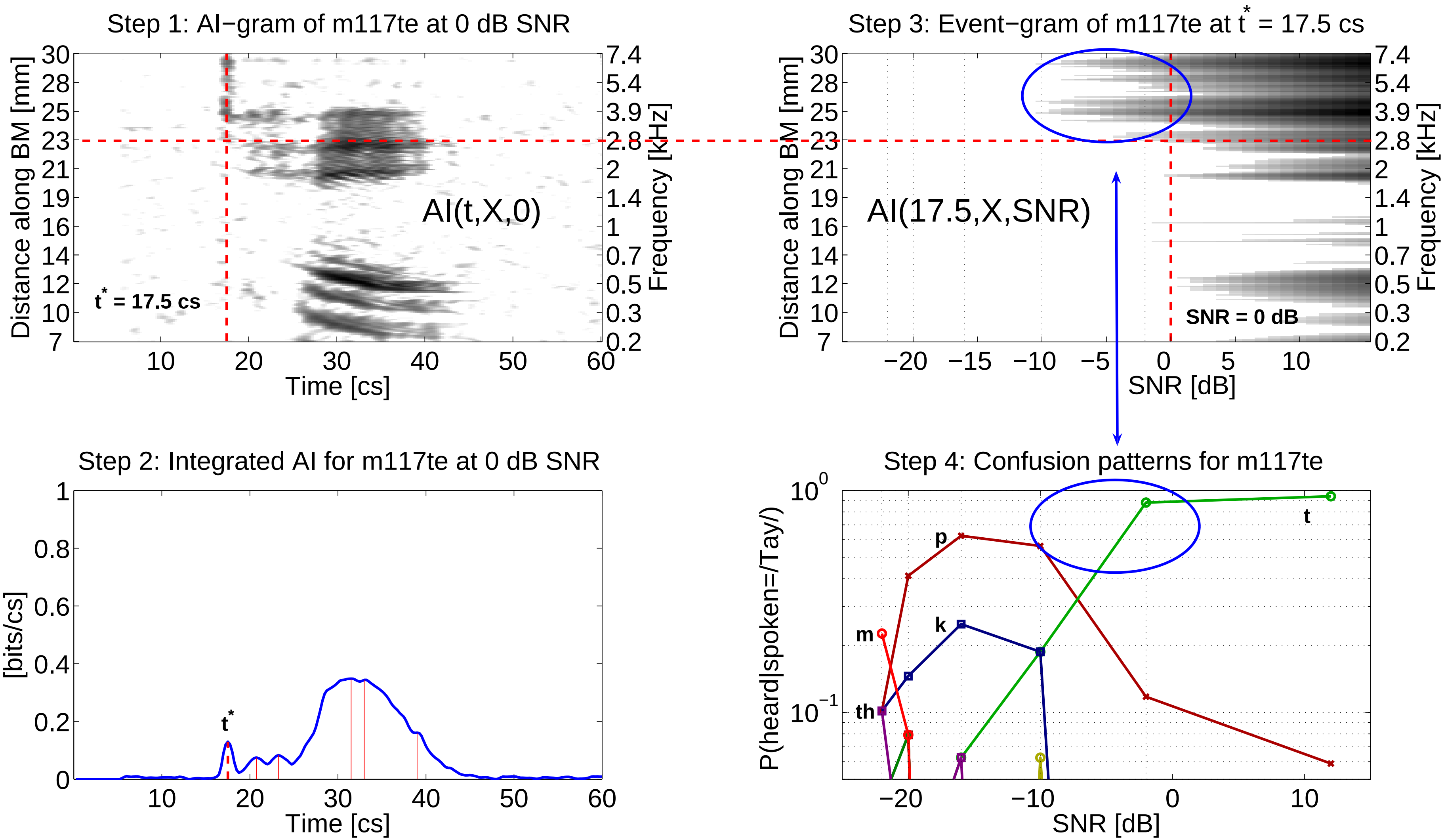
- For a Maximum Entropy (MaxEnt) speech source, the maximum information rate is determined by the SNR
- The AI-gram is a closely related measure:



III–Results (30 mins)

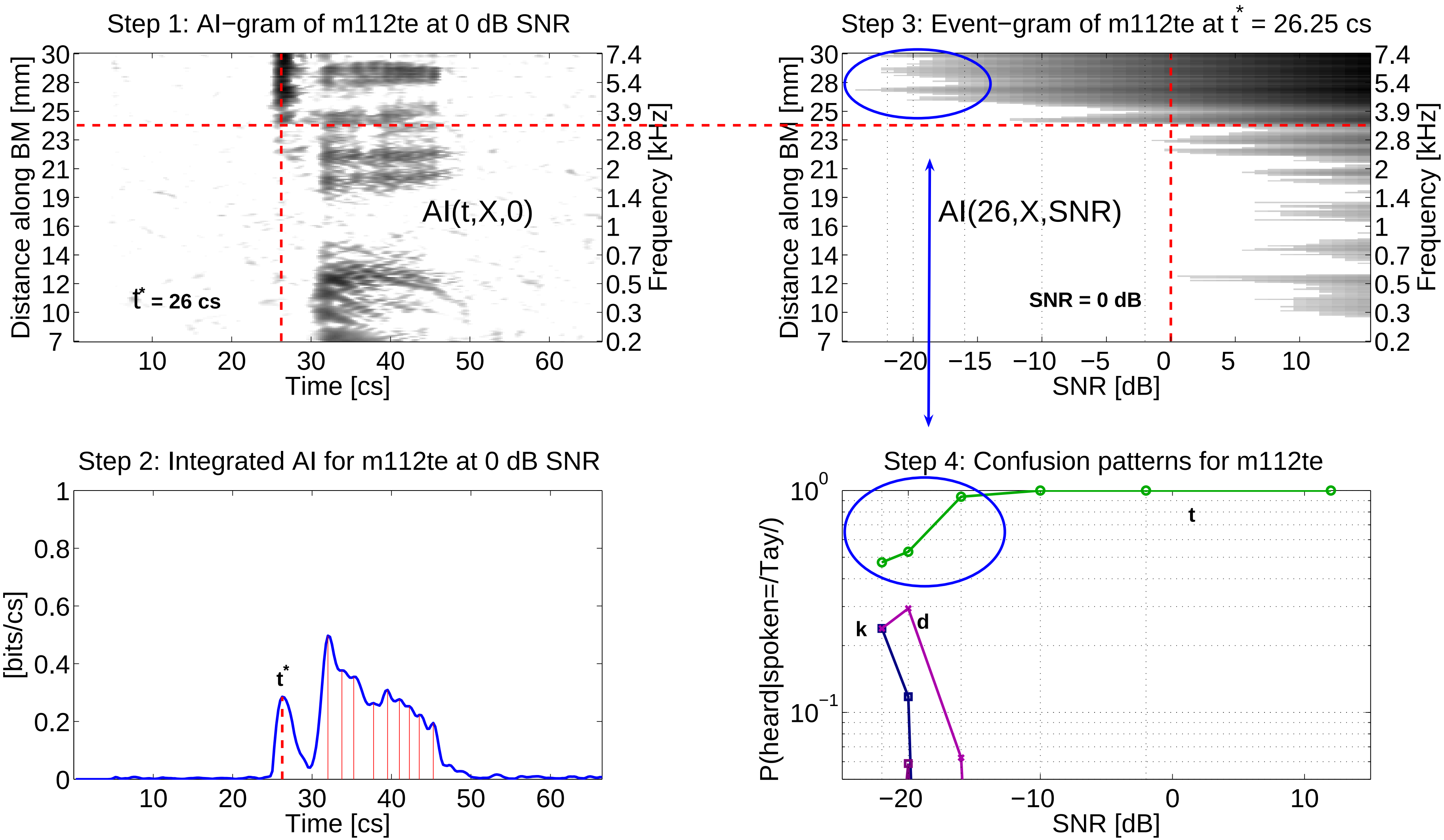
- Examples and Demos of events
  - Plosive CV events
  - Fricative CV events
- Conflicting cues
- DEMOS:
  - Event isolation
  - Consonant morphing
  - Consonant enhancement
  - Conflicting cues within consonants
  - Sentence meaning modification

m117/tɛ/ in speech-weighted noise



- /t/ confusion threshold at $P_c(\mathit{SNR}^* = -2) = 0.9$ correlated to Event-gram

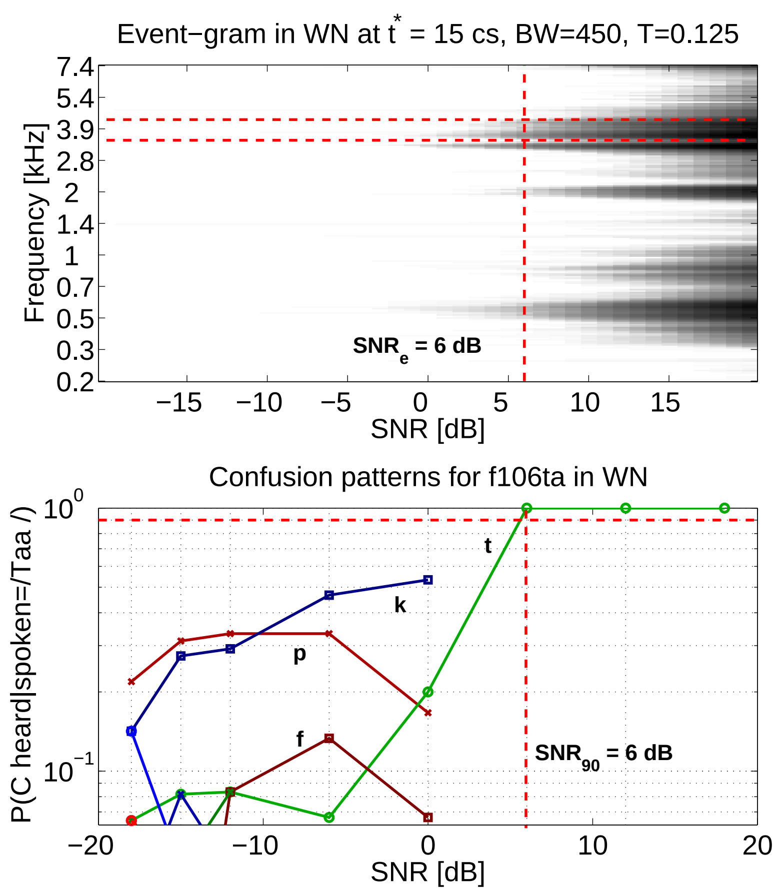
m112/tɛ/ in speech-weighted noise



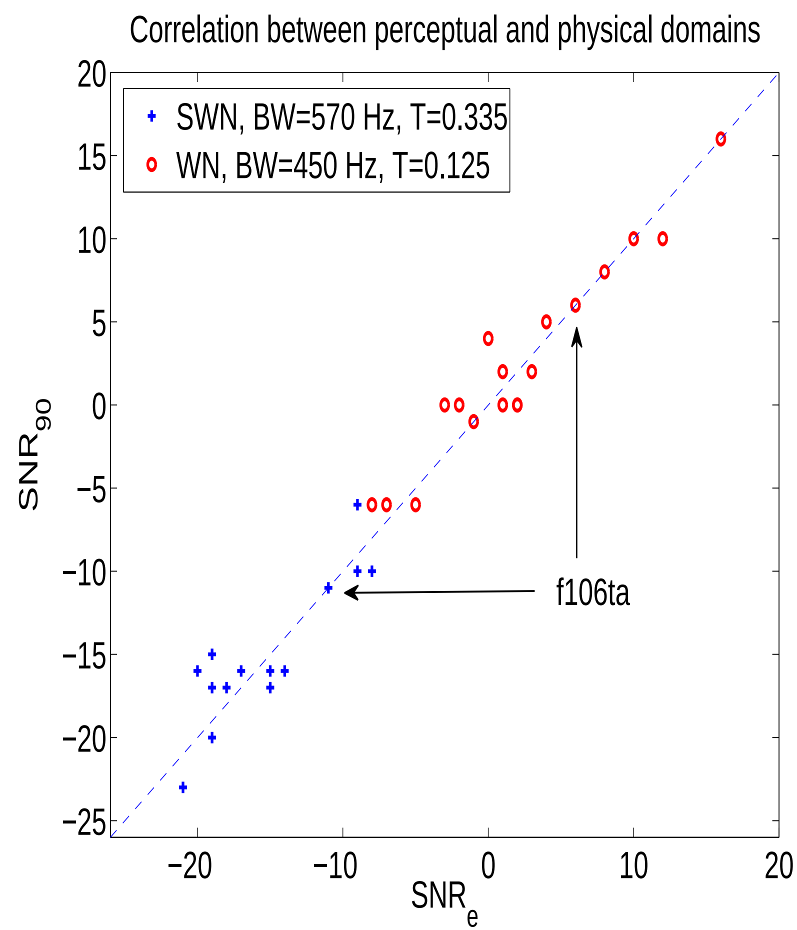
- /t/ confusion threshold at $P_c(\mathit{SNR}^* = -16) = 0.9$ correlated to Event-gram

Correlations of /t/ events

- High correlation across all /t/'s in the database

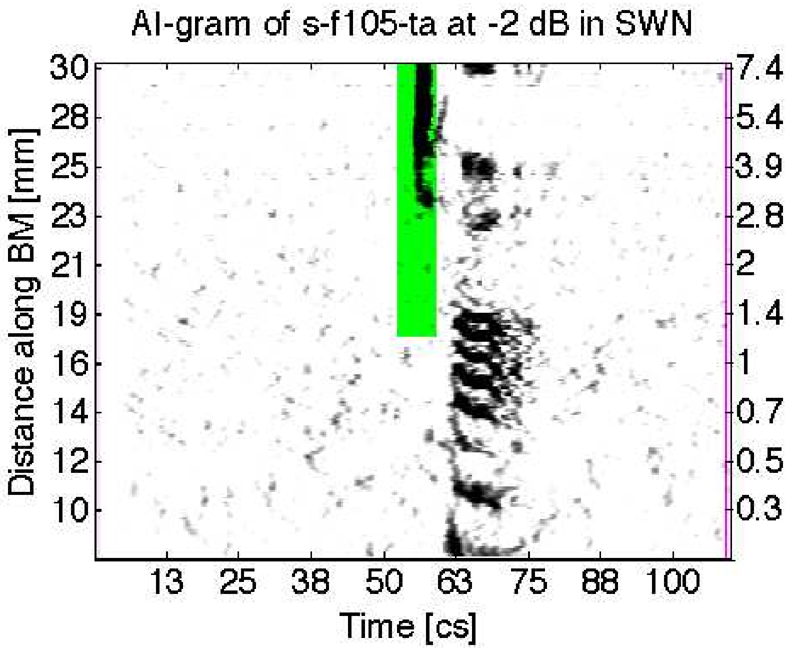


(g)

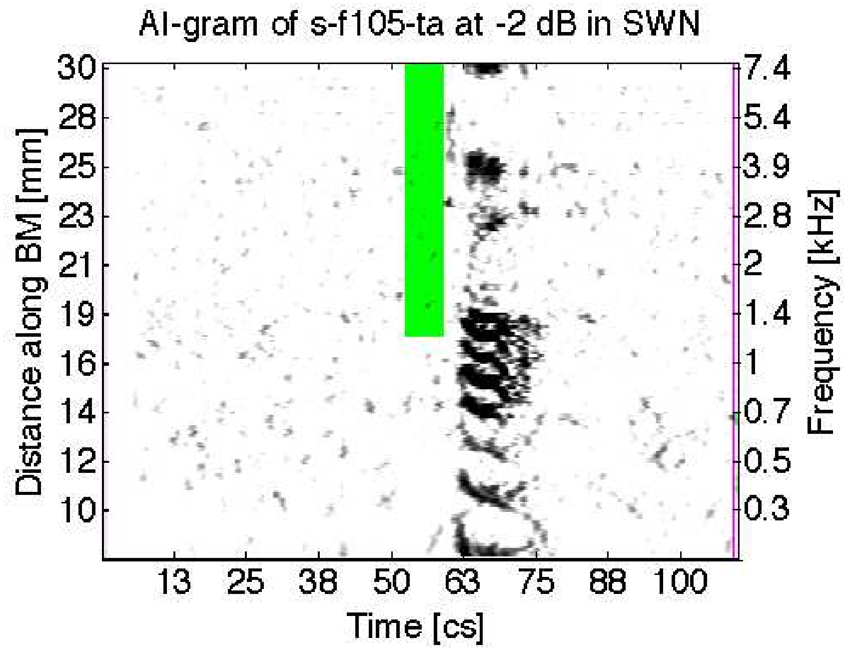


(h)

Masking of /tɑ/ timing cue



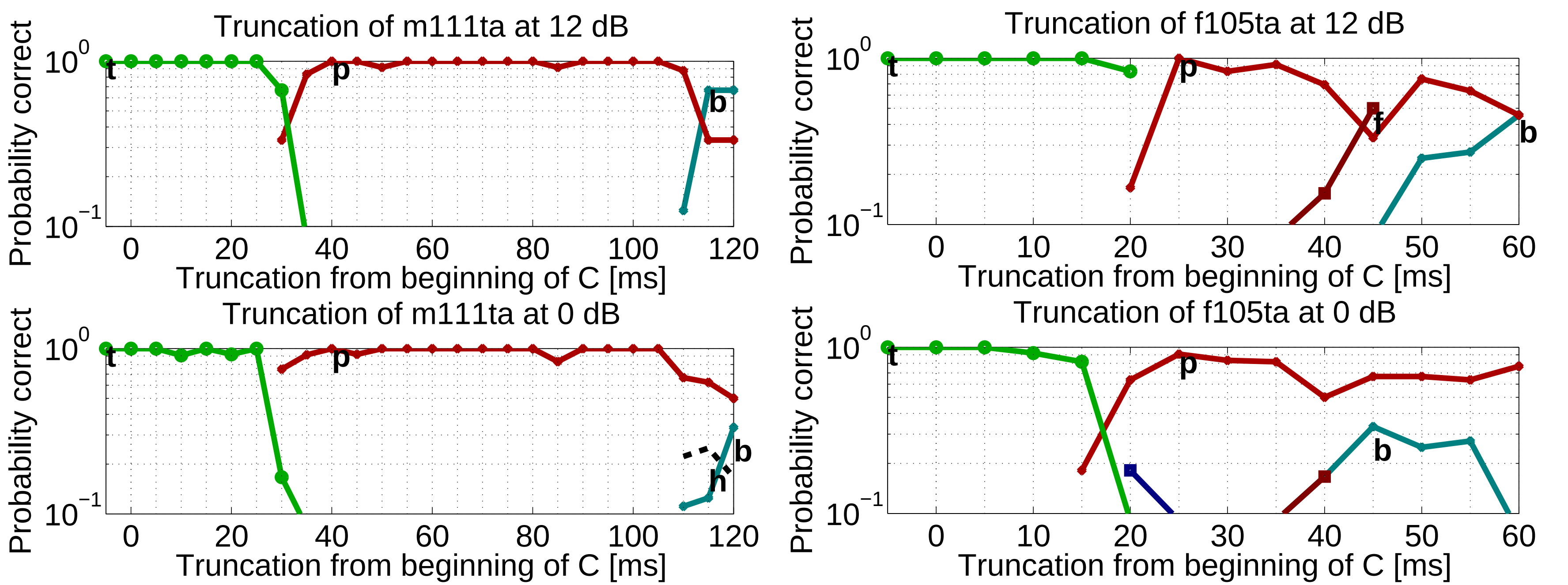
(i) Original /tɑ/



(j) Modified /tɑ/

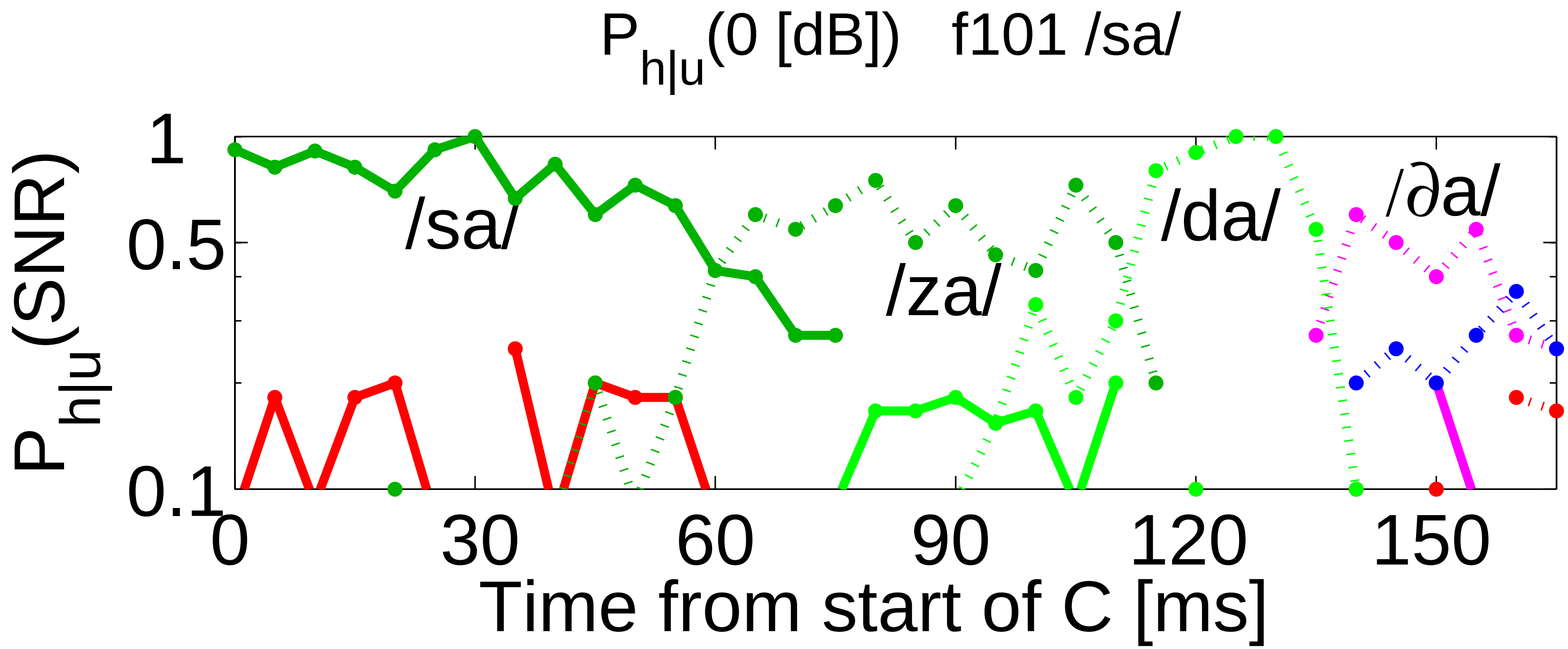
- When the /t/ burst is masked by noise, the perception morphs to /p/
- DEMO 4

Truncation of /tɑ/



- This represents the normal hearing responses to a truncated /tɑ/, from the start of the consonant
- Morphing from /tɑ/ to /pɑ/ to /bɑ/ at 0 and 12 dB SNR
- Similar to Furui 1986, and our extensive results

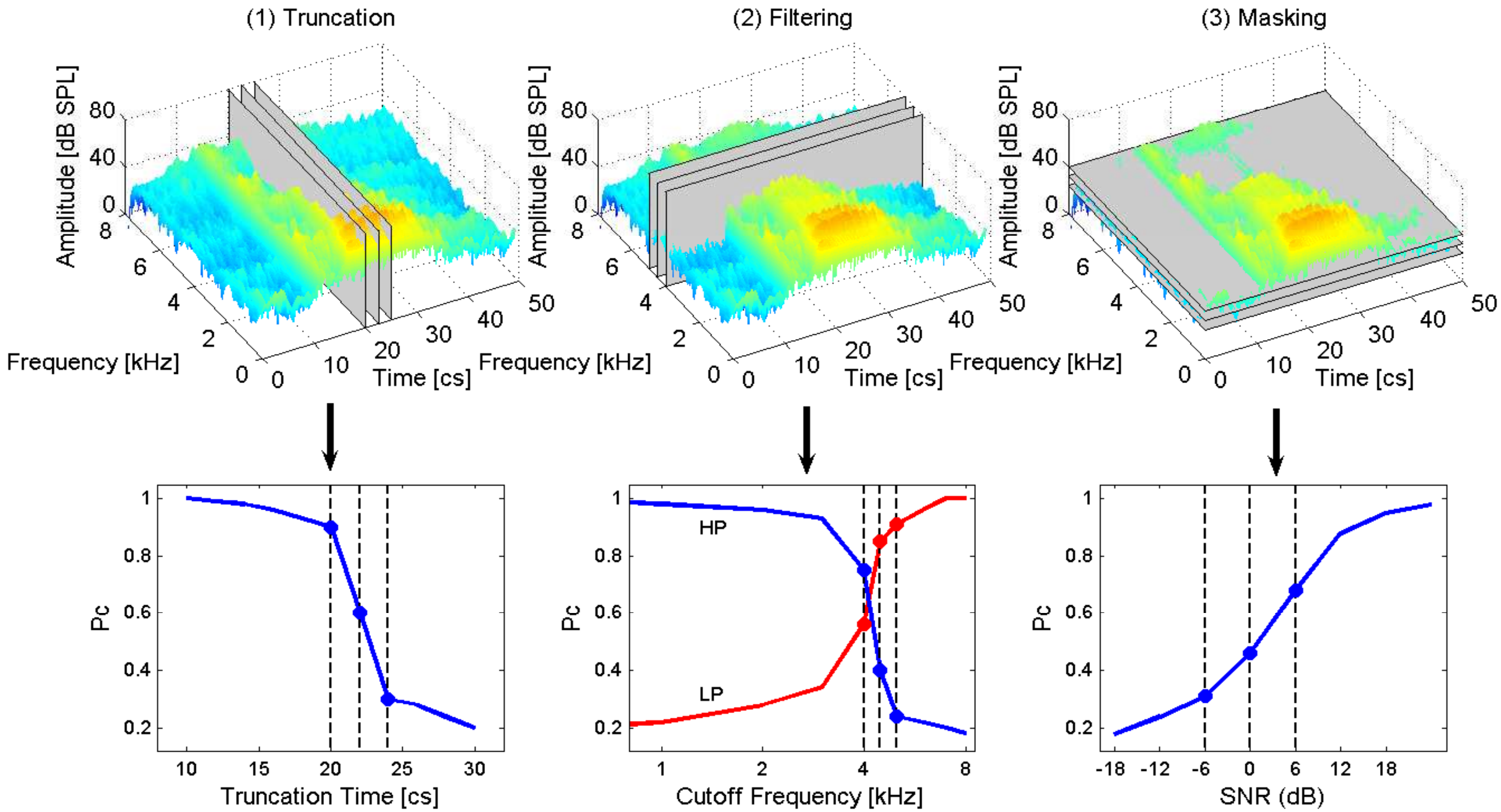
Truncation of f101 /sa/



- This represents the normal hearing responses to a truncated /sɑ/, from the start of the consonant
- Morphing from /sɑ/ to /zɑ/ to /dɑ/ to /ðɑ/
- Duration seems to be a fricatives event

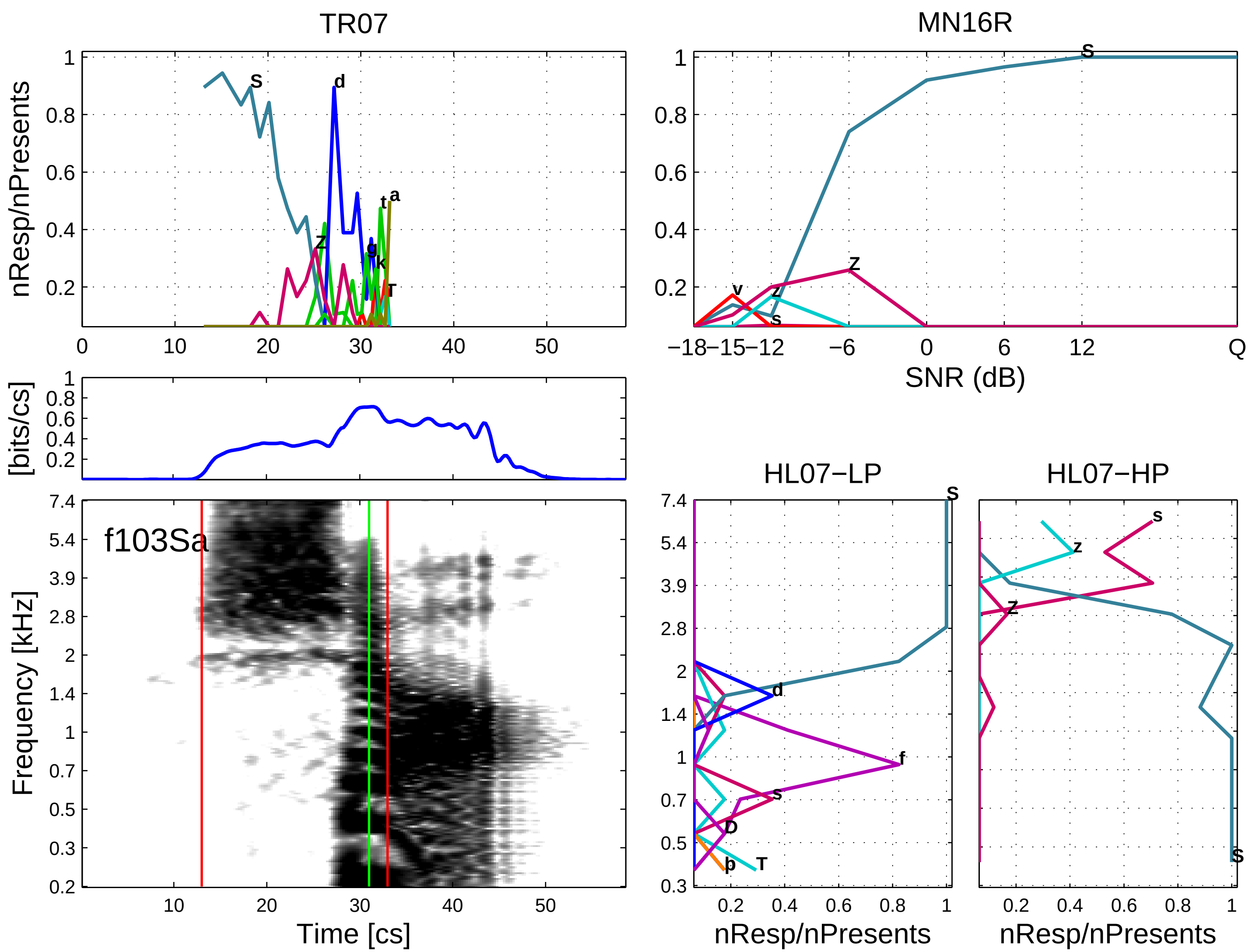
Methods: 3^d Deep Search (3^d-DS)

- 3^d Deep-Search (3^d-DS) via truncation:
  - SNR truncation (i.e., masking)
  - Frequency truncation (High/Low-pass filtering)
  - Time truncation (Furui 1986)



3^d-DS Method /ʃa/

- Truncation in Time, Intensity and Frequency



3^d-DS Method /sa/

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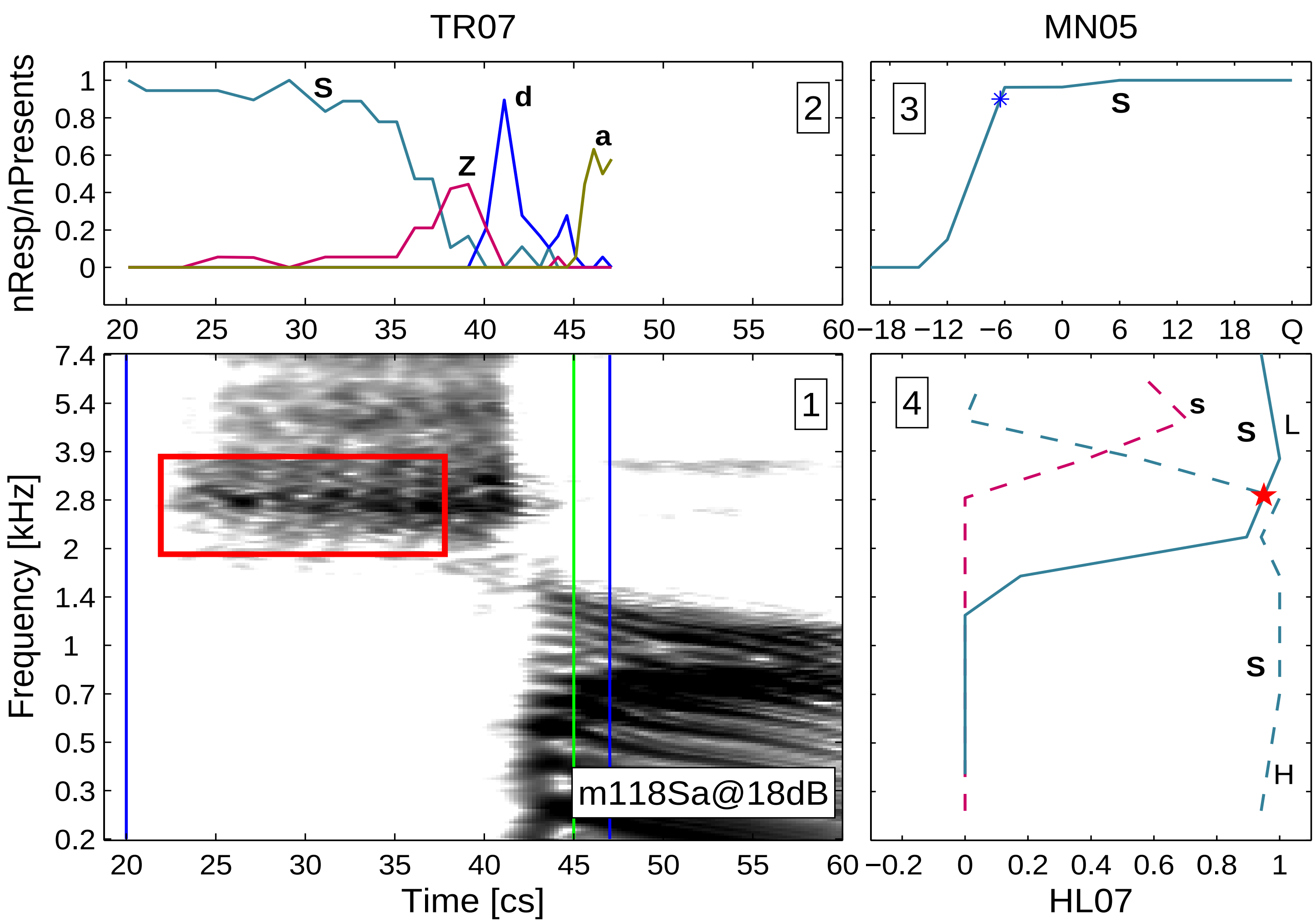

3^d-DS Method /ta/

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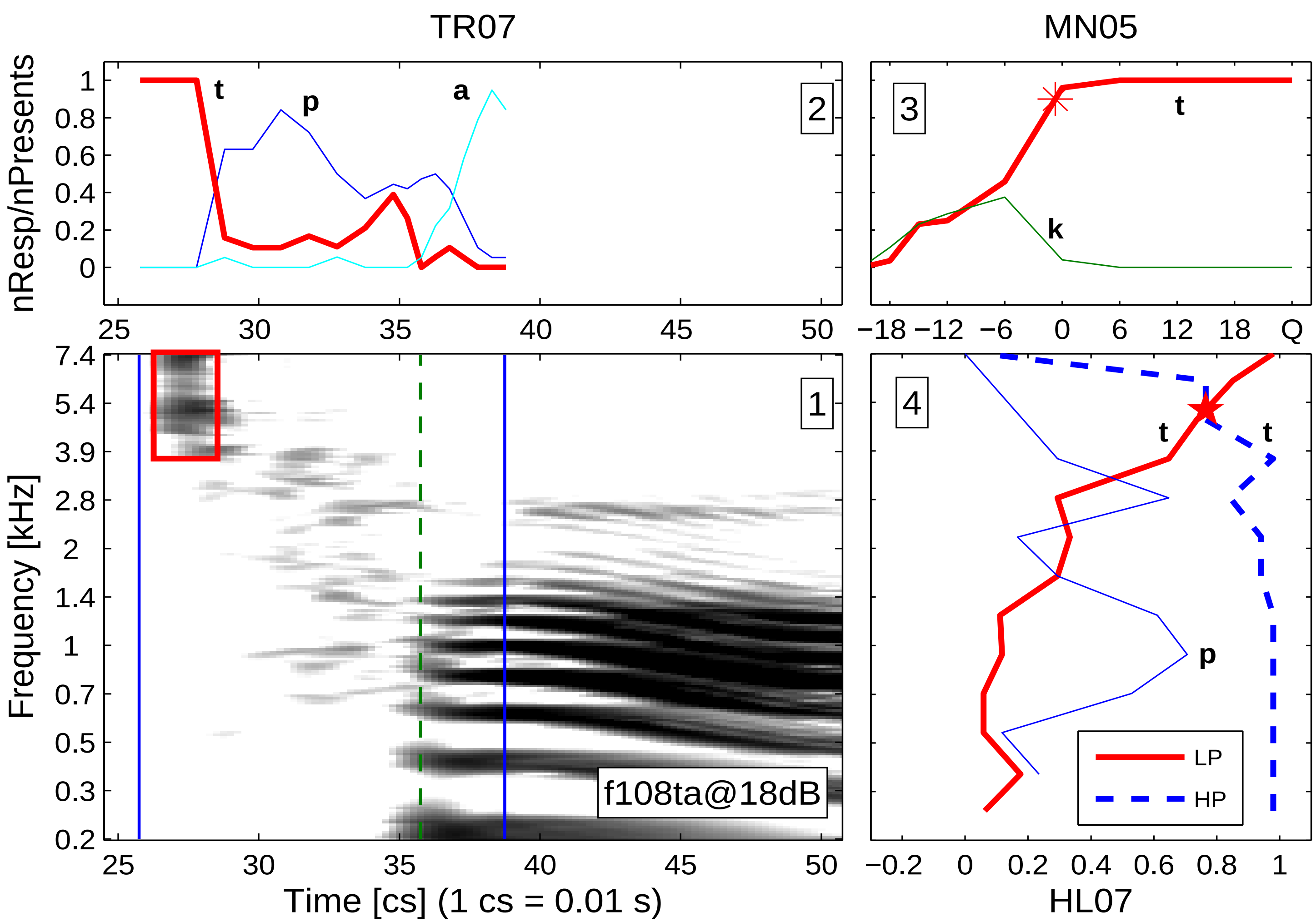
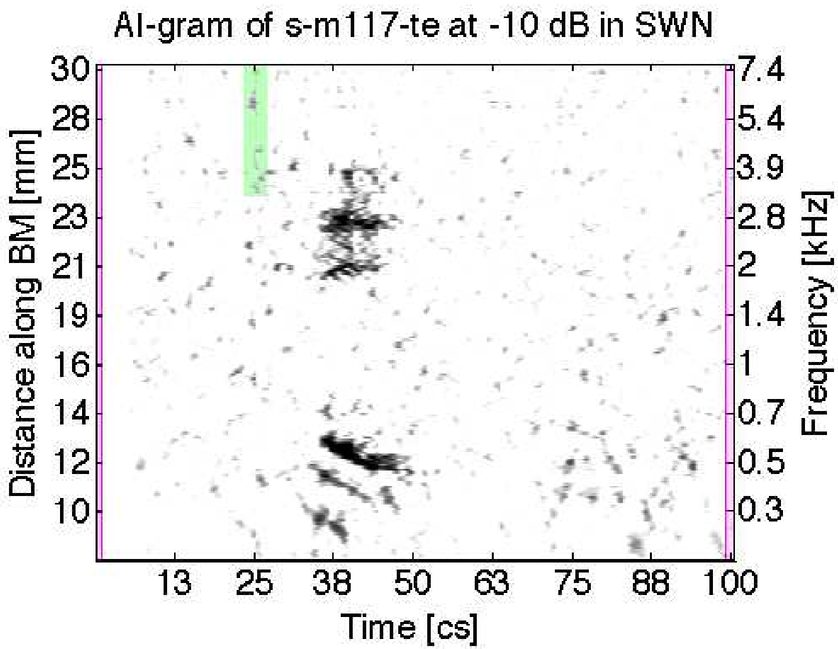
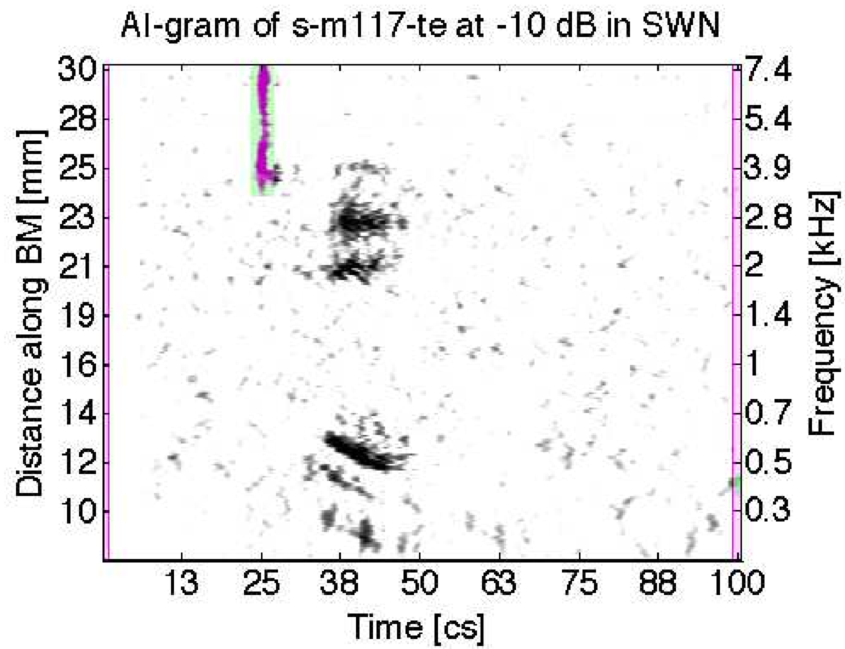


Enhancement of /tɛ/ event



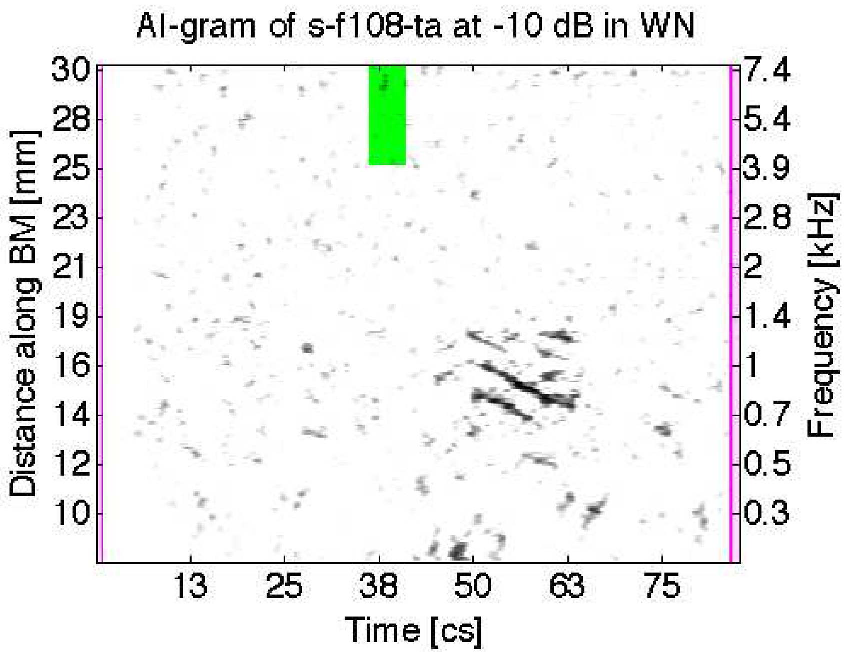
(k) Original /tɛ/



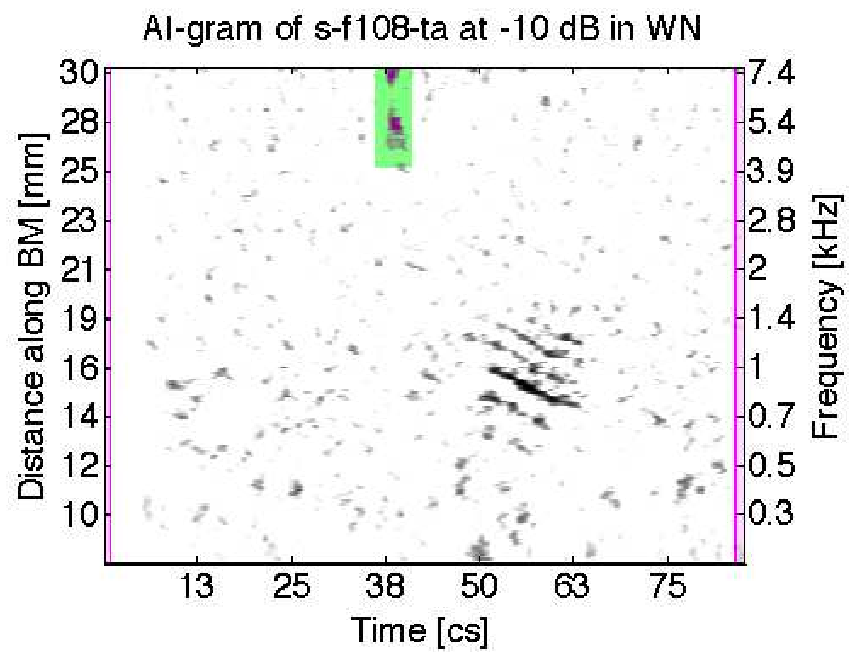
(l) Modified /tɛ/

- The sound is heard as /t/ again, we suppressed the morph (see confusion patterns of slide 4)
- METHODS: The /t/ burst is enhanced (14 dB) on the quiet sound, then noise is added
- DEMO

Enhancement of /tɑ/ event



(m) Original /tɑ/



(n) Modified /tɑ/

- The sound is heard as /t/ again, we increase /t/ recognition
- METHODS: The /t/ burst is enhanced (14 dB) on the quiet sound, then noise is added
- DEMO

Conclusion I

We have:

1. isolated events for CV: Plosives /p, t, k/ and /b, d, g/ and Fricatives /θ, ʃ, ʧ, s, h, f/ and /z, ʒ, v, ð/) + Vowels /o, ɛ, ɪ/
   - for many individual talkers
   - via new tools (AI-gram, Event-gram and 3^d-DS)

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   - *across-frequency timing coincidences*
   - duration and bandwidth

   to discriminate consonants in noise

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- for many individual talkers
- via new tools (AI-gram, Event-gram and 3^d-DS)

2 shown that normal listeners use

- *across-frequency timing coincidences*
- duration and bandwidth

to discriminate consonants in noise

3 developed tools to

- Morphed speech sounds
- Decrease or increase intelligibility. Ex: /tɑ/, /tε/

Conclusion II

We have shown:

1 the existance of conflicting cues

- Thus MaxEnt consonants are NOT redundent

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5 the role of forward and upward masking spread

Conclusion III

This could lead to:

1 Improved automatic speech recognition front-ends

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This could lead to:

1 Improved automatic speech recognition front-ends

2 The design of new hearing aids

Question your basic assumptions

Thanks for your attention
http://hear.ai.uiuc.edu