# The Noisy Speech Chain


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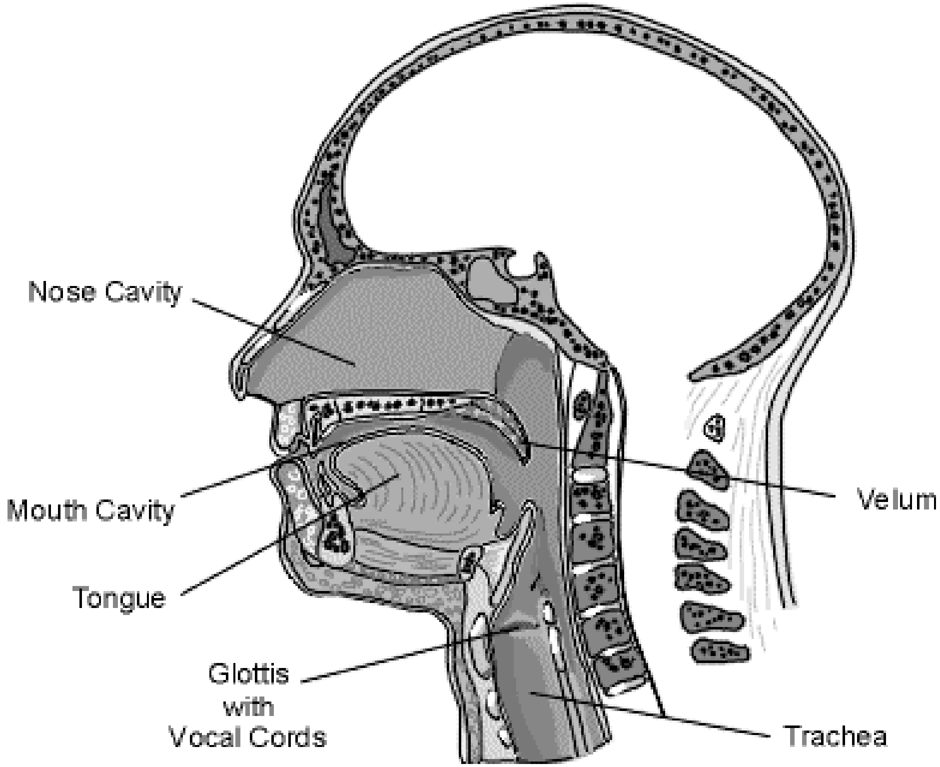
# Outline

- Part I: auditory-based representations and their use in automatic speech recognition (ASR)
- Part II: Speech perception experiments to illustrate the importance of different acoustic cues in noise
- Part III: A time-frequency model to predict the perception of  stimuli of various durations and bandwidths including synthetic speech sounds in noise

# Terminology

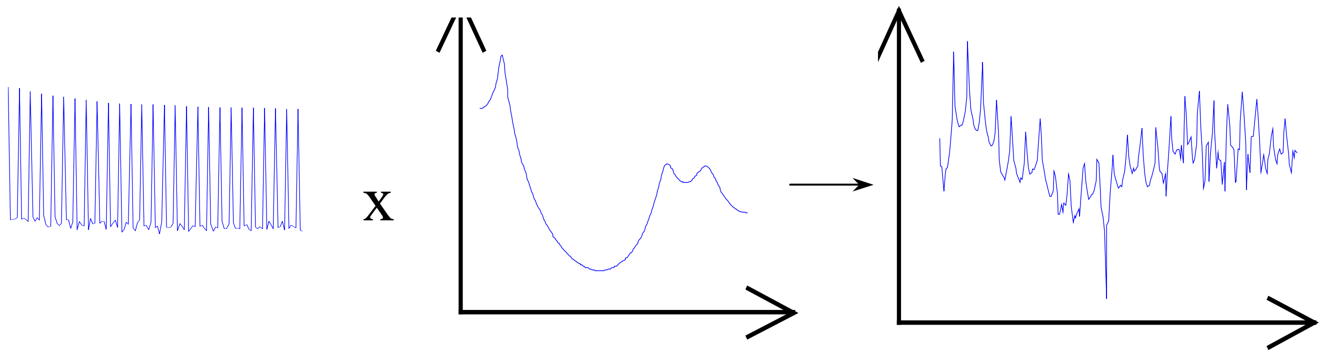
- Speech Production (how sounds are produced)
- Psychoacoustics (perception of a wide range of acoustic stimuli)
- Speech Perception (how speech-like sounds are perceived)

# Speech Production Organs




Ref: Technical University of Berlin

# *LTI Model of Speech Production*




Source Function (periodic and/or noisy)

Vocal Tract Transfer Function

Speech Signal (Frequency Domain)

# *Fundamental Frequency*

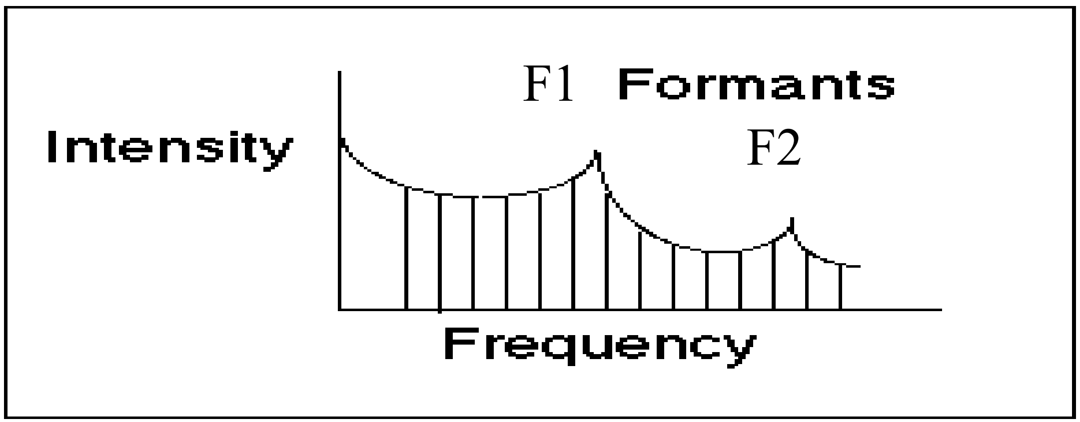
- Fundamental Frequency (F0) is the periodicity induced by the vocal cords for voiced sounds

$T_0 = 1/F_0$

| | Male | Female | Child |
|---|---|---|---|
| F0 (Hz) | 125 | 225 | 300 |

# Pole-Zero Patterns in the Vocal Tract Transfer Function (VTTF)

- Resonances of the vocal tract (formants) are critical to sound identification are correlated with the size of the vocal tract.

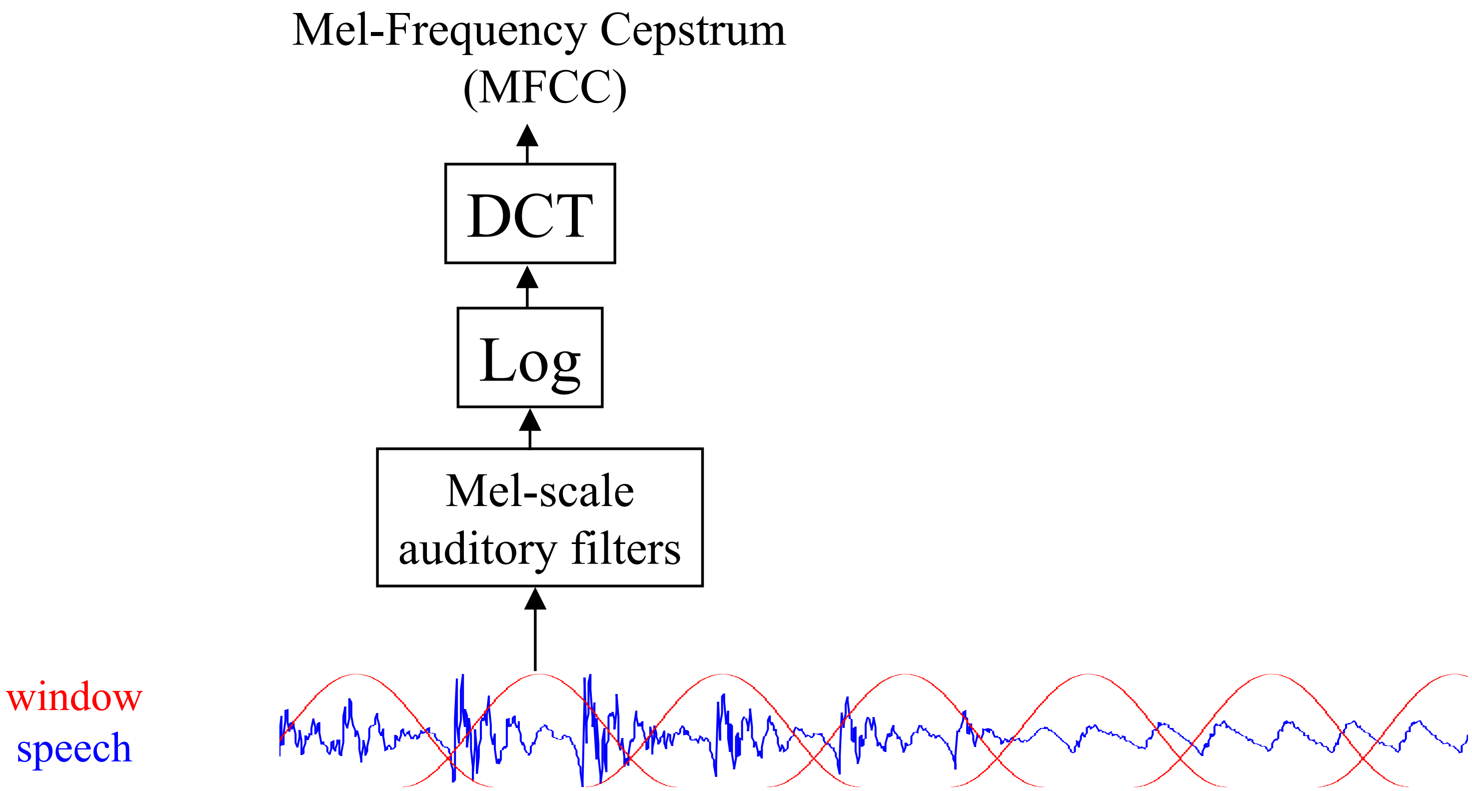


# *Speech in Noise*

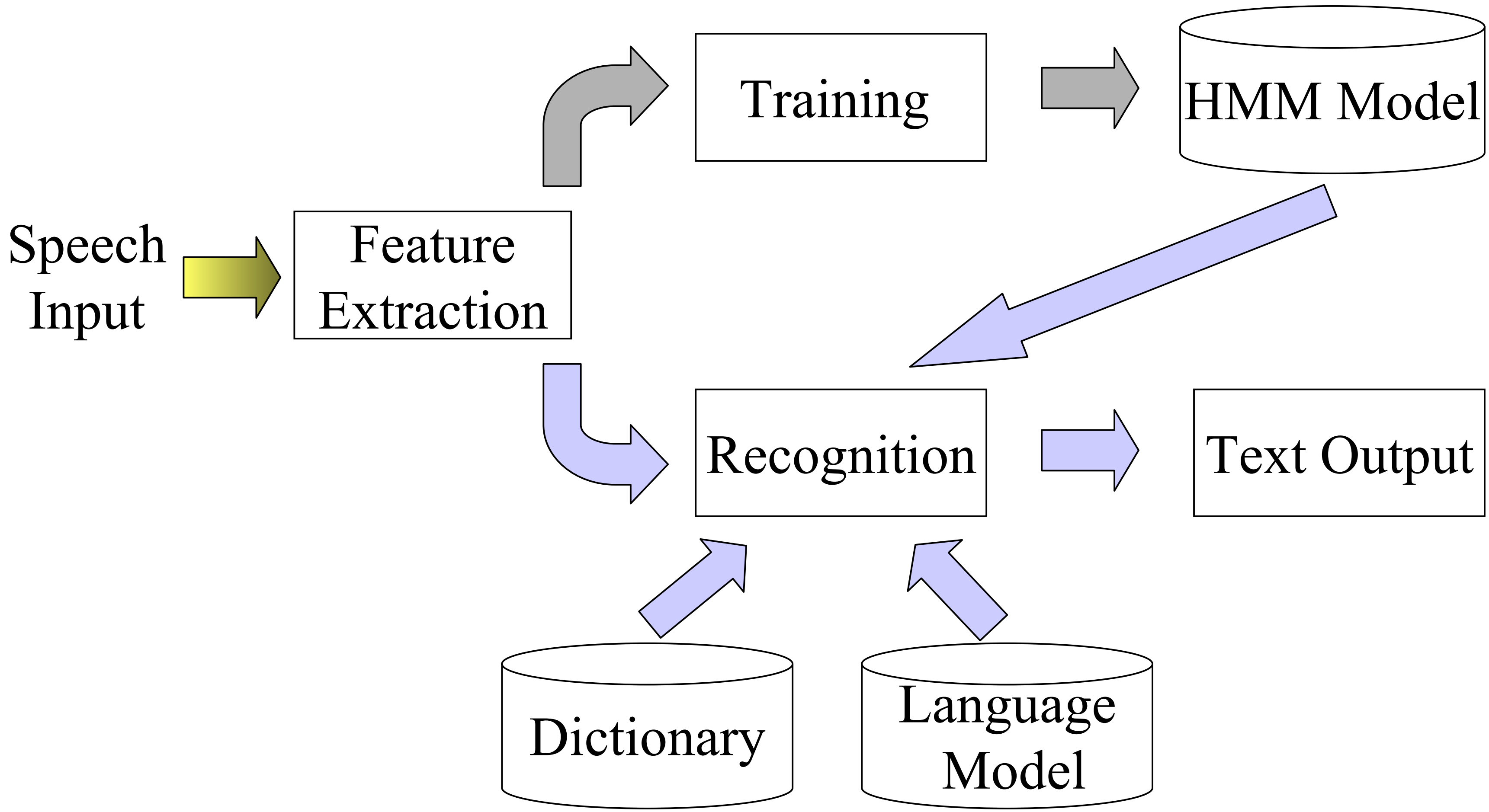
**Healthy-hearing are remarkably adept at perceiving speech in noise. However,**

- The most common complaint of hearing-aid users is listening to speech in naturally noisy environments.
- The performance of automatic speech recognition (ASR) systems degrades significantly in the presence of noise.

# Front-end: feature extraction



# Typical ASR Systems



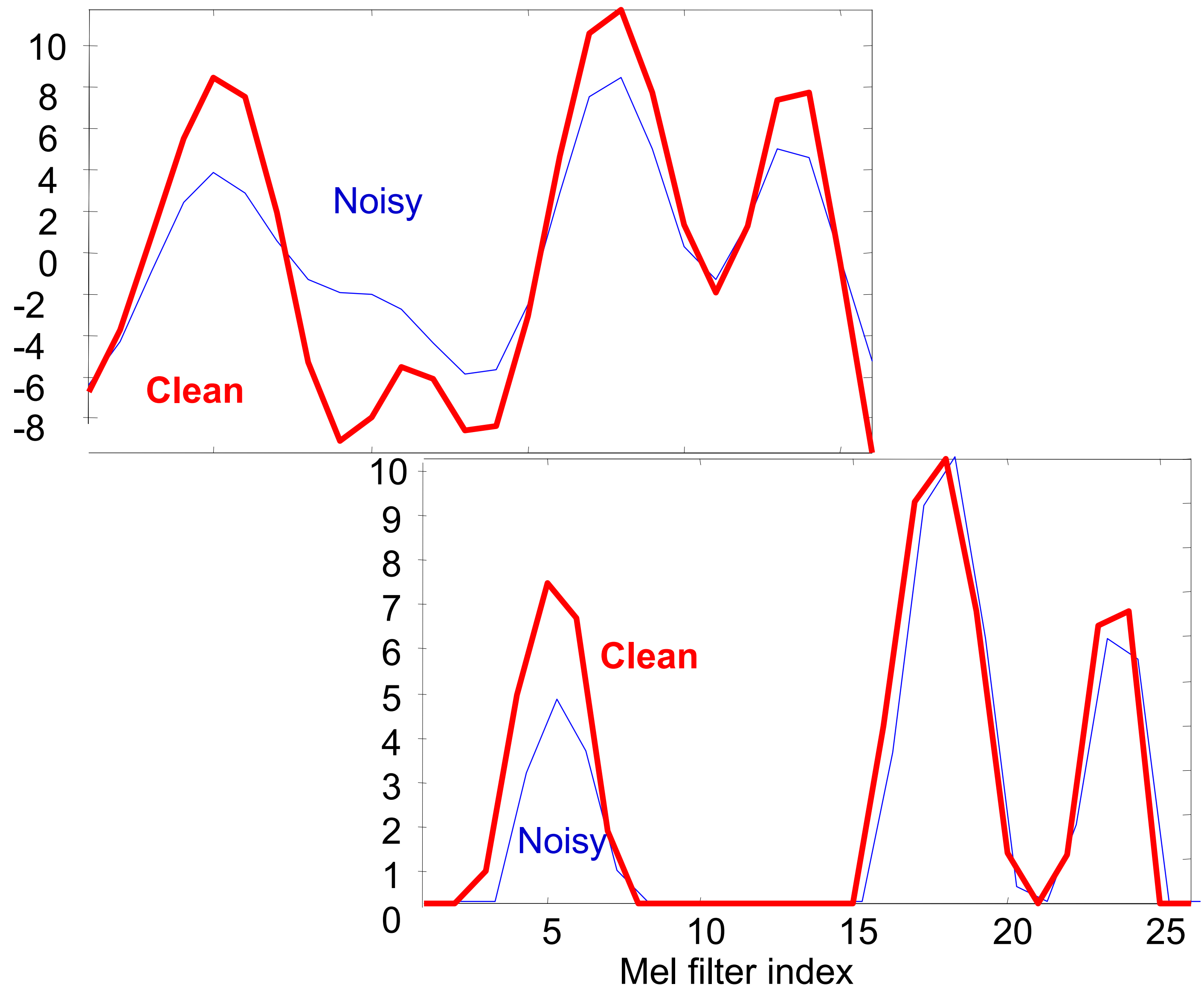
# The ‘Robust’ Human Auditory System

***The auditory system is extremely robust to noise due to both:***

- ***“Intelligent” High-Level Processing***
- ***Inherently Robust Auditory Representation***

# Auditory-based signal representations (spapl, 1997-present)

- Adaptation (sensitivity to onsets and offsets): modeled after FM experiments
- Spectral sharpening: physiological and perceptual evidence
- Exploiting the fact that the VTTF moves slowly in time
- Not all ‘uniform’ segments are equally-important




Clean and noisy log Mel spectra before (upper panel) peak isolation and peak-to-valley ratio locking, and after (lower panel).

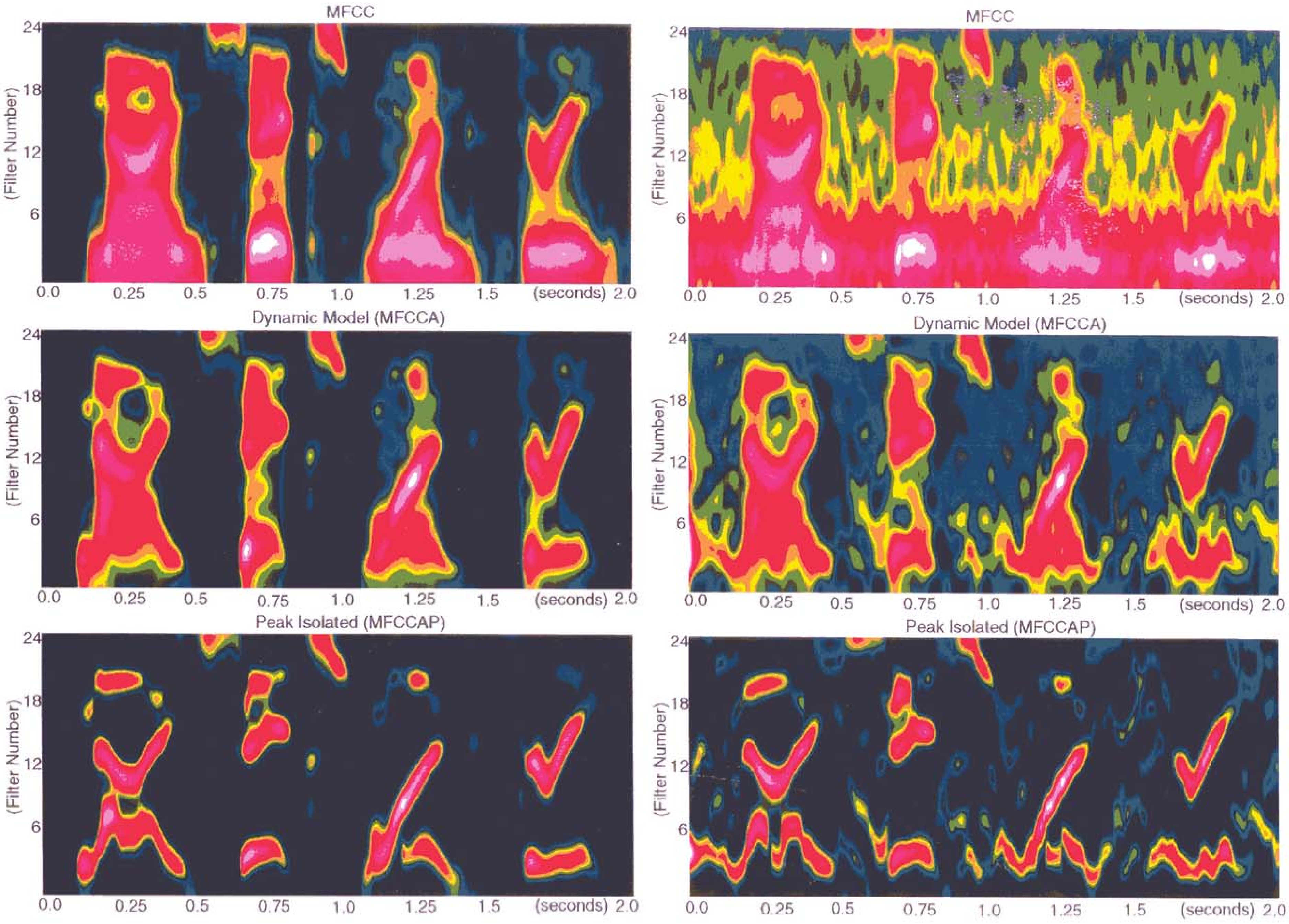

MFCC
Dynamic Model (MFCCA)
Peak Isolated (MFCCAP)
(Filter Number)
24
18
12
6
0.0
0.25
0.5
0.75
1.0
1.25
1.5
(seconds) 2.0

*Fig. 11*

(Strope and Alwan, 1997,1998)

These techniques improved ASR in noise significantly.

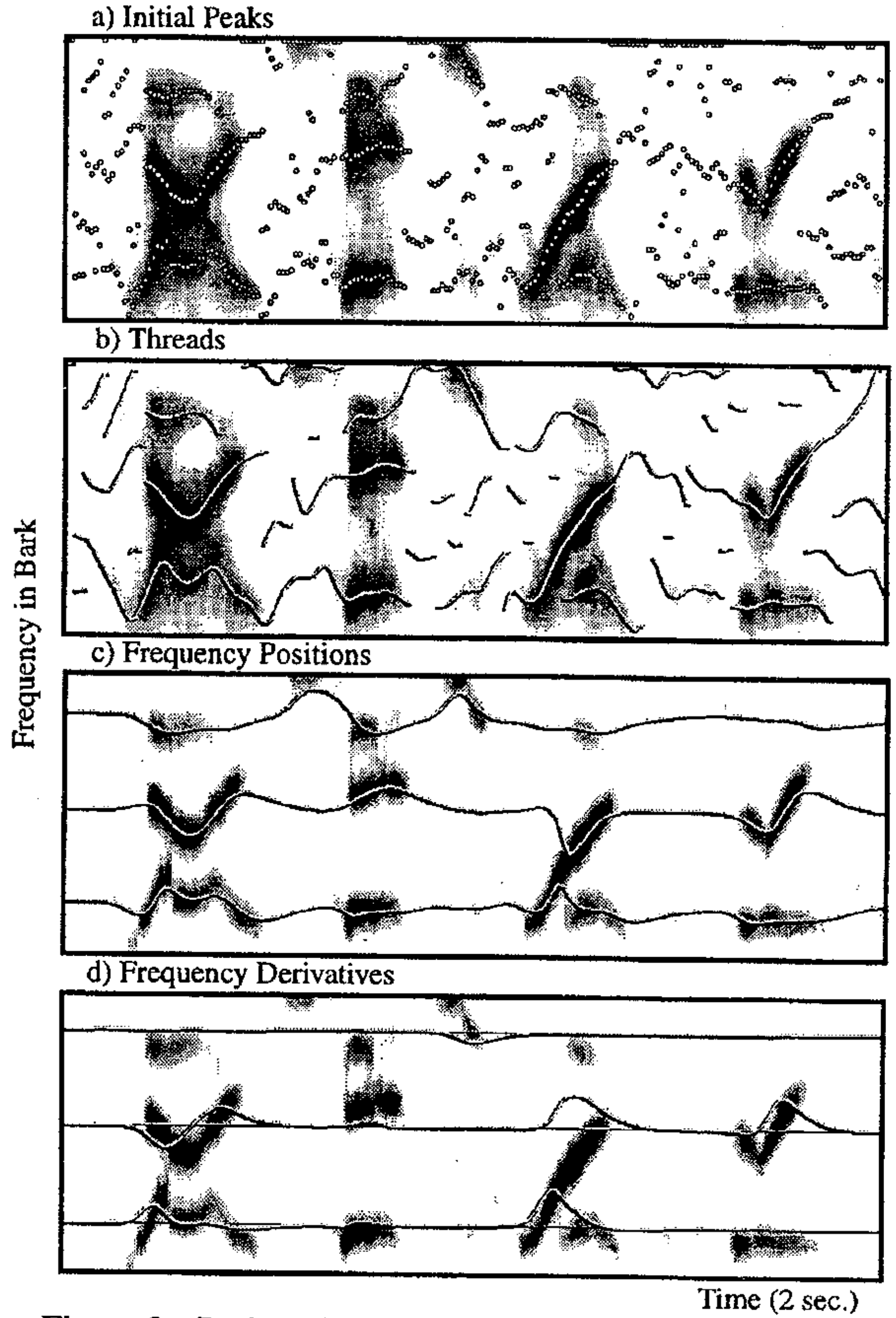
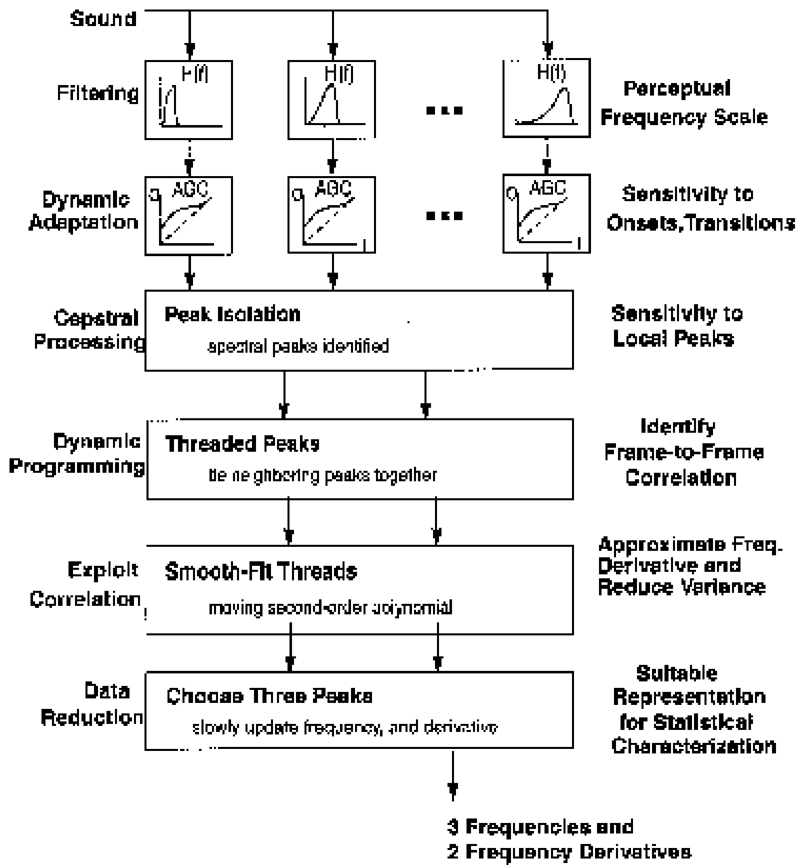


**Figure 2.** Peak positions and motion.

# *Overall System*



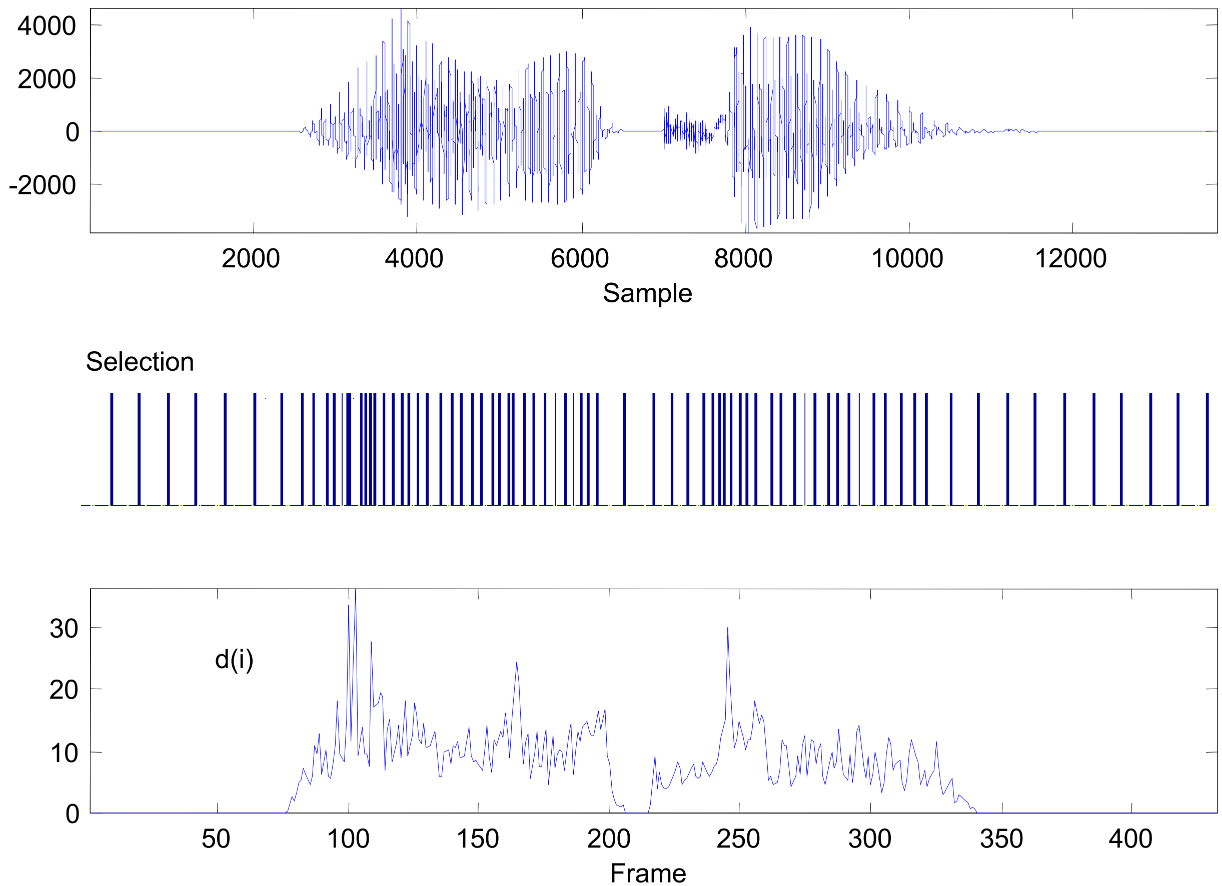

**Focus: adaptation and temporal correlations of local spectral peaks.**

**(Strope and Alwan, 1997)**

# *Variable Frame Rate Analysis (VFR) (Zhu and Alwan, 2000)*

- Spectral changes are important perceptual cues for discrimination. Such changes can occur over very short time intervals.
- Computing frames every 10 ms, as commonly done in ASR, is not sufficient to capture such dynamic changes.

# An Example of VFR



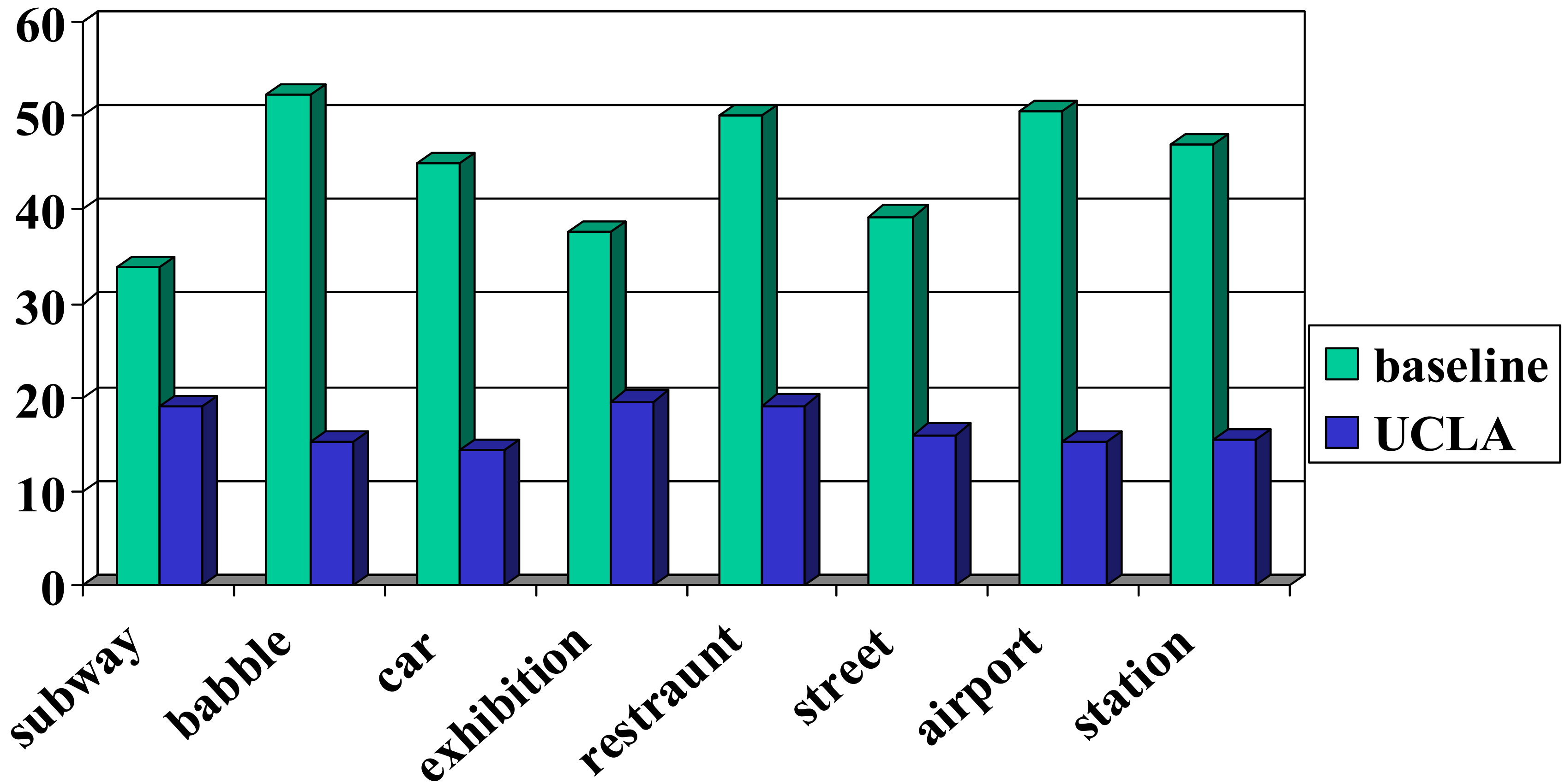

Speech waveform

Frames selected

Inter-frame distance d(i)

Frame selection in VFR for a digit string “one two” with silence.

# Aurora II Clean Training Results in Word Error Rate (%)



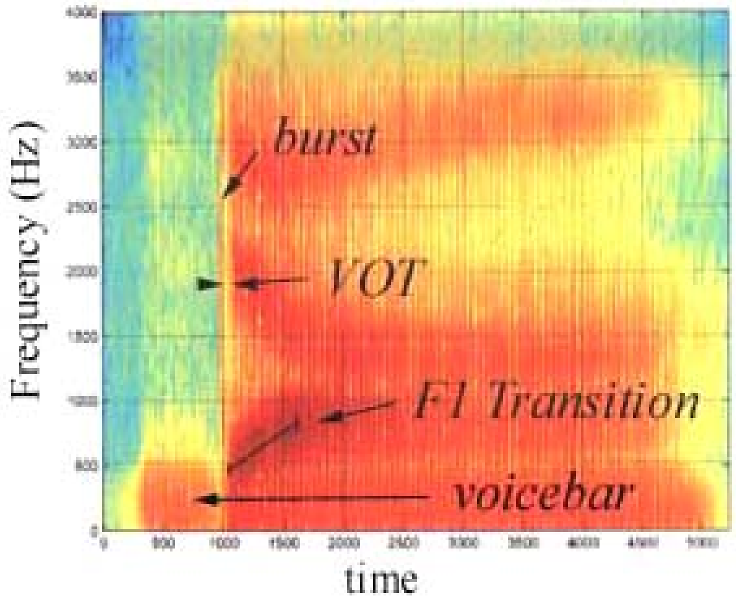
# *Part I Summary*

- Modeling aspects of human audition and knowing what is important in the speech signal can improve ASR in noise. However, we are yet to match human performance in noise!
- Speaker adaptation techniques that utilize formant-like information have also been successful (Cui and Alwan, in revision)

# *Part II: Phonological Features*

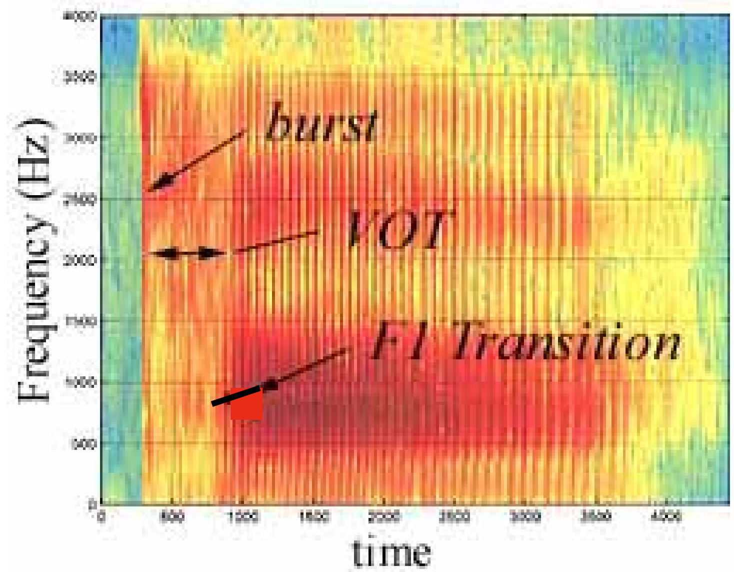
- Sounds can be characterized by a small number of constituents or features (Jakobson et al., 1963; Chomsky and Halle, 1968).
- The mapping from the linguistic domain to the acoustic domain is not necessarily one-to-one.
- Miller and Nicely (1954) presented /Ca/ syllables in noise to listeners and examined how different consonants were perceived. They analyzed confusion matrices using information theoretic approaches assuming that the underlying features: voicing, place of articulation, nasality, affrication, and duration.

# Case Study: Voicing in Syllable–Initial Plosives (M. Chen and Alwan, 2000)




/da/

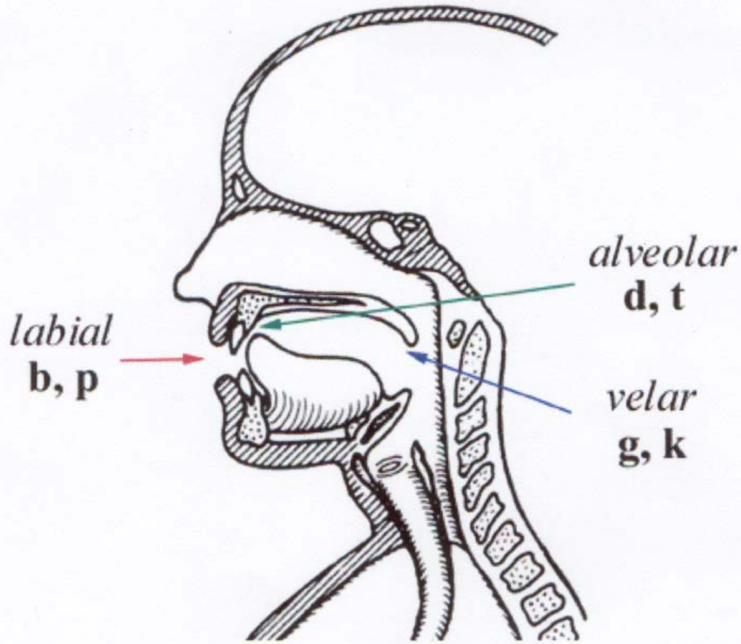
/ta/



# SPEECH TOKENS

Manner of Articulation: *Plosives*

3 Places of Articulation:




Consonant-Vowel Tokens across 3 Vowels:
**/a/ /i/ /u/**

9 Pairs with Distinguishing Feature : **Voicing**

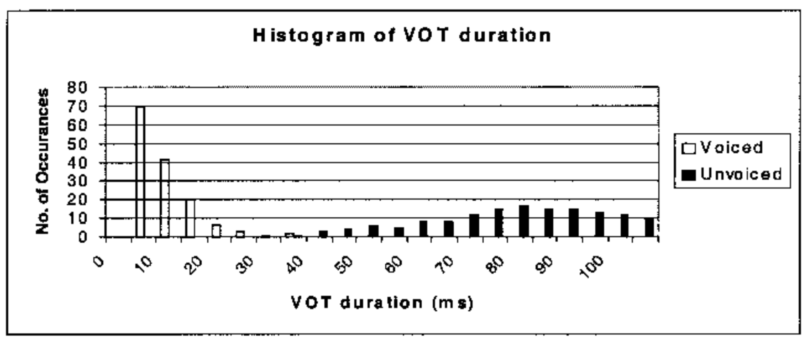
2 Male & 2 Female Talkers, 4 Repetitions Each per CV

Total: 16 Tokens per CV

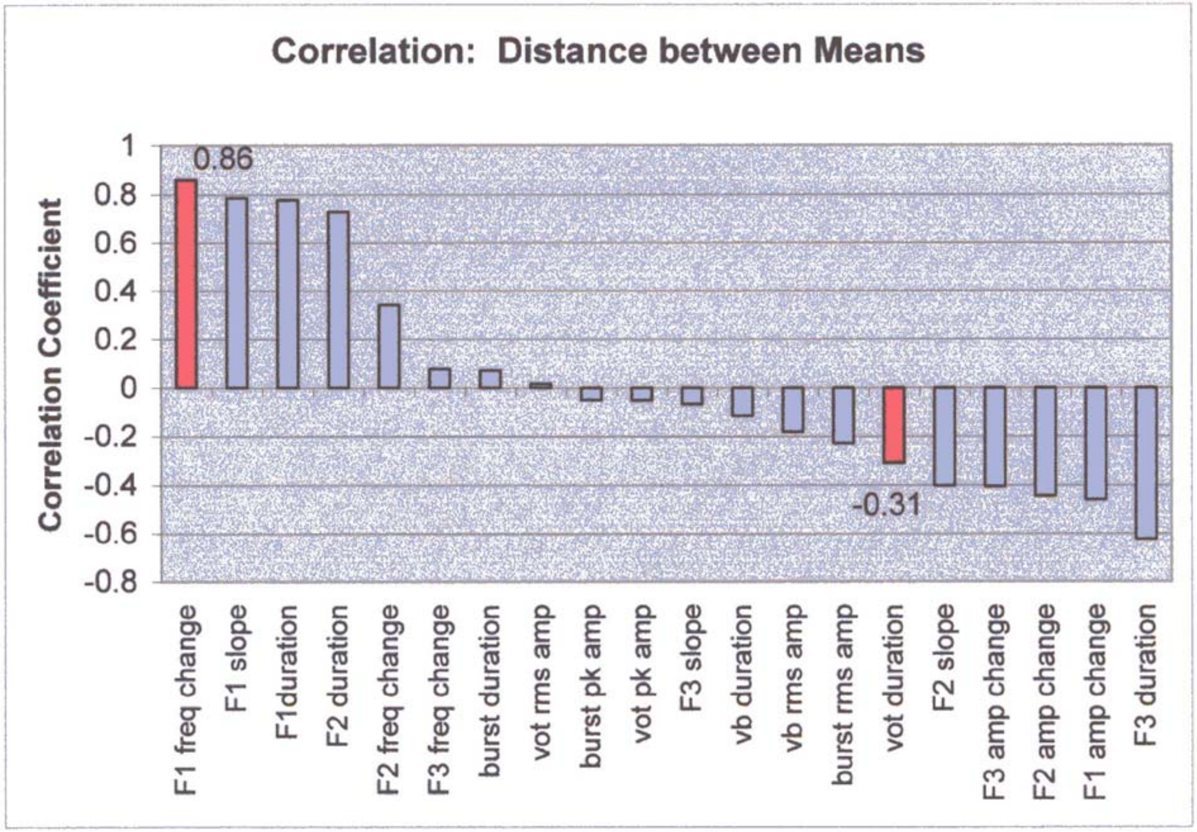
# Percent correct classification

| | voicebar duration | burst duration | VOT duration | F0 freq change |
|---|---|---|---|---|
| bapa | 71.9% | 68.8% | **100.0%** | 65.6% |
| data | 75.0% | 75.0% | **100.0%** | 68.8% |
| gaka | 65.6% | 68.8% | **100.0%** | 65.6% |
| bipi | 75.0% | 62.5% | **100.0%** | 65.6% |
| diti | 75.0% | 65.6% | **100.0%** | 71.9% |
| giki | 75.0% | 56.3% | **100.0%** | **81.3%** |
| bupu | 68.8% | 62.5% | **100.0%** | 68.8% |
| dutu | 75.0% | 59.4% | **100.0%** | 75.0% |
| guku | 78.1% | 59.4% | **100.0%** | 62.5% |

| | F1 | | | F2 | | | F3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | duration | freq chg | slope | duration | freq chg | slope | duration | freq chg | slope |
| bapa | 75.0% | **100.0%** | **96.9%** | 65.6% | 62.5% | 59.4% | 65.6% | 71.9% | 65.6% |
| data | **93.8%** | **100.0%** | **87.5%** | **81.3%** | **84.4%** | 75.0% | 62.5% | **87.5%** | **81.3%** |
| gaka | **81.3%** | **100.0%** | **93.8%** | **87.5%** | **100.0%** | 78.1% | 65.6% | 62.5% | 59.4% |
| bipi | 75.0% | **84.4%** | 71.9% | 62.5% | **87.5%** | **87.5%** | **81.3%** | **90.6%** | **93.8%** |
| diti | **84.4%** | **81.3%** | 75.0% | 71.9% | **84.4%** | **87.5%** | 68.8% | 78.1% | **87.5%** |
| giki | 65.6% | 59.4% | 62.5% | 59.4% | 71.9% | 71.9% | 68.8% | 59.4% | 62.5% |
| bupu | **84.4%** | 78.1% | 75.0% | 62.5% | 75.0% | 75.0% | 68.8% | 68.8% | 62.5% |
| dutu | 68.8% | 65.6% | 59.4% | 59.4% | 75.0% | 75.0% | 68.8% | 62.5% | 62.5% |
| guku | 71.9% | 65.6% | 75.0% | 56.3% | 56.3% | 59.4% | 62.5% | 62.5% | 56.3% |



# CORRELATION BETWEEN ACOUSTIC FEATURES & PERCEPTUAL THRESHOLDS

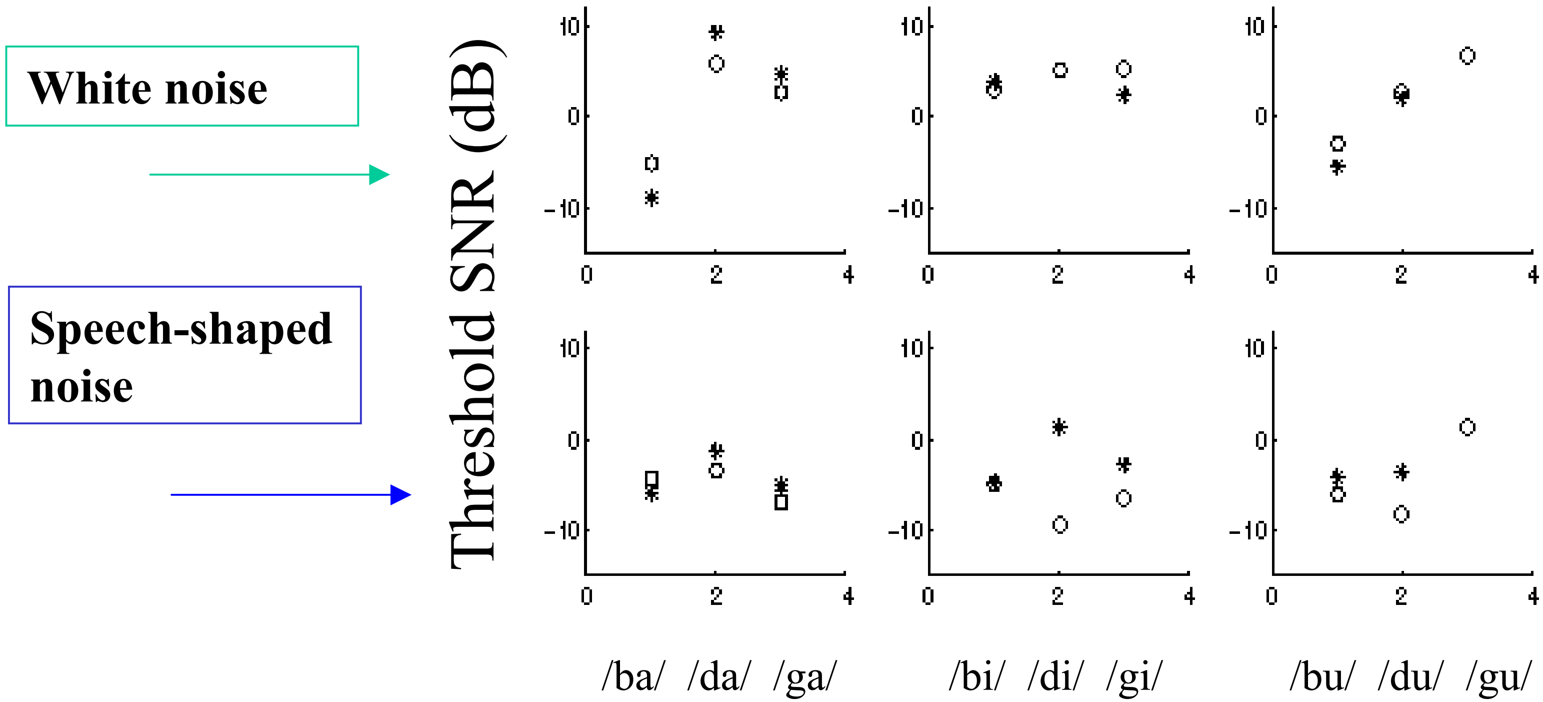



- Highest correlation with F1transition
  *(0.86 for F1 frequency change)*
- No apparent correlation with VOT
  *(-0.31 for VOT duration)*

# Summary

- **For syllable-initial plosives, voicing is clearly manifested by differences in the VOT. Differences in F1 results in perfect classification for only the /Ca/ syllables.**
- **In noise, robustness of the voicing feature is dependent on the vowel context. Lower thresholds were highly correlated with differences in the F1 transition which are most dominant for the /Ca/ syllables.**
- **Temporal cues, such as differences in burst duration and amplitude appear to be secondary cues**

# *The effect of the noise masker shape (Alwan, 1992; Hant and Alwan, 2000)*

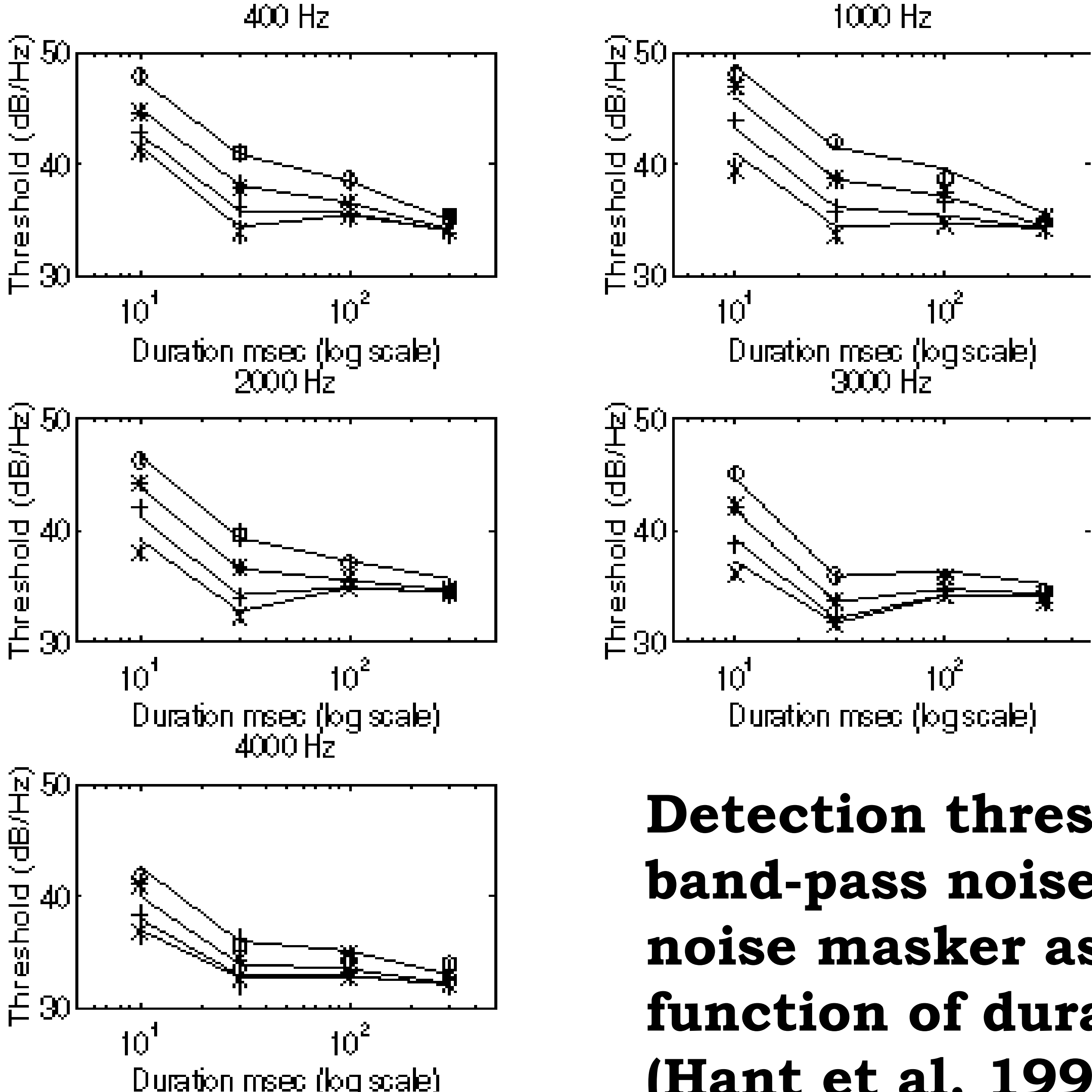



O CVs with burst

* CVs with no burst

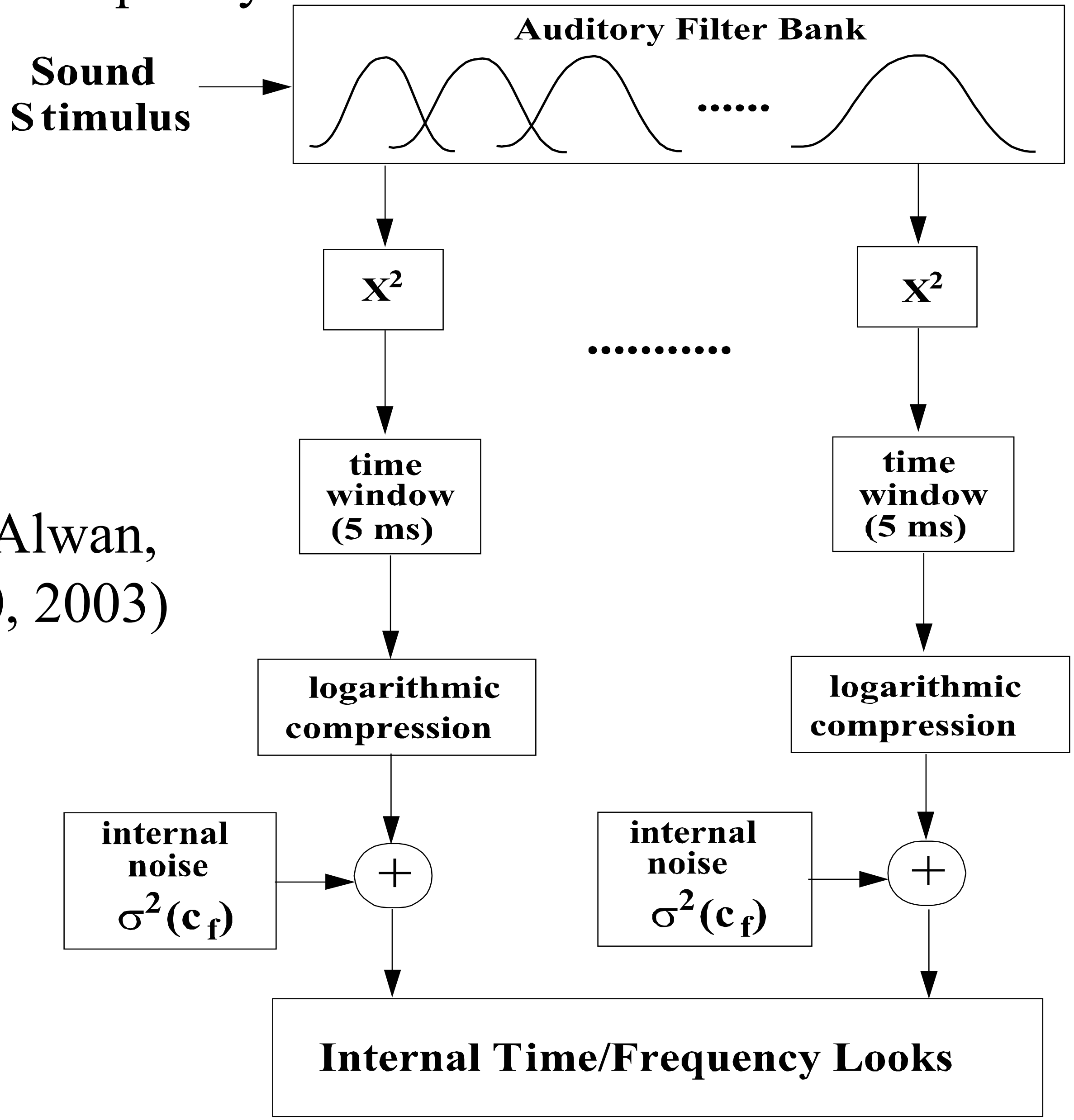
# *Part III*

- Traditional masking models focus on long-duration, narrow-band signals
- To predict noise-masking of wide-band and non-stationary signals such as speech, the effects of signal duration and bandwidth need to be taken into account
- Previous models: temporal integration (Plomp et al., 1959), multi-band excitation model (Plomp, 1970), multi-look in time model (Viemeister & Wakefield, 1991), duration-dependent filters (Hant et al, 1997), and multi-look in time and frequency model (van Schijndel et al., 1999).

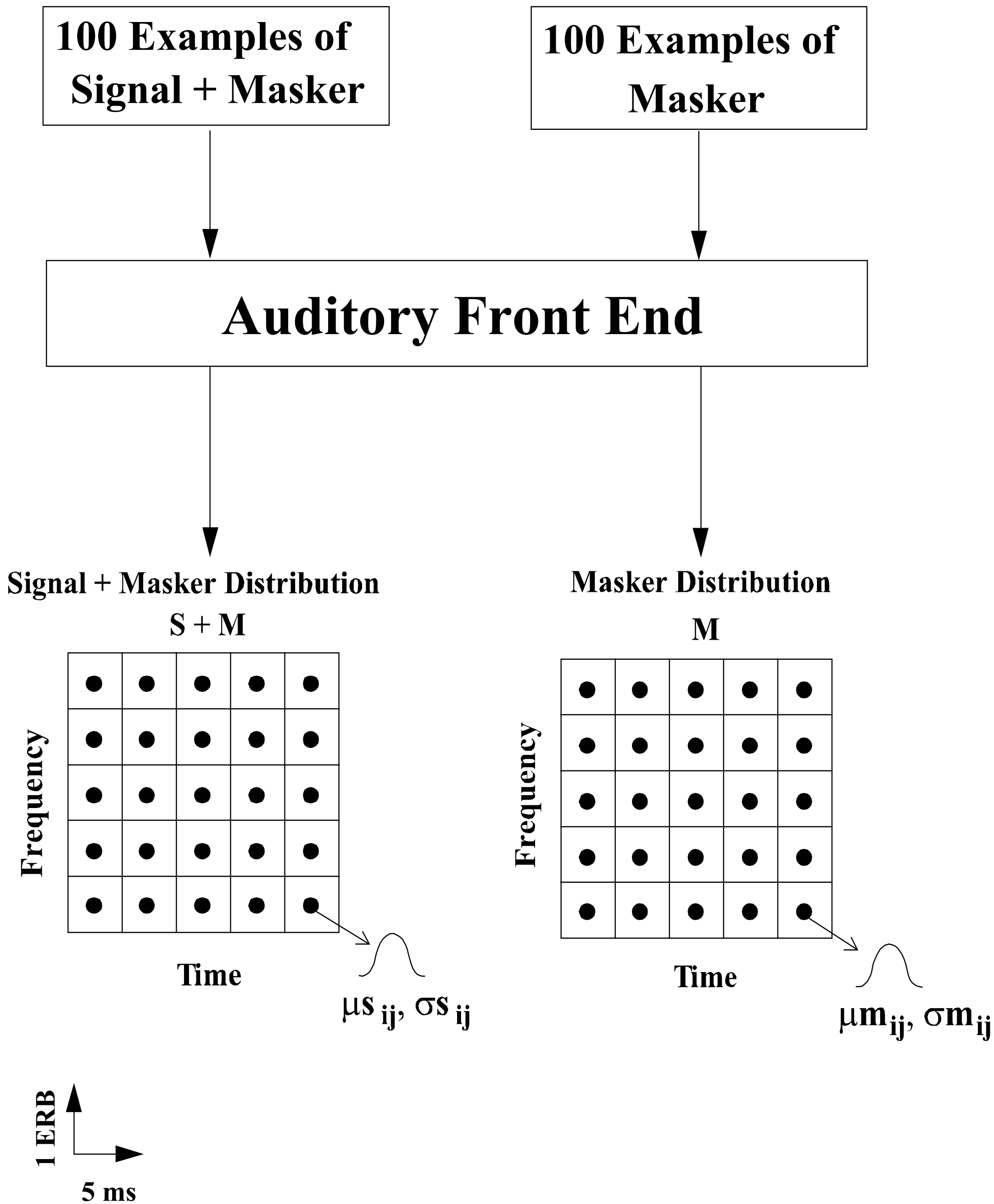



**Detection thresholds of band-pass noises in a noise masker as a function of duration (Hant et al. 1997)**

# A time-frequency model




(Hant and Alwan, 1999, 2000, 2003)


100 Examples of Signal + Masker
100 Examples of Masker
Auditory Front End
Signal + Masker Distribution
S + M
Frequency
Time
μs ij, σs ij
Masker Distribution
M
Frequency
Time
μmij, σmij
1 ERB
5 ms

# *Model Predictions*

Model predicts well the noise masking of:

• bandpass noises of various durations (10-300 ms), bandwidths (1-8 CB), and center frequencies (400-4000 Hz),

•tone glides and synthetic formant transitions with durations varying between 10-100 ms, and frequencies between 300-4000 Hz (except for 1500 Hz, 100 ms glides), and

•stop bursts.

The model also predicted well the discrimination of synthetic CV syllables (/bV, dV, gV/ in 3 vowel contexts (/a/, /i/, /u/) and 2 noise maskers (exception: /bi,di/).

# Acknowledgements

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