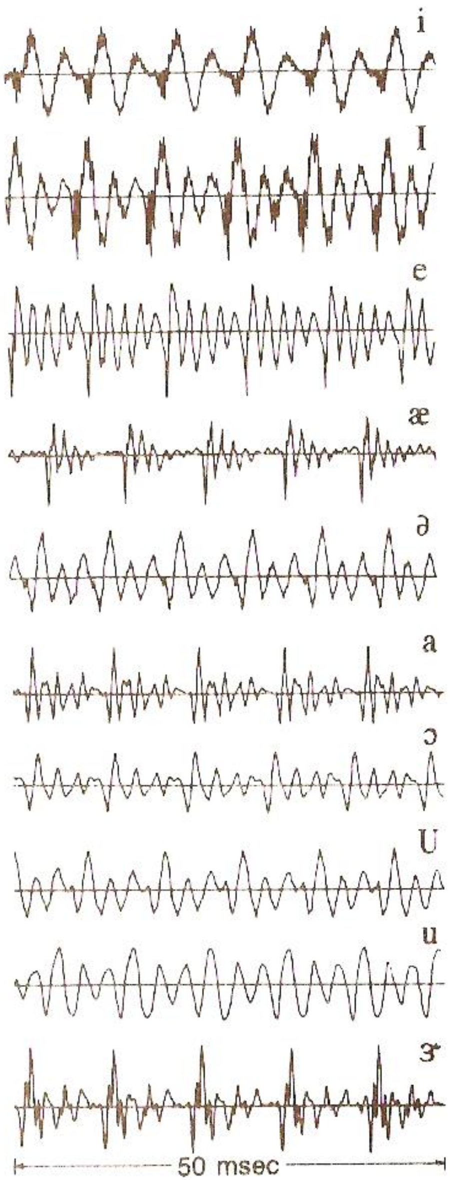
7.0 Speech Signals and Front-end Processing

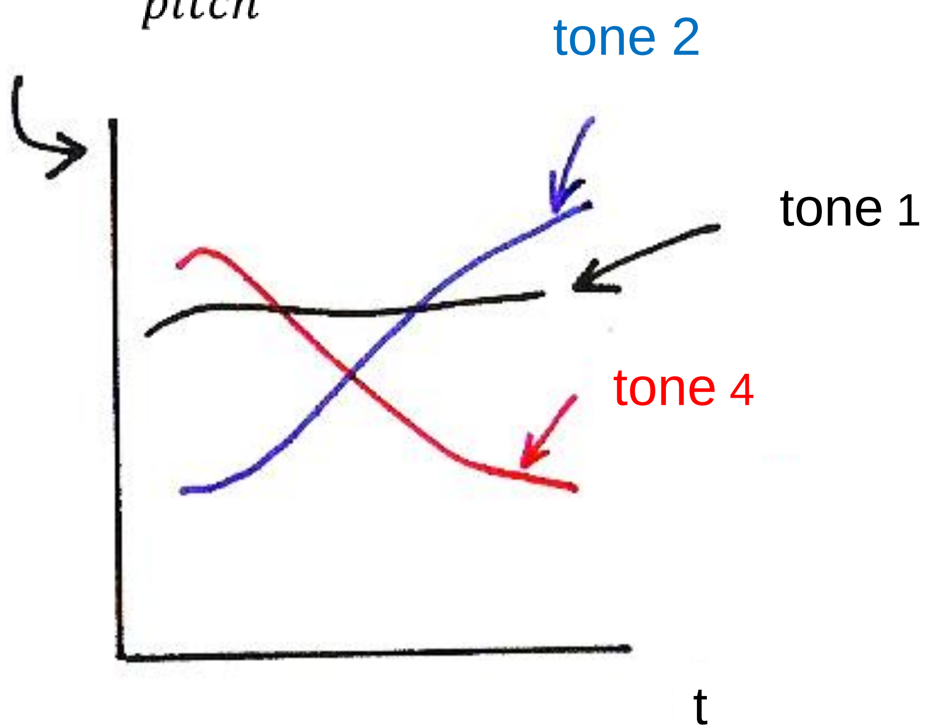
References: 1. 3.3, 3.4 of Becchetti

3. 9.3 of Huang

Waveform plots of typical vowel sounds - Voiced（濁音）

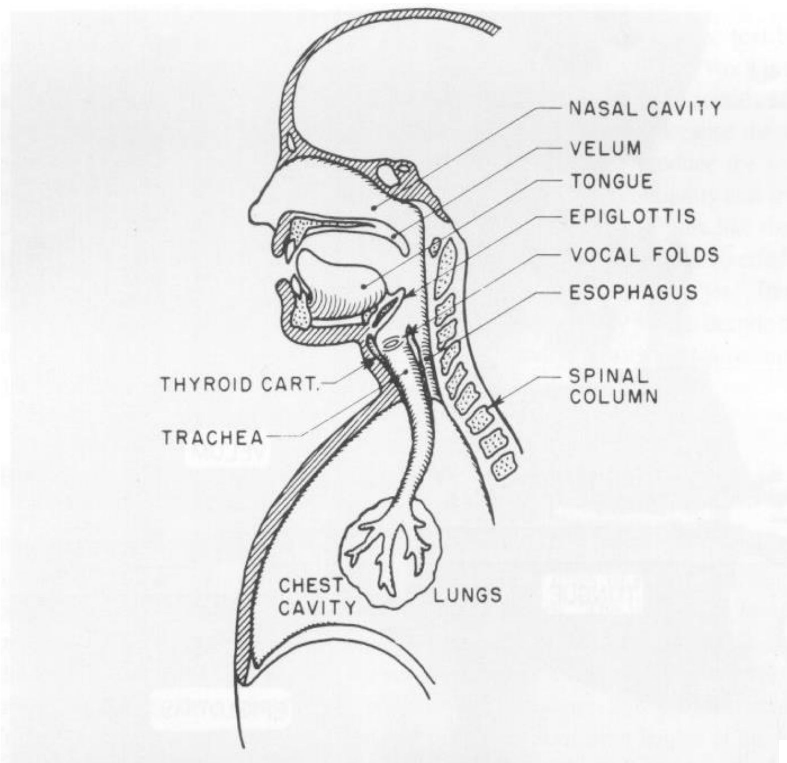


$$F_0 = \frac{1}{pitch}$$ (音高)

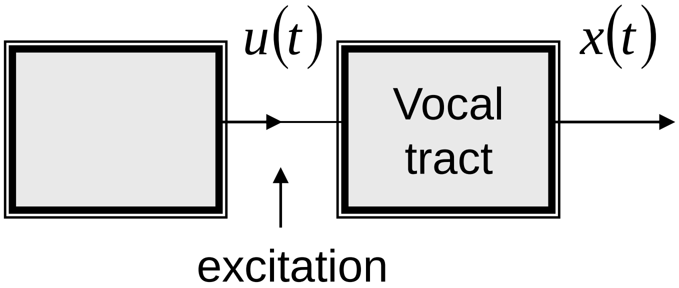


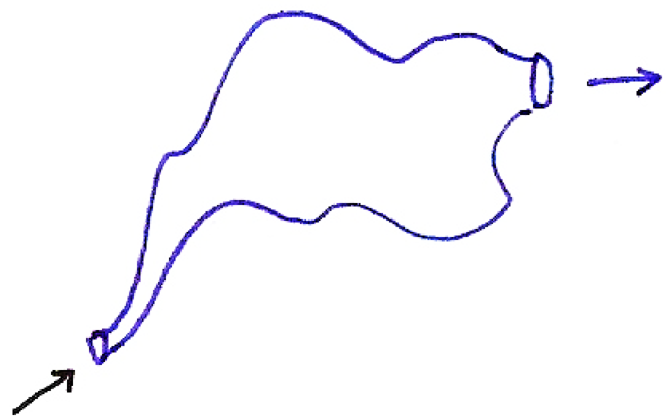
Speech Production and Source Model

- Human vocal mechanism

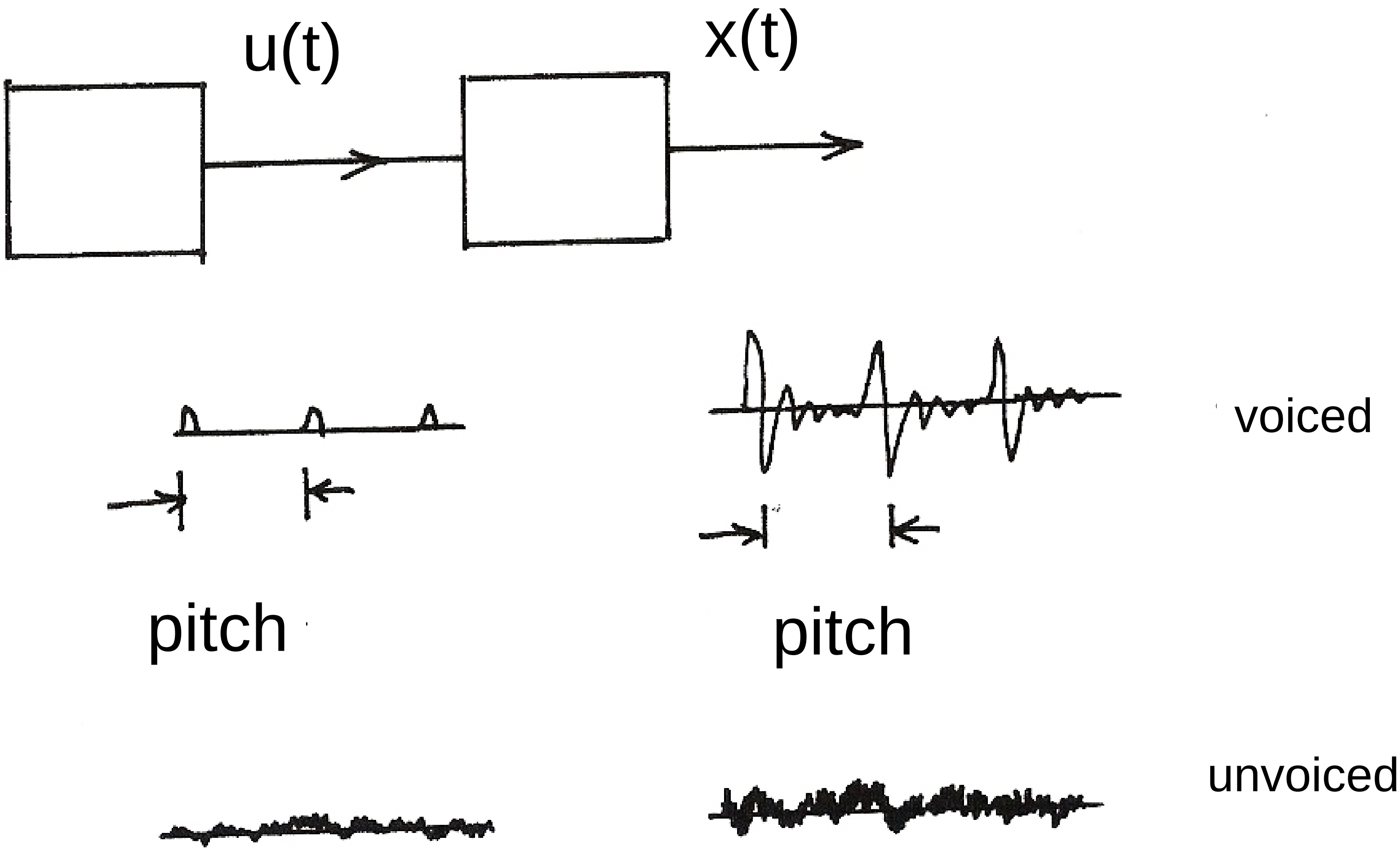


- Speech Source Model



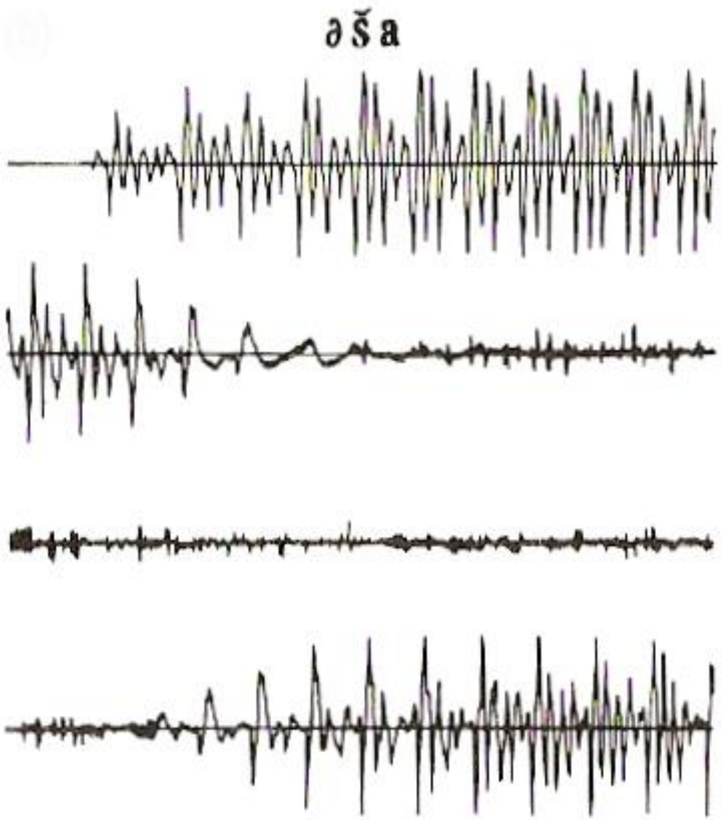


Voiced and Unvoiced Speech

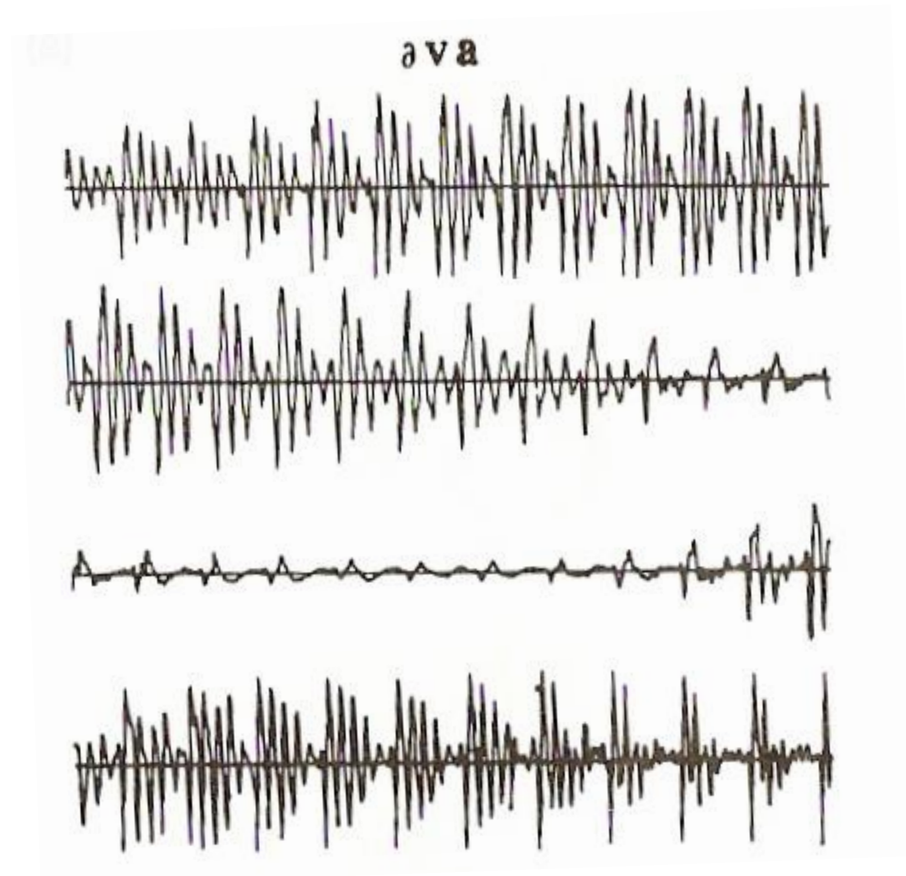


Waveform plots of typical consonant sounds

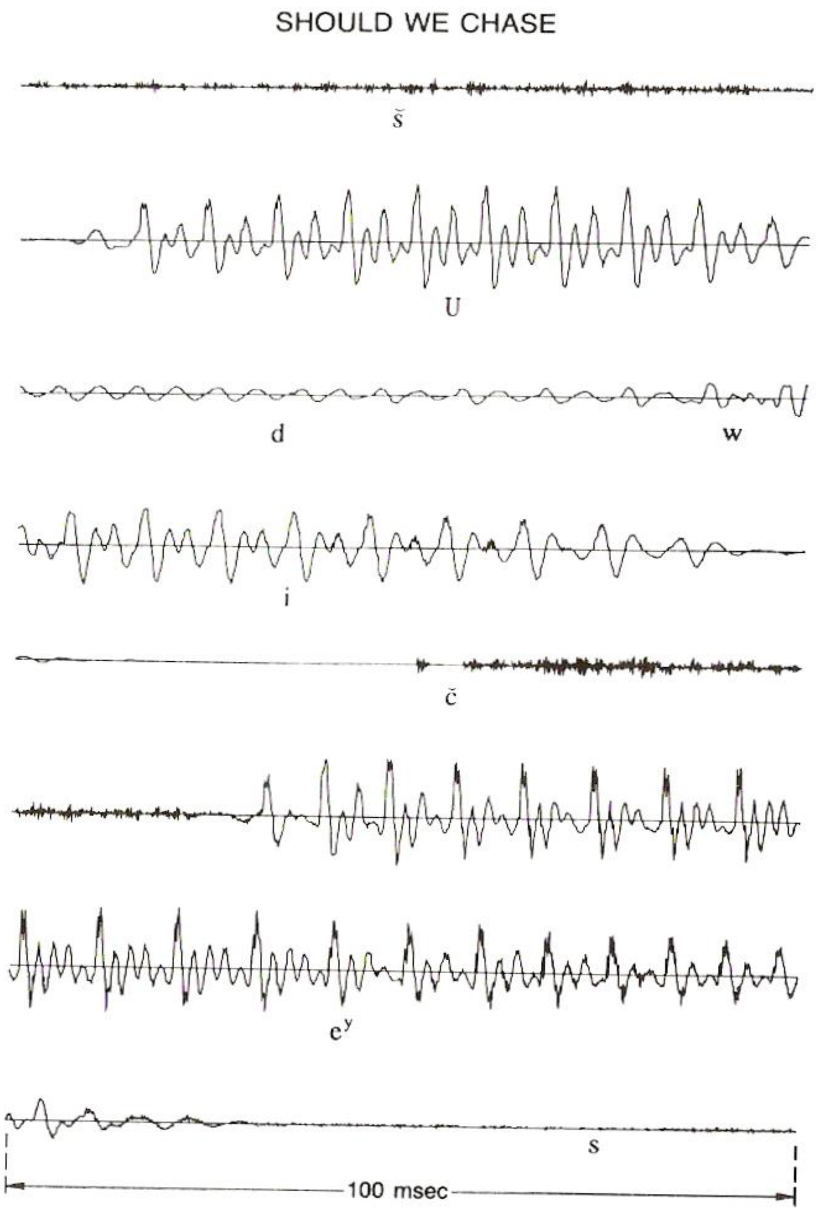
Unvoiced（清音）



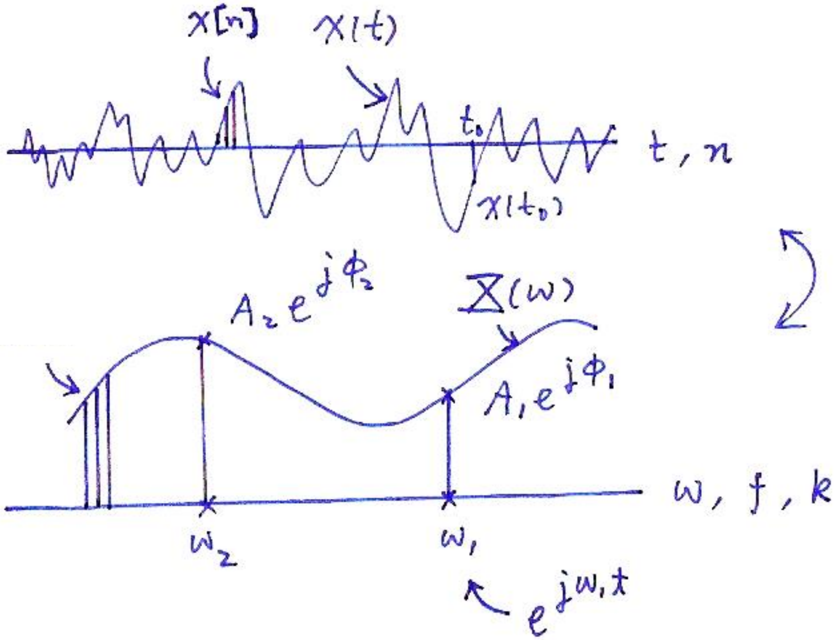
Voiced（濁音）



Waveform plot of a sentence



Time and Frequency Domains **(P.12 of 2.0)**

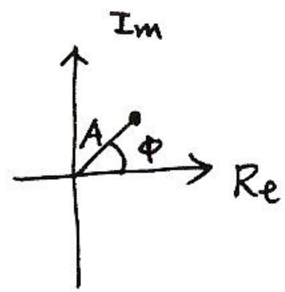


X[k]

time domain

1-1 mapping
Fourier Transform
Fast Fourier Transform (FFT)

frequency domain



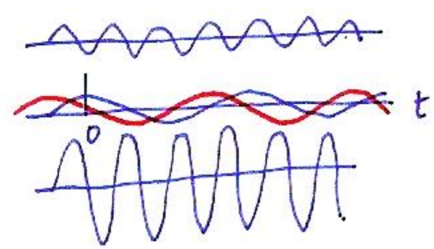
$$Re\{e^{j\omega_1 t}\} = \cos(\omega_1 t)$$

$$Re\{(A_1\, e^{j\phi_1})\,(e^{j\omega_1 t})\} = A_1\cos(\omega_1 t + \phi_1)$$

$$\vec{X} = a_1\vec{i} + a_2\vec{j} + a_3\vec{k}$$

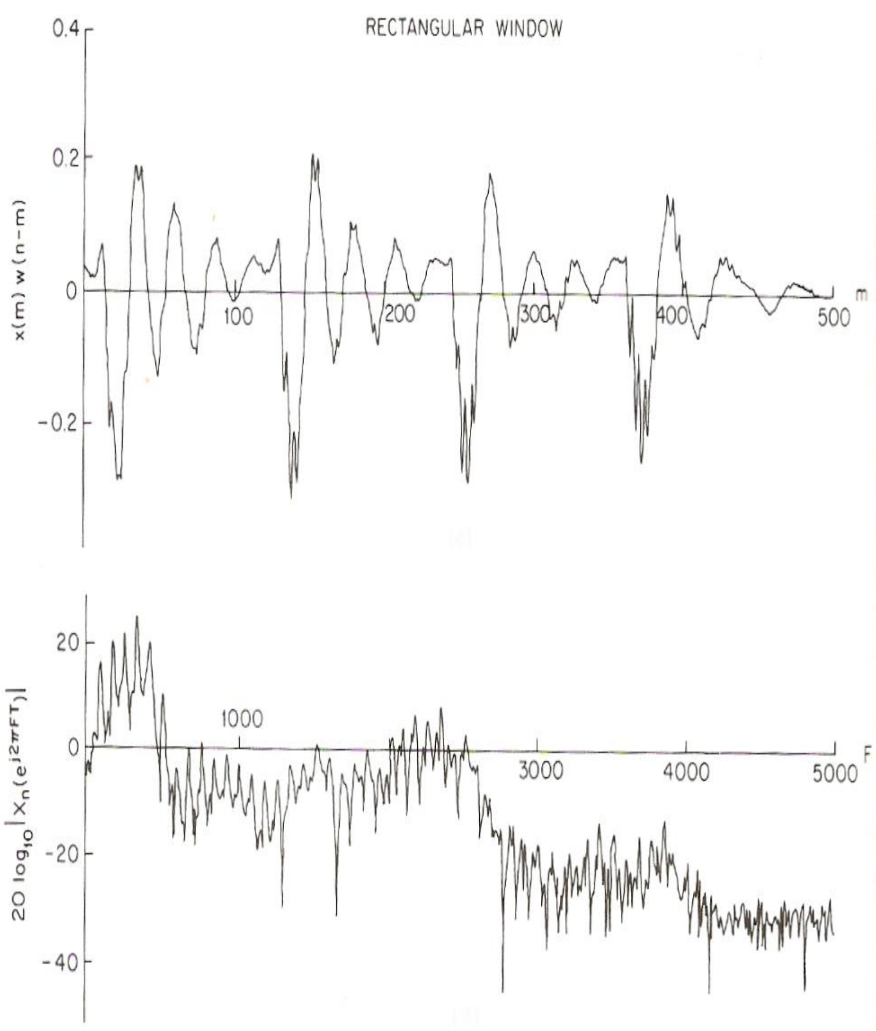
$$\vec{X} = \sum_i a_i\, x_i$$

$$x(t) = \sum_i a_i\; x_i\,(t)$$

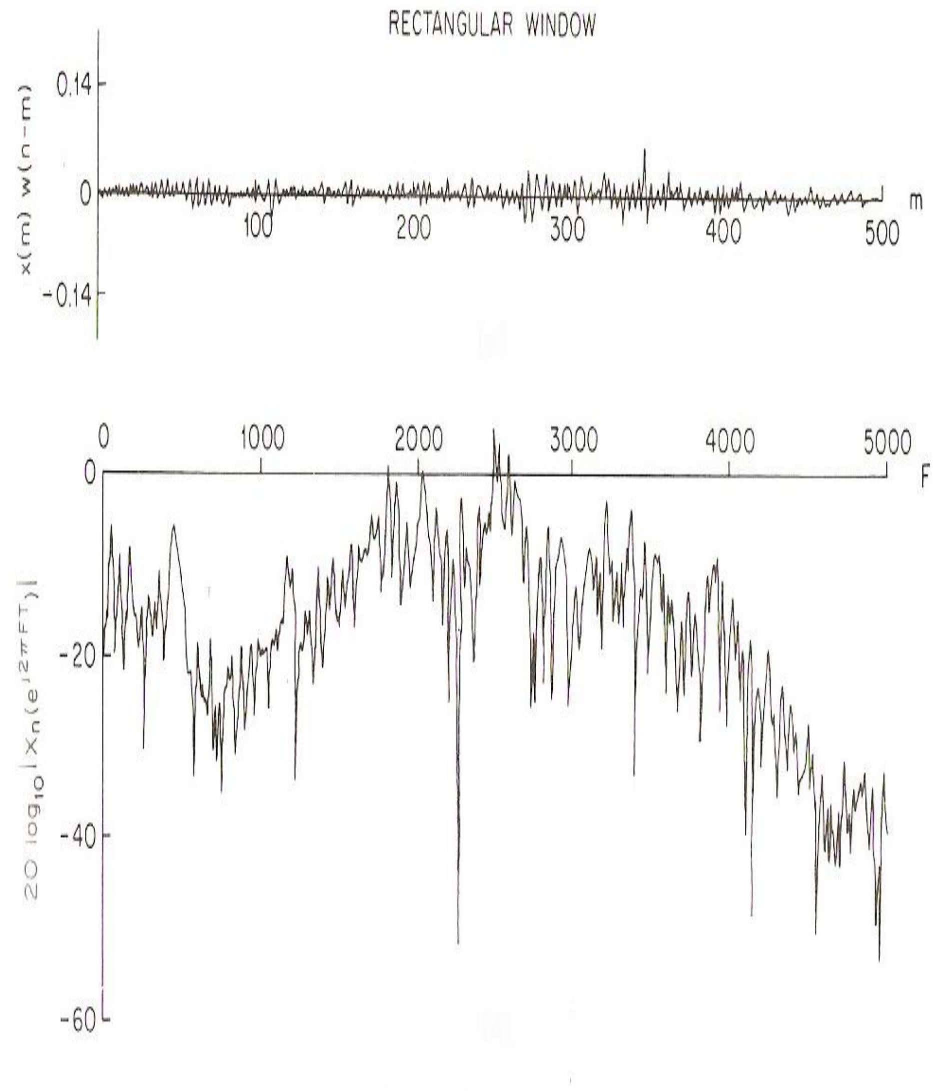


Frequency domain spectra of speech signals

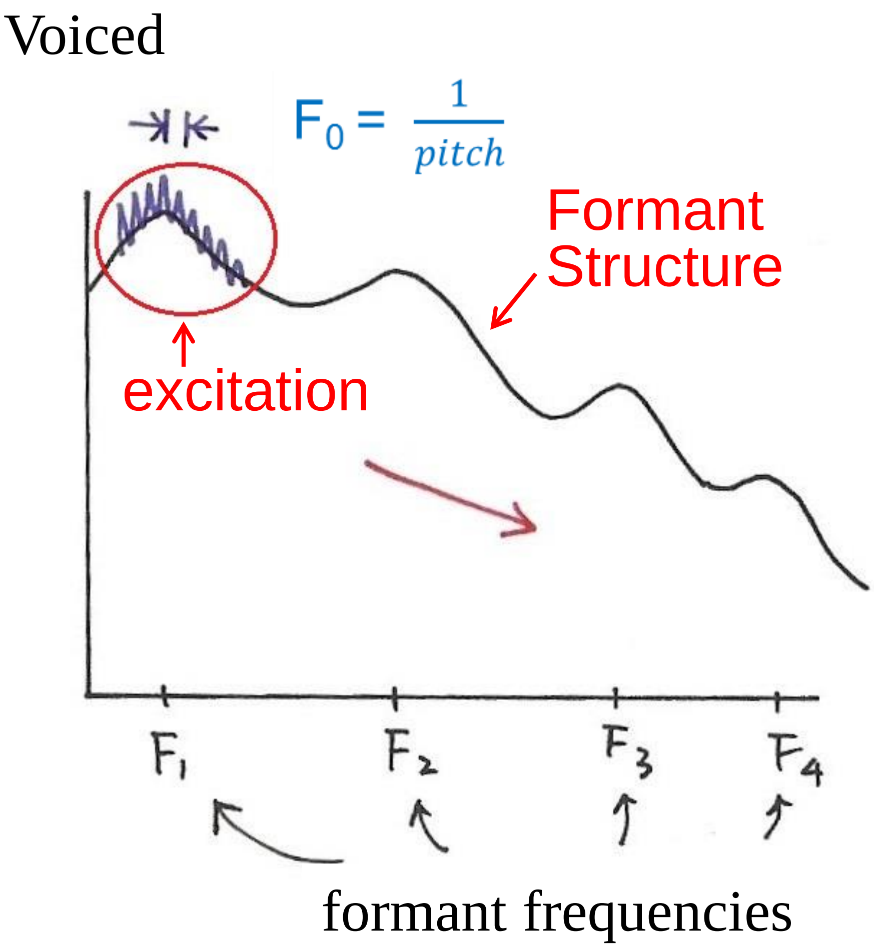
Voiced

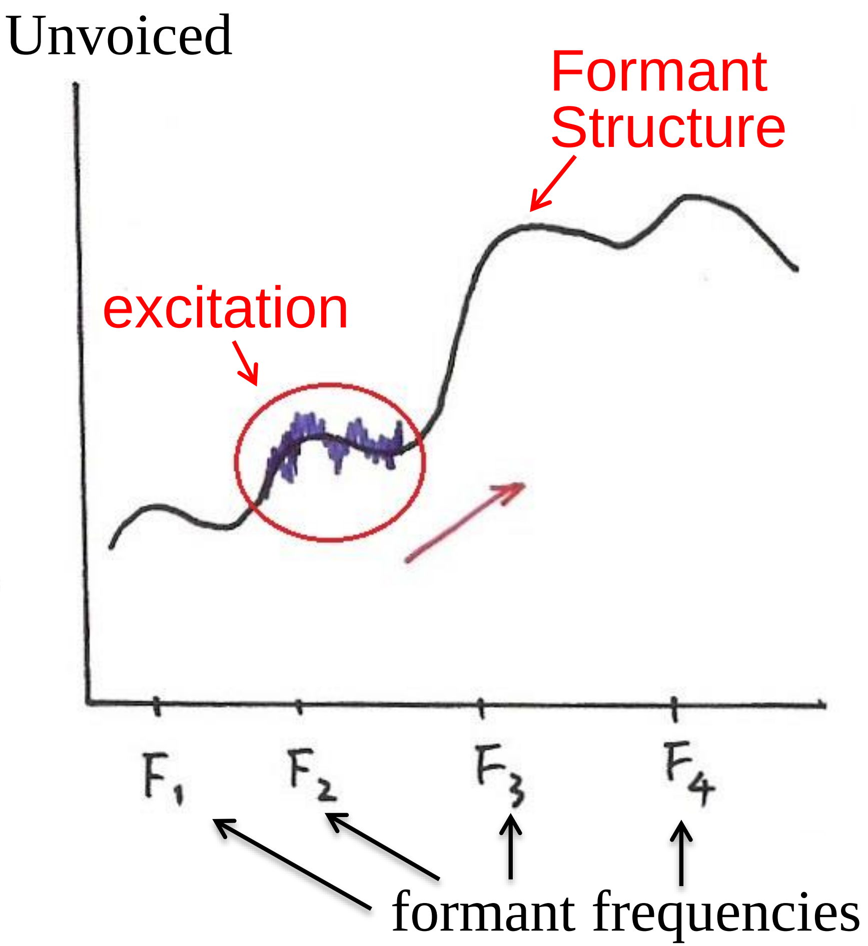


Unvoiced

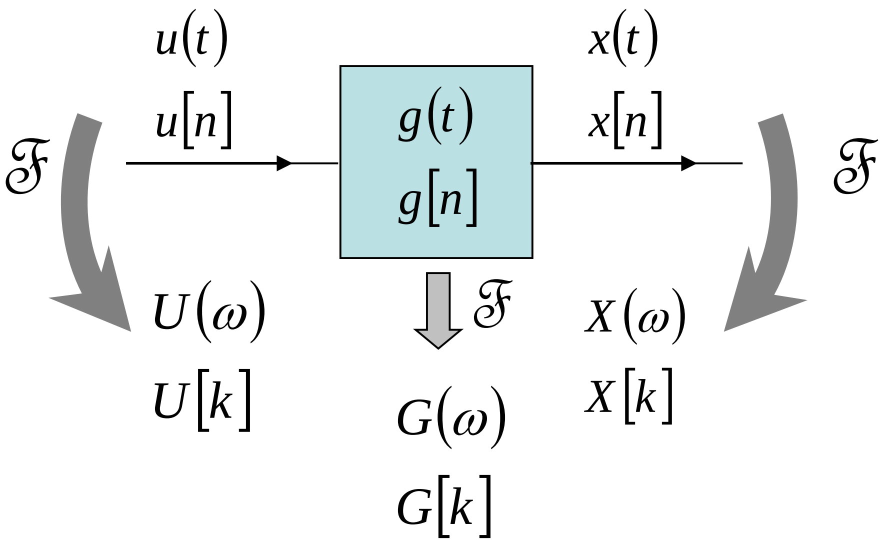


Frequency Domain





Input/Output Relationship for Time/Frequency Domains



excitation

formant structure

$$x(t) = u(t) * g(t) = \int_{\tau} u(\tau) g(t-\tau) d\tau$$

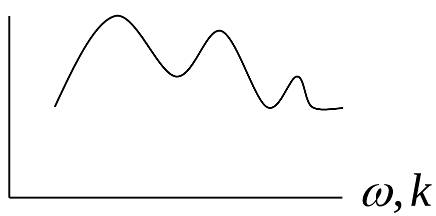
$$x[n] = u[n] * g[n] = \sum_{k} u[k] g[n-k]$$

time domain: convolution

$$X(\omega) = U(\omega) G(\omega)$$

$$X[k] = U[k] G[k]$$

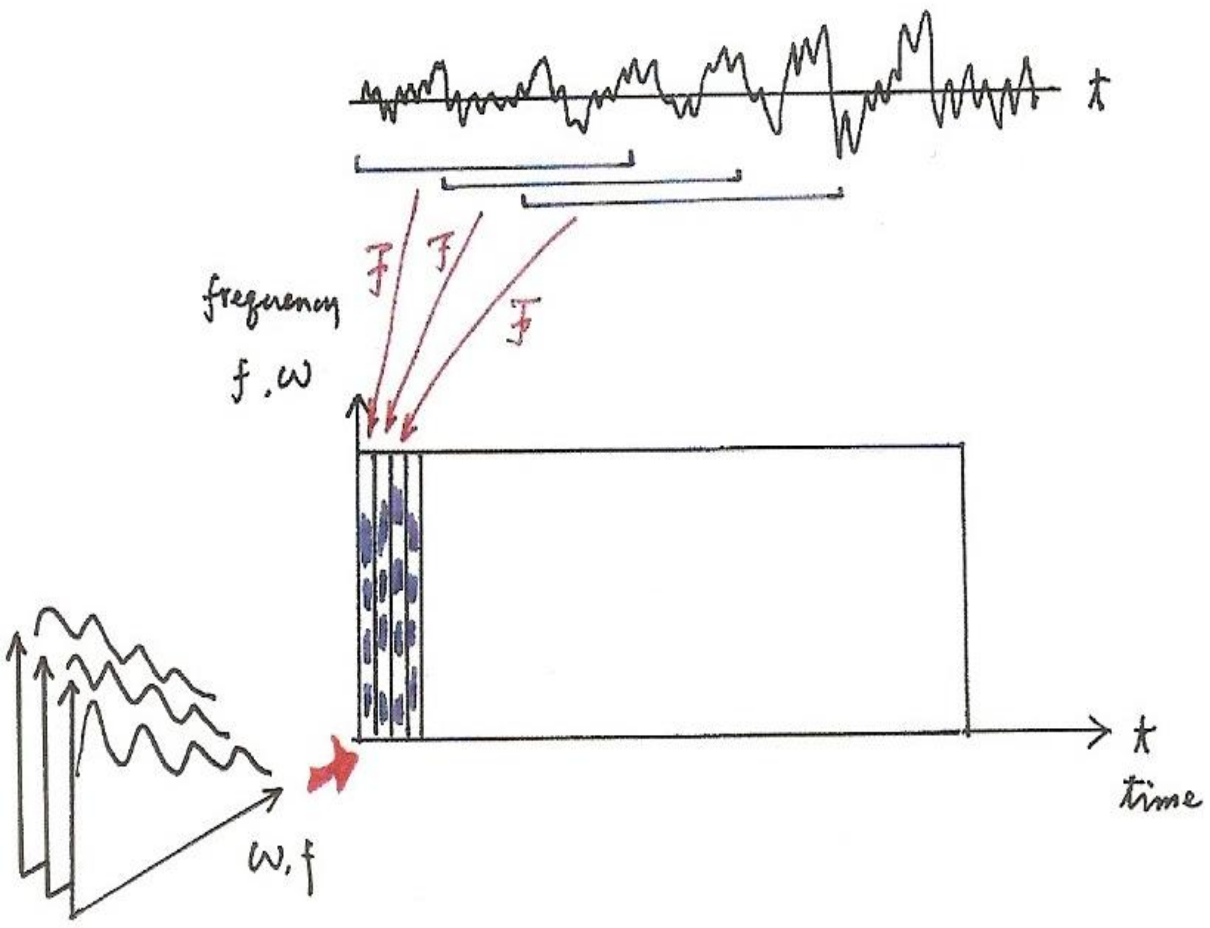
frequency domain: product



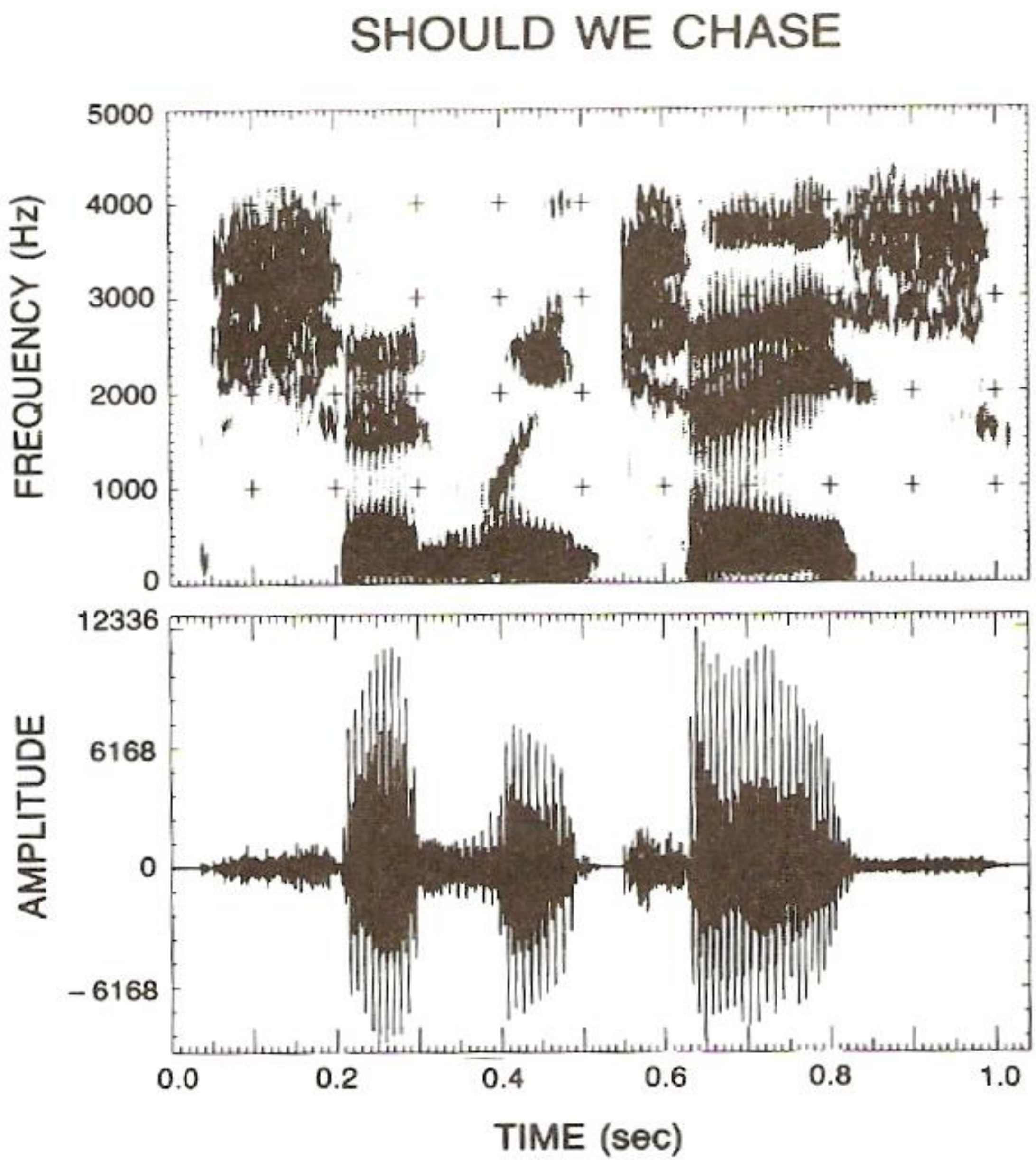
$g(t), G(\omega)$: Formant structure: differences between phonemes

$u(t), U(\omega)$: excitation

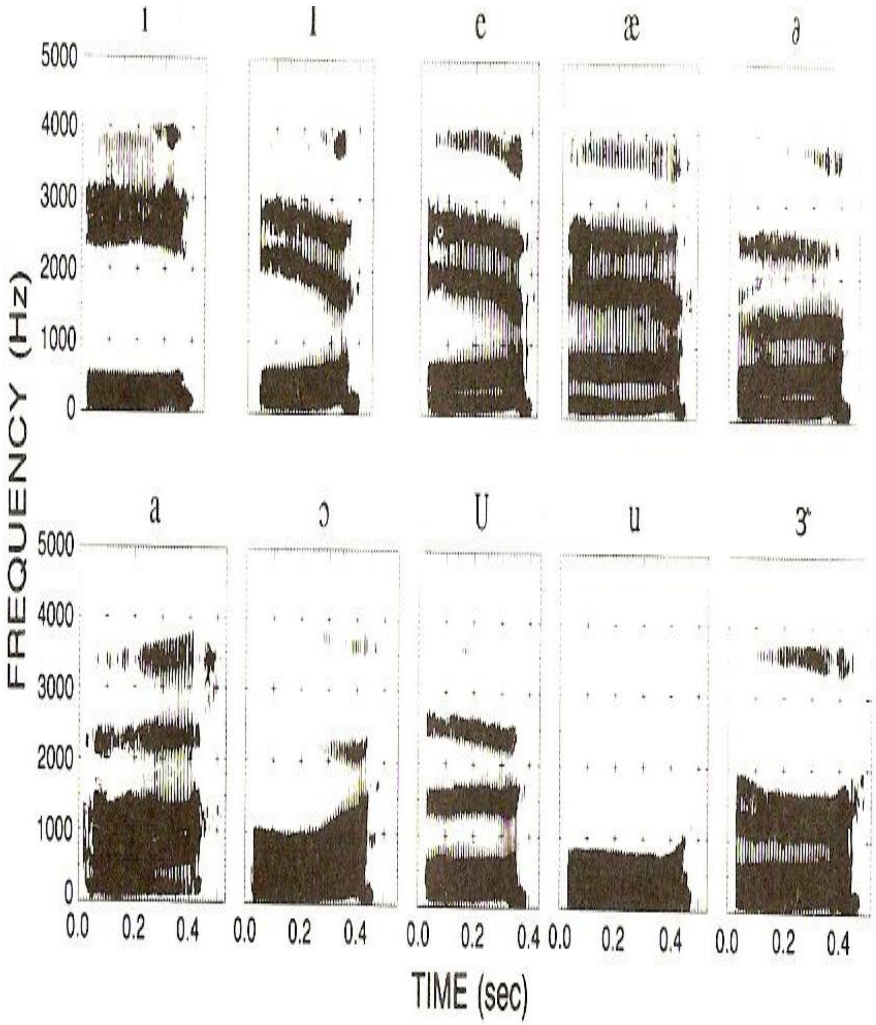
Spectrogram

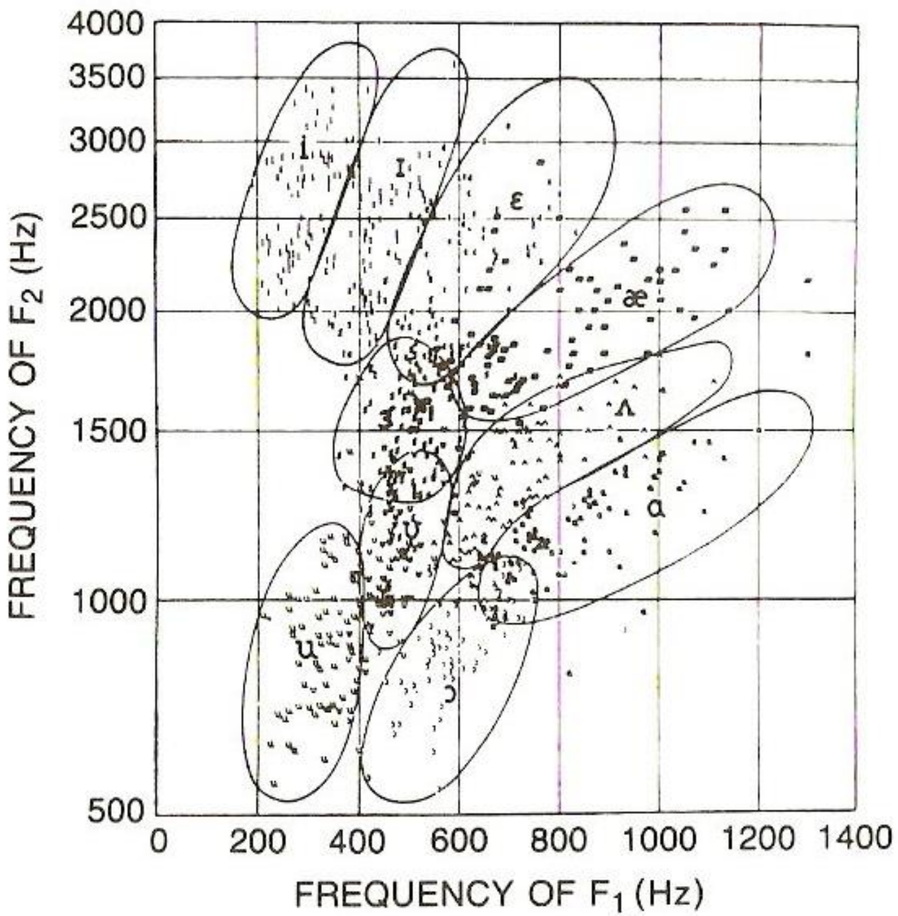


Spectrogram

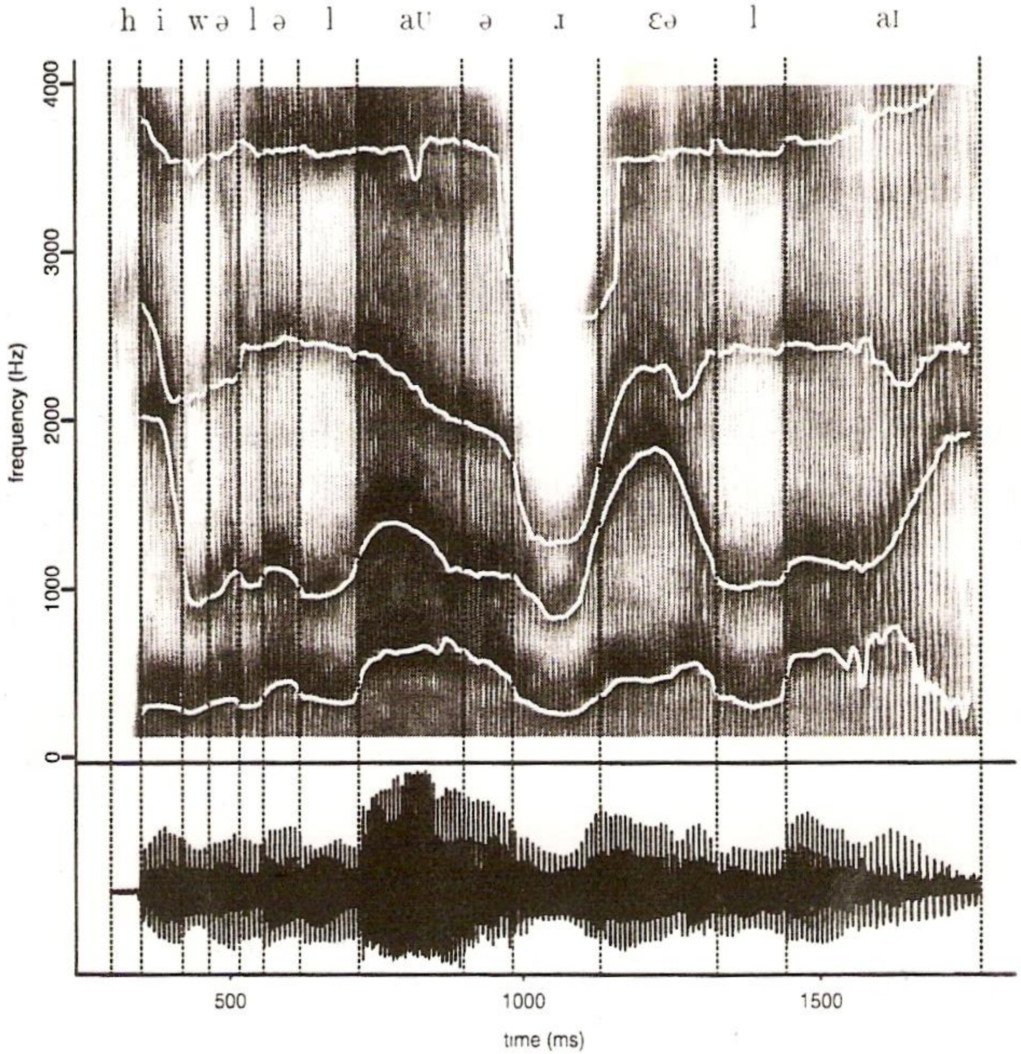


Formant Frequencies





Formant frequency contours

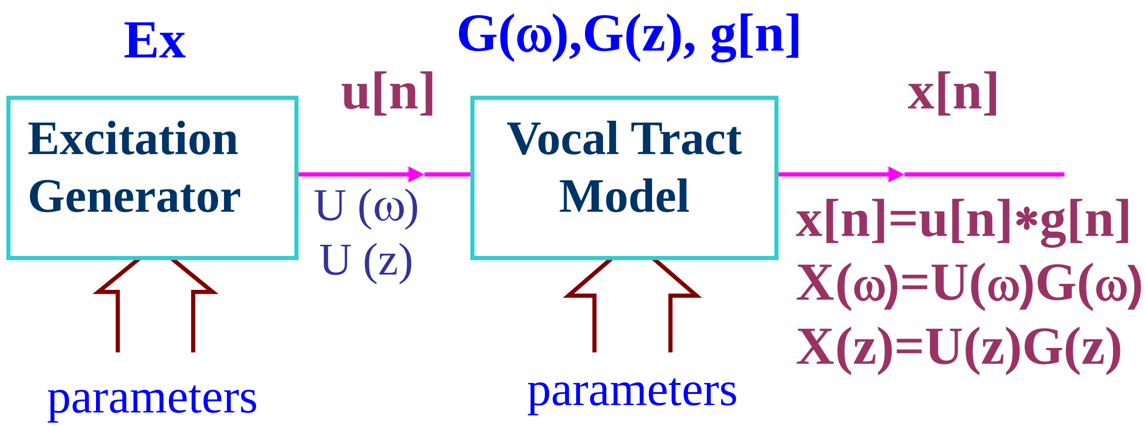


He will allow a rare lie.

Reference: 6.1 of Huang, or 2.2, 2.3 of Rabiner and Juang

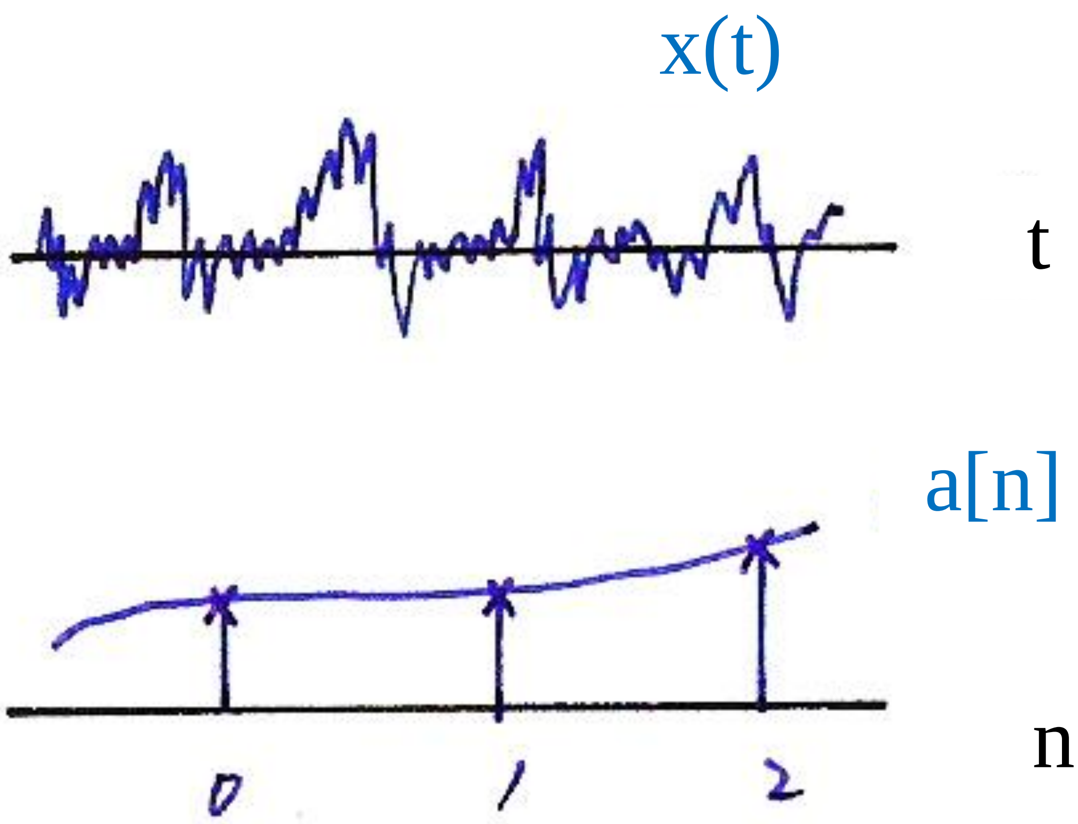
Speech Signals

- **Voiced/unvoiced** 濁音、清音
- **Pitch/tone** 音高、聲調
- **Vocal tract** 聲道
- **Frequency domain/formant frequency**
- **Spectrogram representation**
- **Speech Source Model**



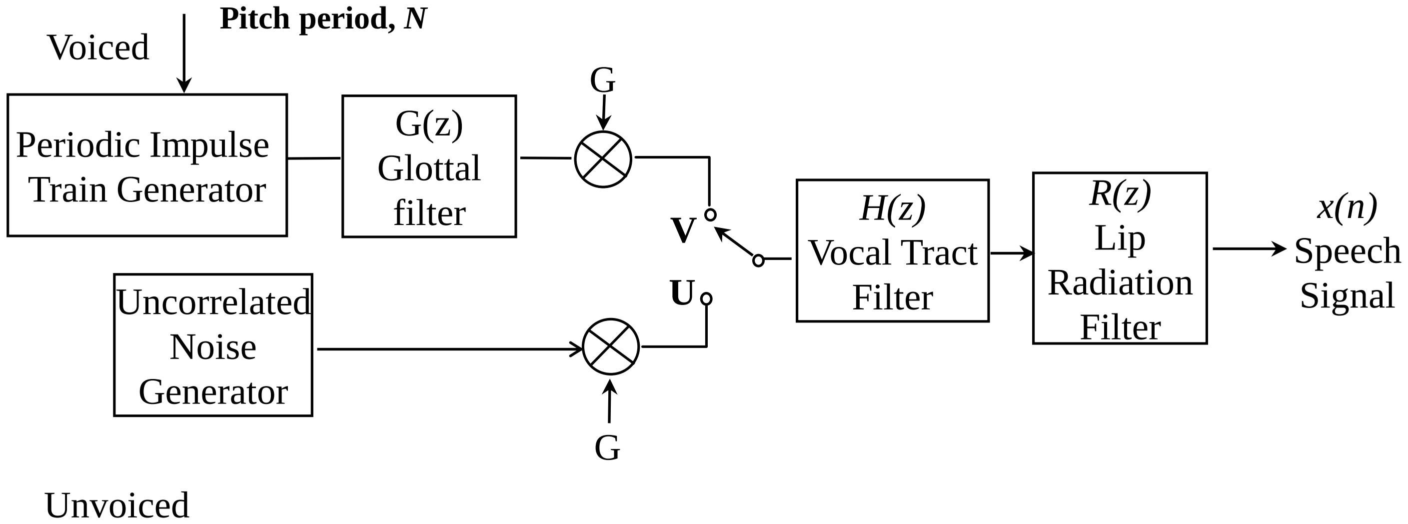
  – digitization and transmission of the parameters will be adequate
  – at receiver the parameters can produce x[n] with the model
  – much less parameters with much slower variation in time lead to much less bits required
  – the key for low bit rate speech coding

Speech Source Model

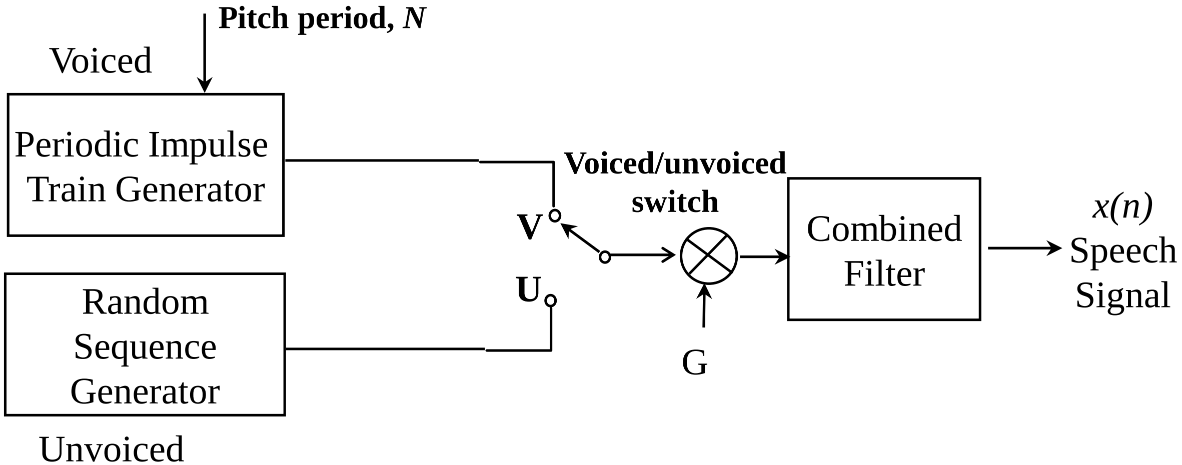


Speech Source Model

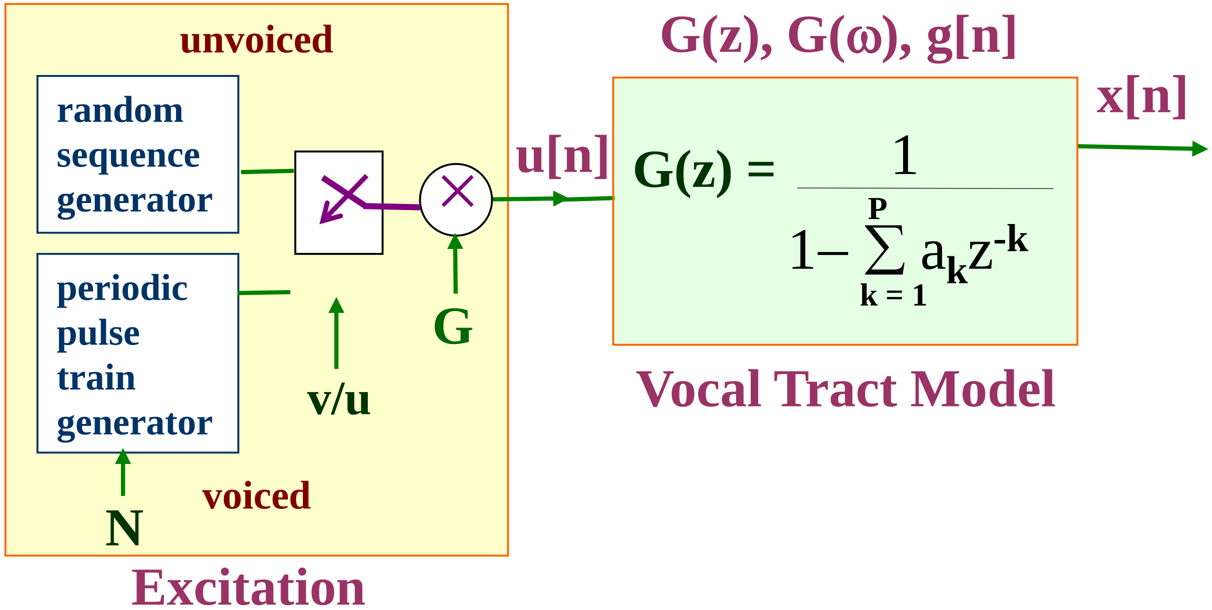
- **Sophisticated model for speech production**



- **Simplified model for speech production**



Simplified Speech Source Model



– Excitation parameters

v/u : voiced/ unvoiced

N : pitch for voiced

G : signal gain

→ excitation signal u[n]

– Vocal Tract parameters

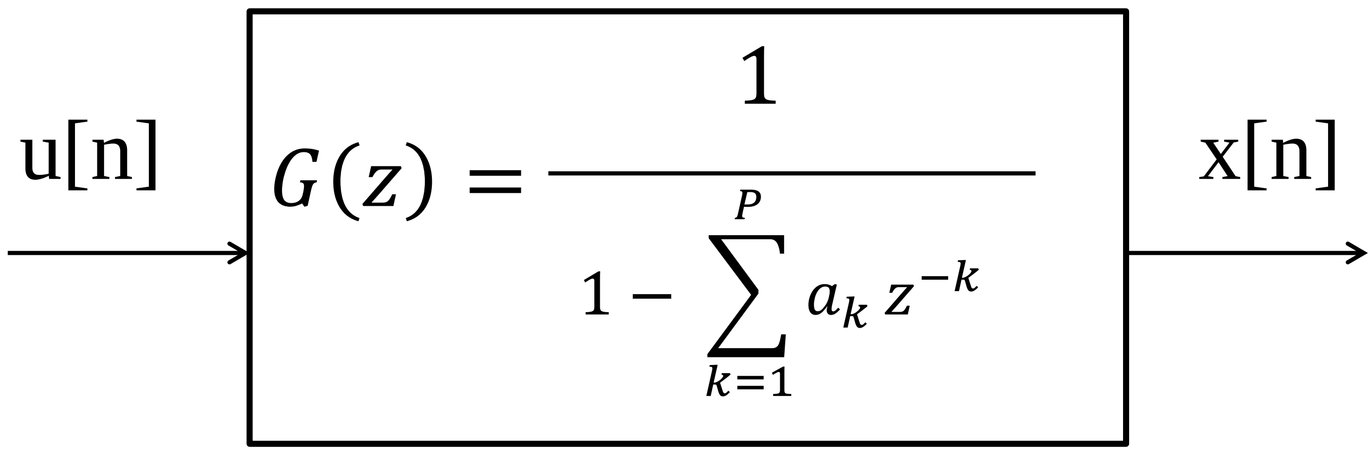
$\{a_k\}$: LPC coefficients

→formant structure of speech signals

– A good approximation, though not precise enough

Reference: 3.3.1-3.3.6 of Rabiner and Juang, or 6.3 of Huang

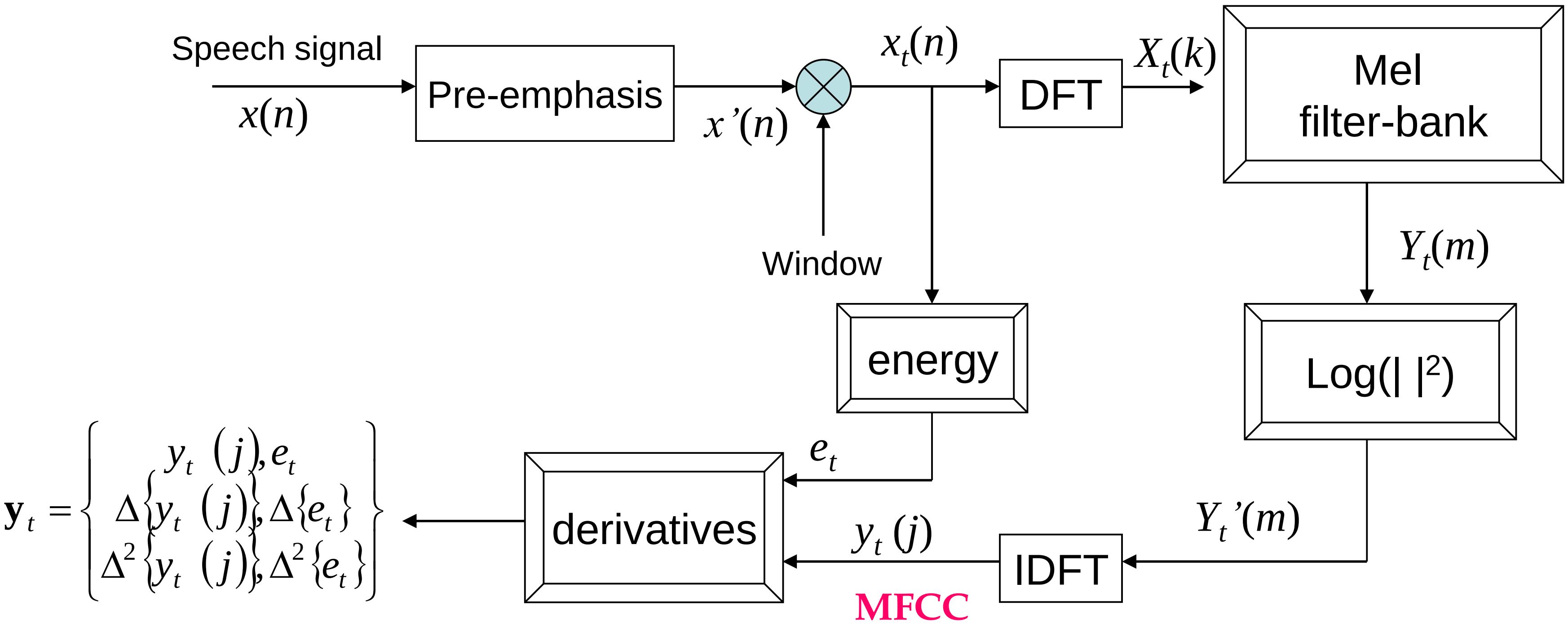
Speech Source Model



$$x[n] - \sum_{k=1}^{P} a_k\, x[n-k] = u[n]$$

Feature Extraction - MFCC

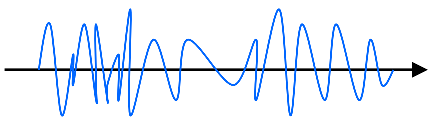
- **Mel-Frequency Cepstral Coefficients (MFCC)**
  - Most widely used in the speech recognition
  - Has generally obtained a better accuracy at relatively low computational complexity
  - The process of MFCC extraction :



Pre-emphasis

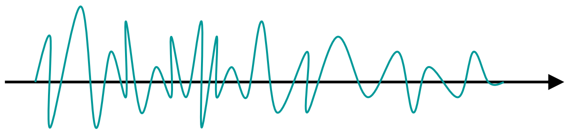
- The process of Pre-emphasis :
  - a high-pass filter

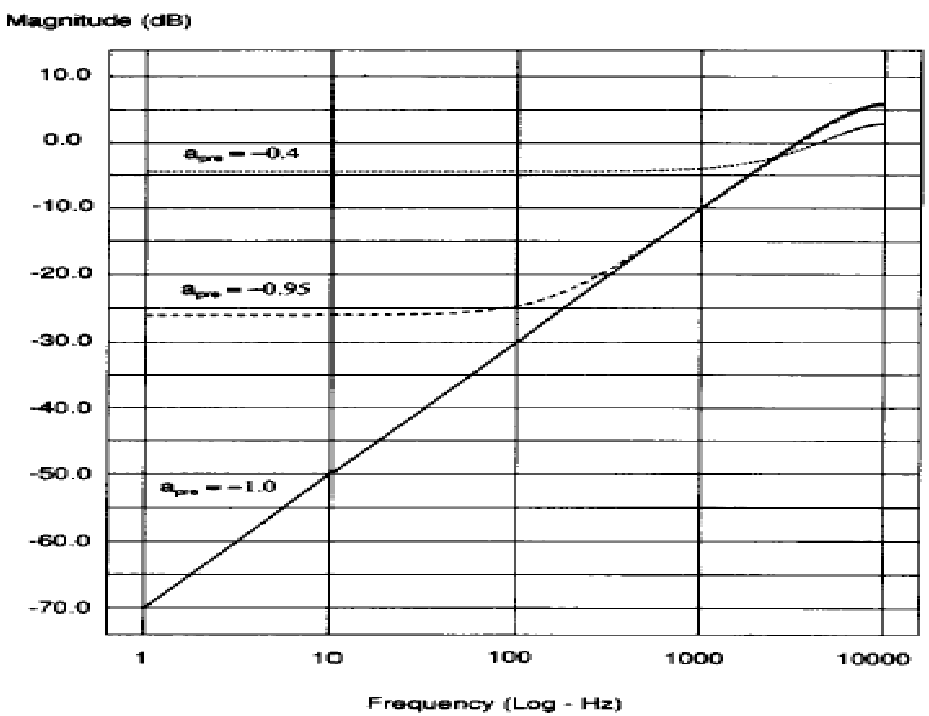
Speech signal $x(n)$

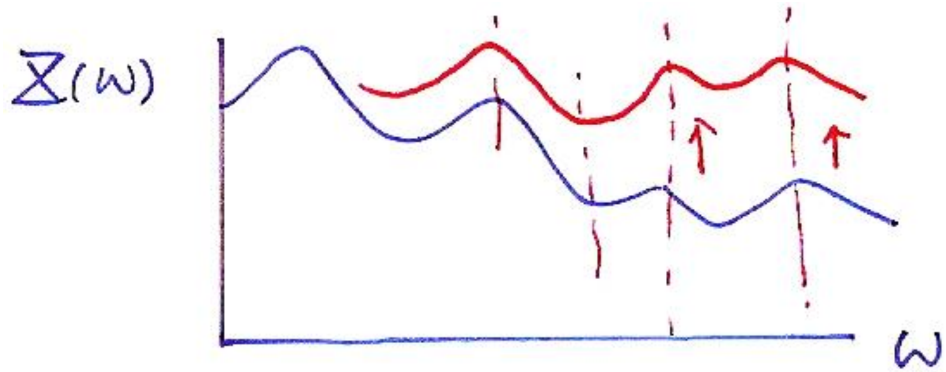


$$H(z)=1-a\cdot z^{-1}\quad 0<a\leq 1$$

$x'(n)=x(n)-ax(n-1)$







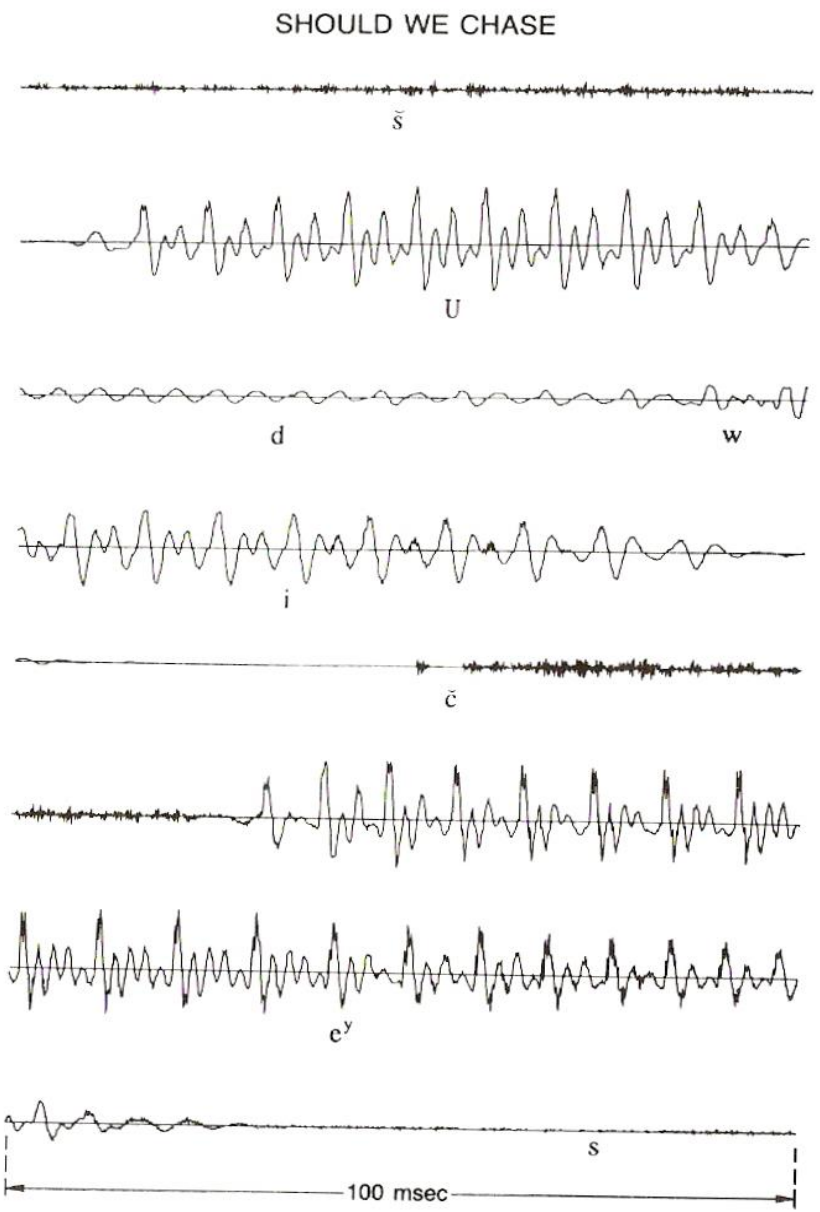
Why pre-emphasis?

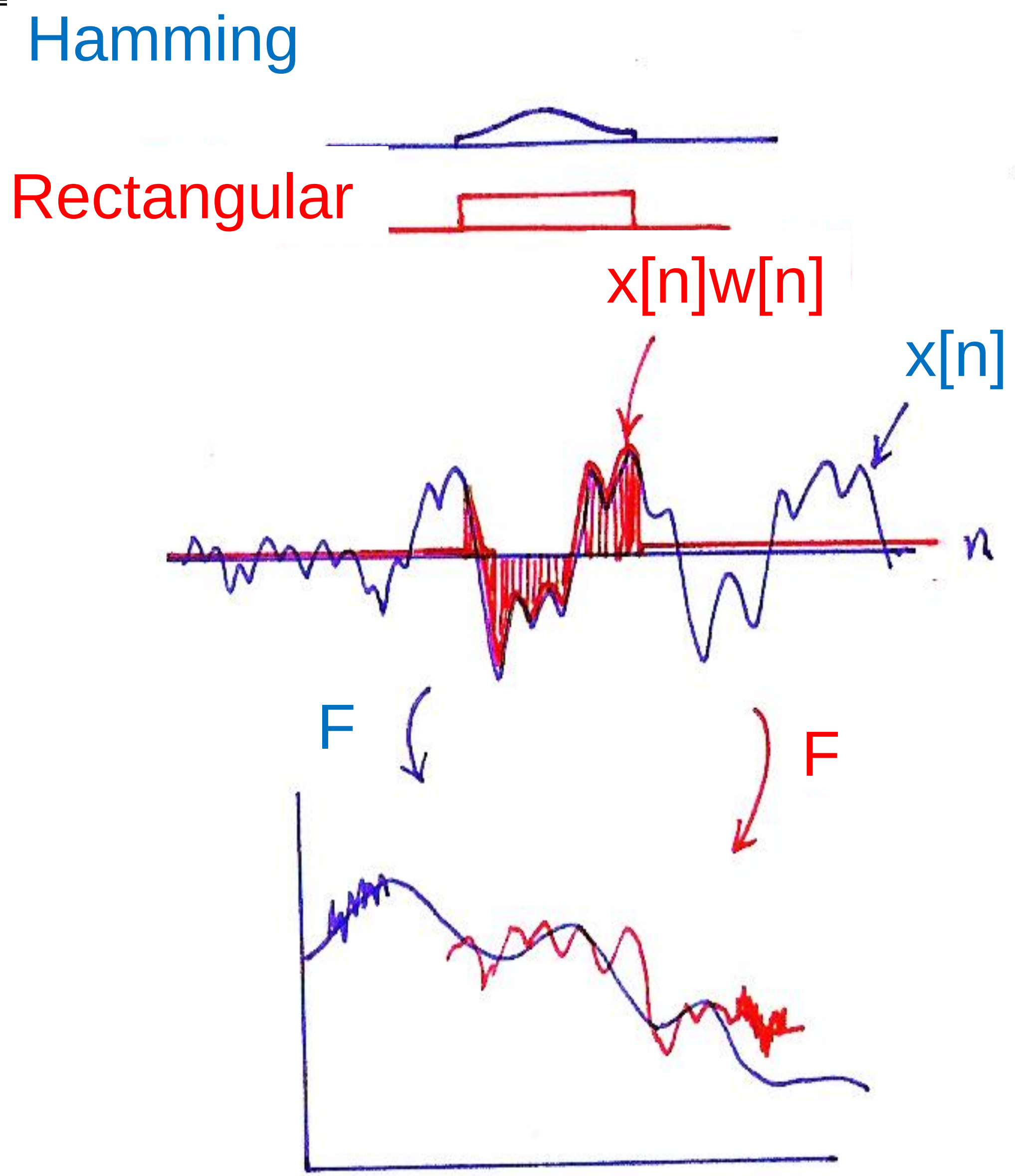
- **Reason :**
  - Voiced sections of the speech signal naturally have a negative spectral slope (attenuation) of approximately 20 dB per decade due to the physiological characteristics of the speech production system
  - High frequency formants have small amplitude with respect to low frequency formants. A pre-emphasis of high frequencies is therefore helpful to obtain similar amplitude for all formants

Why Windowing?

- **Why dividing the speech signal into successive and overlapping frames?**
  – Voice signals change their characteristics from time to time. The characteristics remain unchanged only in short time intervals (short-time stationary, short-time Fourier transform)
- **Frames**
  – **Frame Length :** the length of time over which a set of parameters can be obtained and is valid. Frame length ranges between **20 ~ 10** ms
  – **Frame Shift:** the length of time between successive parameter calculations
  – **Frame Rate:** number of frames per second

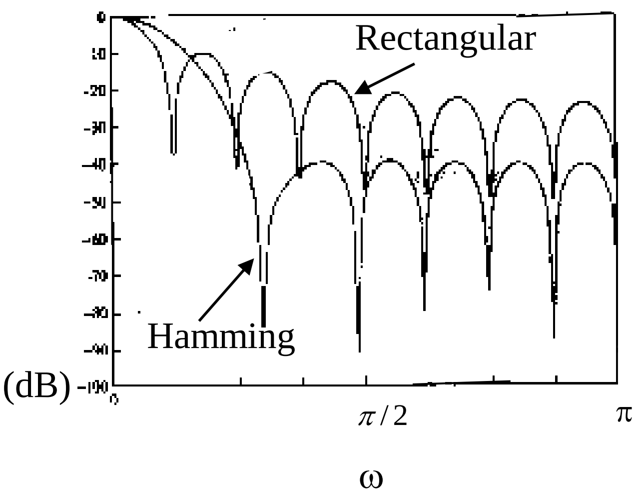
Waveform plot of a sentence



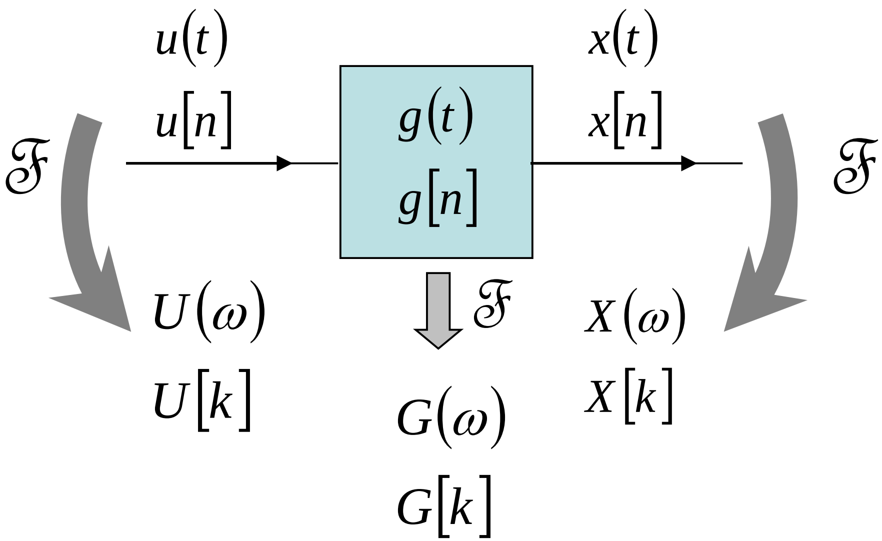


Effect of Windowing (1)

- **Windowing :**
  - $x_t(n)=w(n)\bullet x'(n)$, $w(n)$: the shape of the window (product in time domain)
    - $X_t(\omega)=W(\omega)*X'(\omega)$, *: convolution (convolution in frequency domain)
  - Rectangular window ($w(n)$=1 for $0 \le n \le L-1$):
    - simply extract a segment of the signal
    - whose frequency response has high side lobes
  - *Main lobe* : spreads out the narrow band power of the signal (that around the formant frequency) in a wider frequency range, and thus reduces the local frequency resolution in formant allocation
  - *Side lobe* : swap energy from different and distant frequencies



Input/Output Relationship for Time/Frequency Domains



excitation — formant structure

$$x(t) = u(t) * g(t) = \int_\tau u(\tau) g(t-\tau) d\tau$$

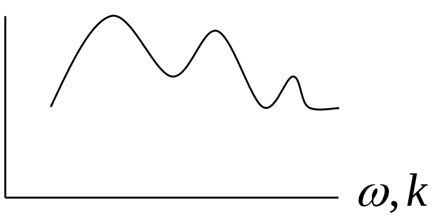
$$x[n] = u[n] * g[n] = \sum_k u[k] g[n-k]$$

time domain: convolution

$$X(\omega) = U(\omega) G(\omega)$$

$$X[k] = U[k] G[k]$$

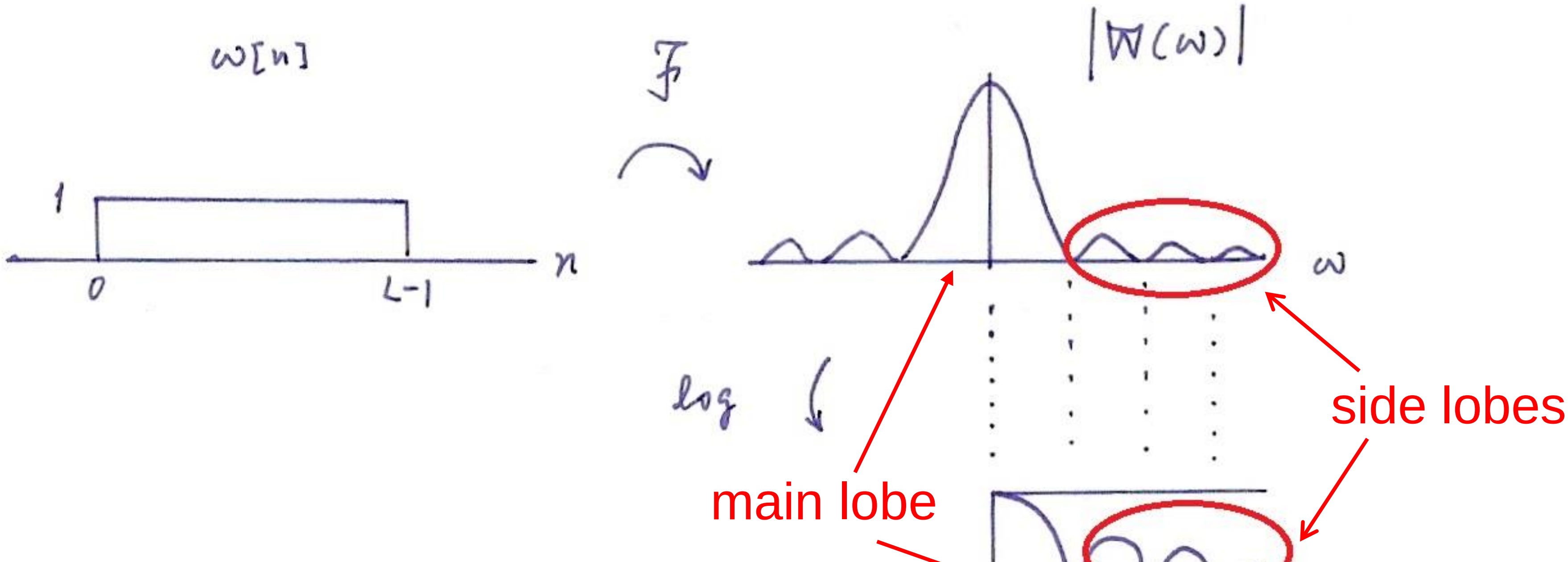
frequency domain: product

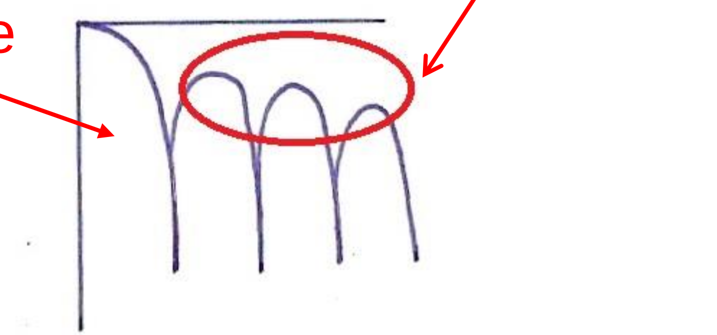


$g(t), G(\omega)$: Formant structure: differences between phonemes

$u(t), U(\omega)$: excitation

Windowing





– *Main lobe* : spreads out the narrow band power of the signal (that around the formant frequency) in a wider frequency range, and thus reduces the local frequency resolution in formant allocation

– *Side lobe* : swap energy from different and distant frequencies

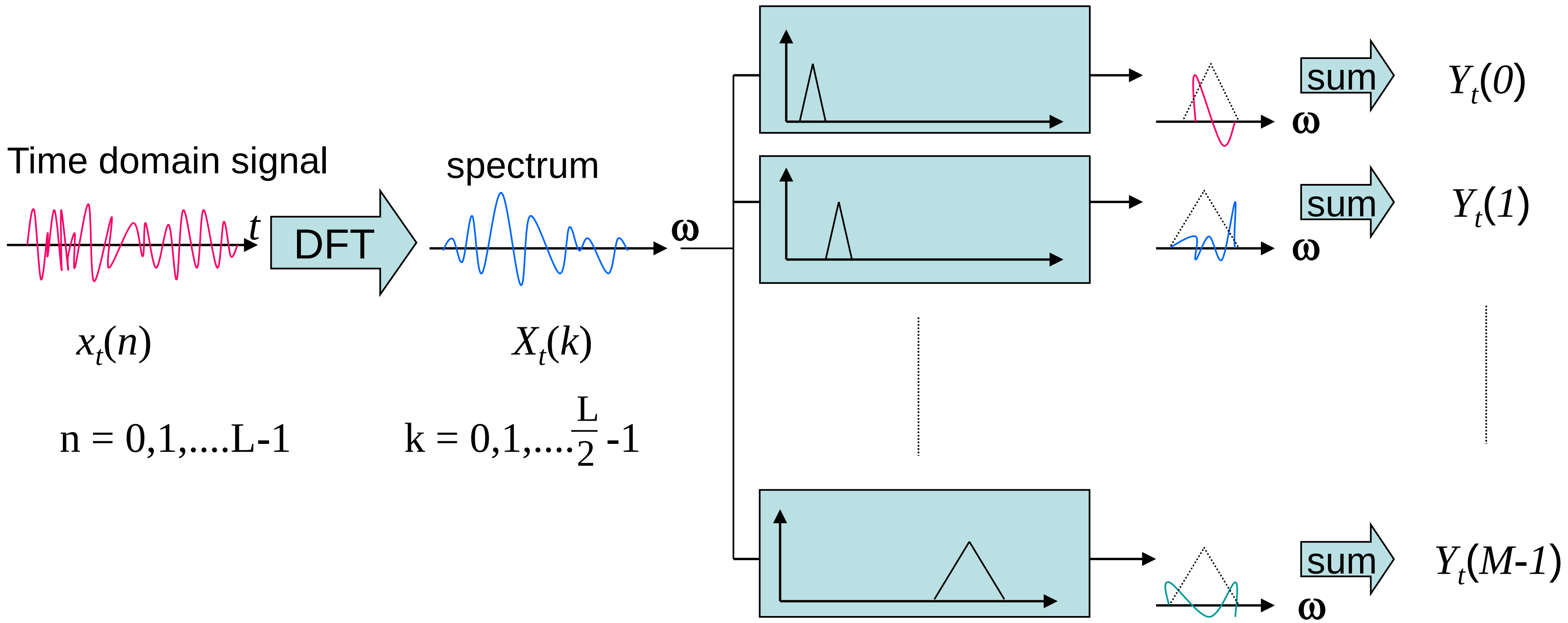
Effect of Windowing (2)

- **Windowing (Cont.):**
  - For a designed window, we wish that
    - the main lobe is as narrow as possible
    - the side lobe is as low as possible
      - However, it is impossible to achieve both simultaneously. Some trade-off is needed
  - The most widely used window shape is the Hamming window

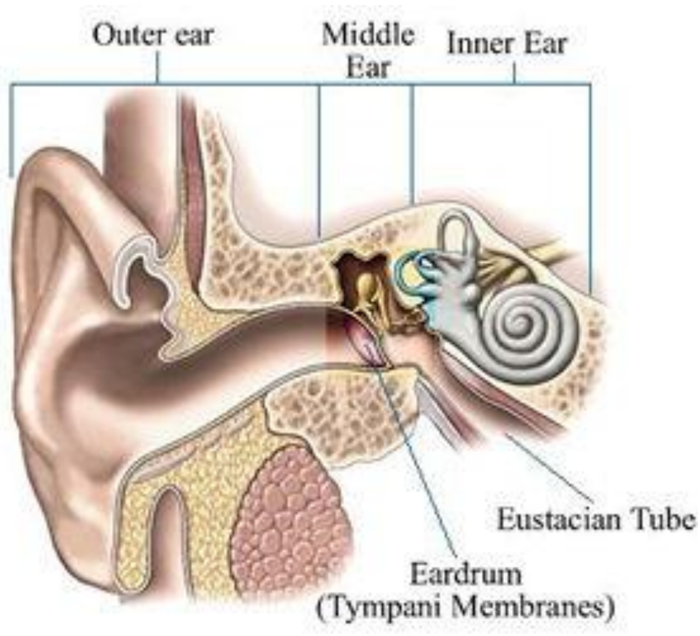
$$w(n) = \begin{cases} 0.54 - 0.46\cos\left(\dfrac{2\pi n}{L-1}\right), & n = 0,1,\ldots\ldots, L-1 \\ 0 & \text{otherwise} \end{cases}$$

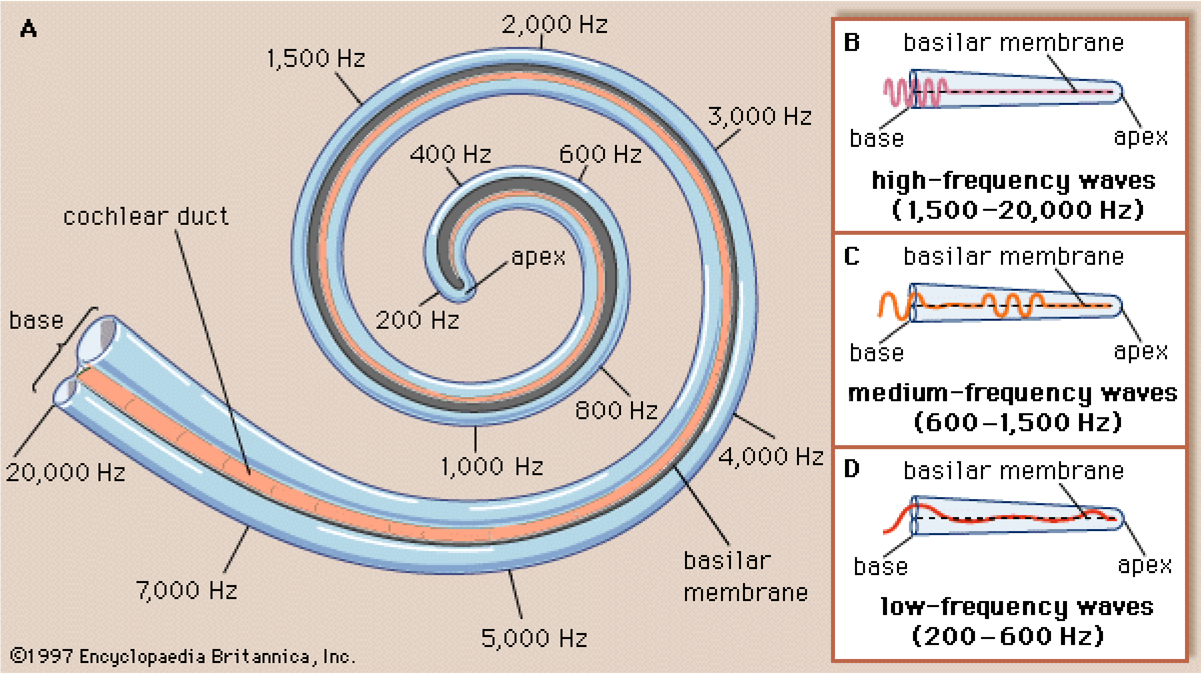
DFT and Mel-filter-bank Processing

- **For each frame of signal (*L* points, e.g., L=512),**
  - the Discrete Fourier Transform (DFT) is first performed to obtain its spectrum (*L* points, for example *L*=512)
  - The bank of filters based on Mel scale is then applied, and each filter output is the sum of its filtered spectral components (*M* filters, and thus *M* outputs, for example *M*=24)

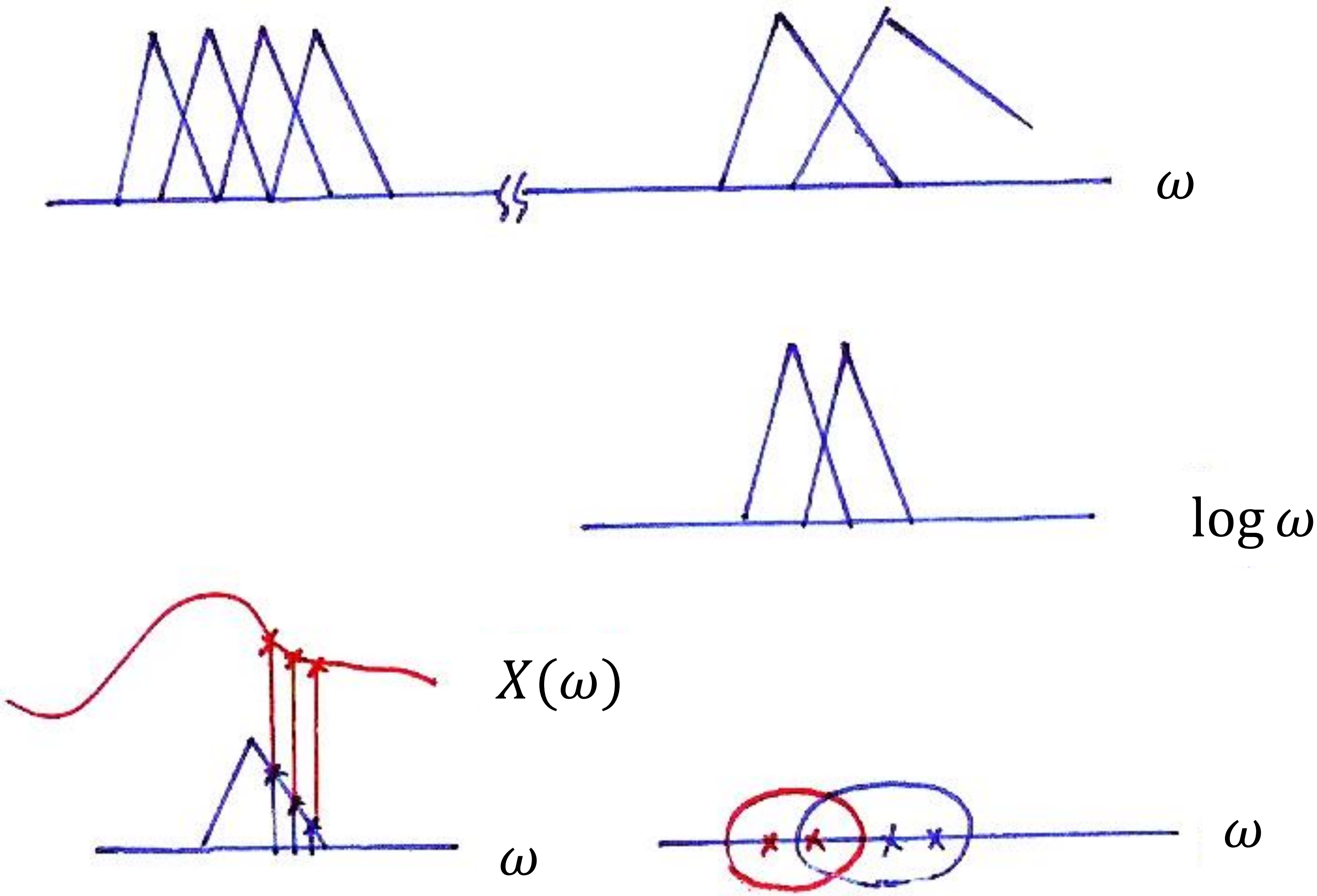


Peripheral Processing for Human Perception



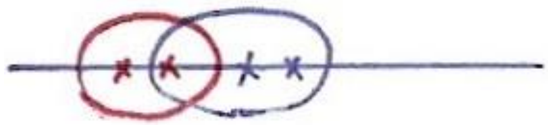


Mel-scale Filter Bank

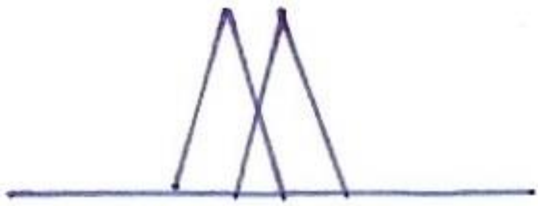


Why Filter-bank Processing?

- **The filter-bank processing simulates human ear perception**
  - Frequencies of a complex sound within a certain frequency band cannot be individually identified.
  - When one of the components of this sound falls outside this frequency band, it can be individually distinguished.
  - This frequency band is referred to as the critical band.
  - These critical bands somehow overlap with each other.
  - The critical bands are roughly distributed linearly in the logarithm frequency scale (including the center frequencies and the bandwidths), specially at higher frequencies.
  - Human perception for pitch of signals is proportional to the *logarithm* of the frequencies (relative ratios between the frequencies)



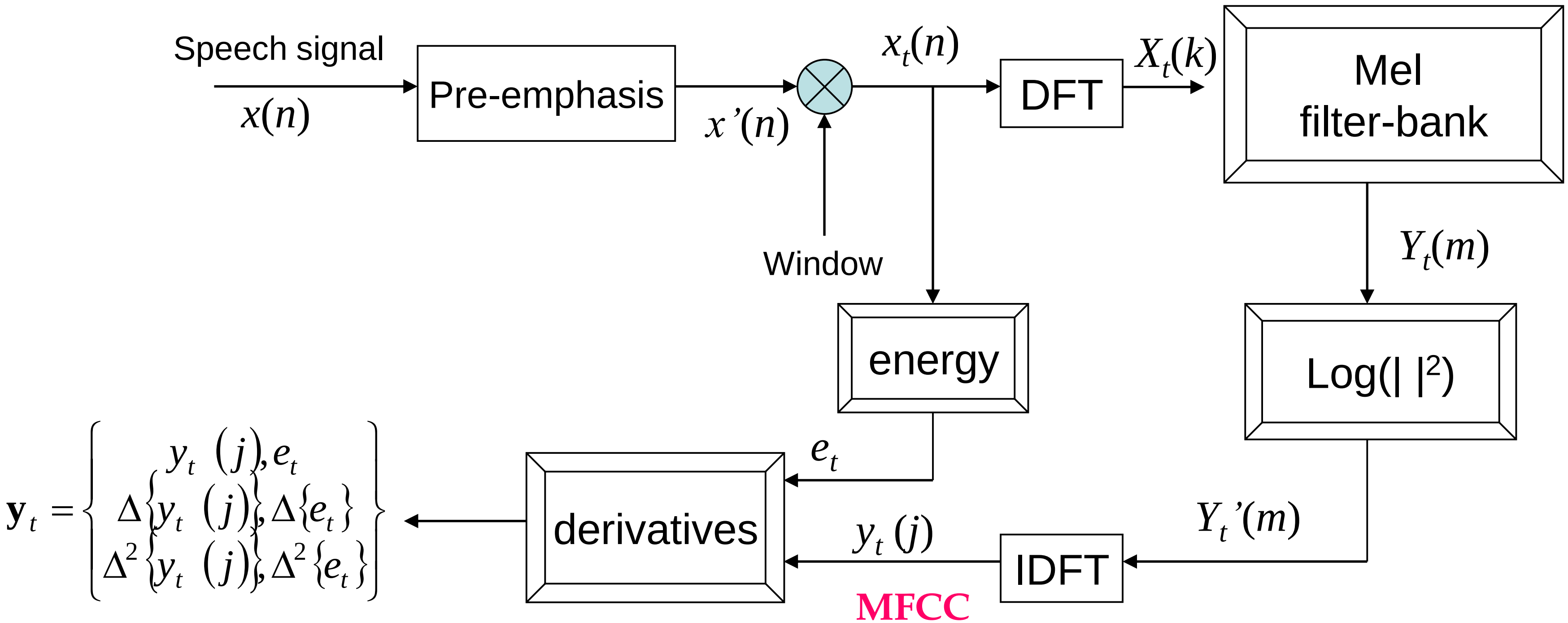
ω



$\log \omega$

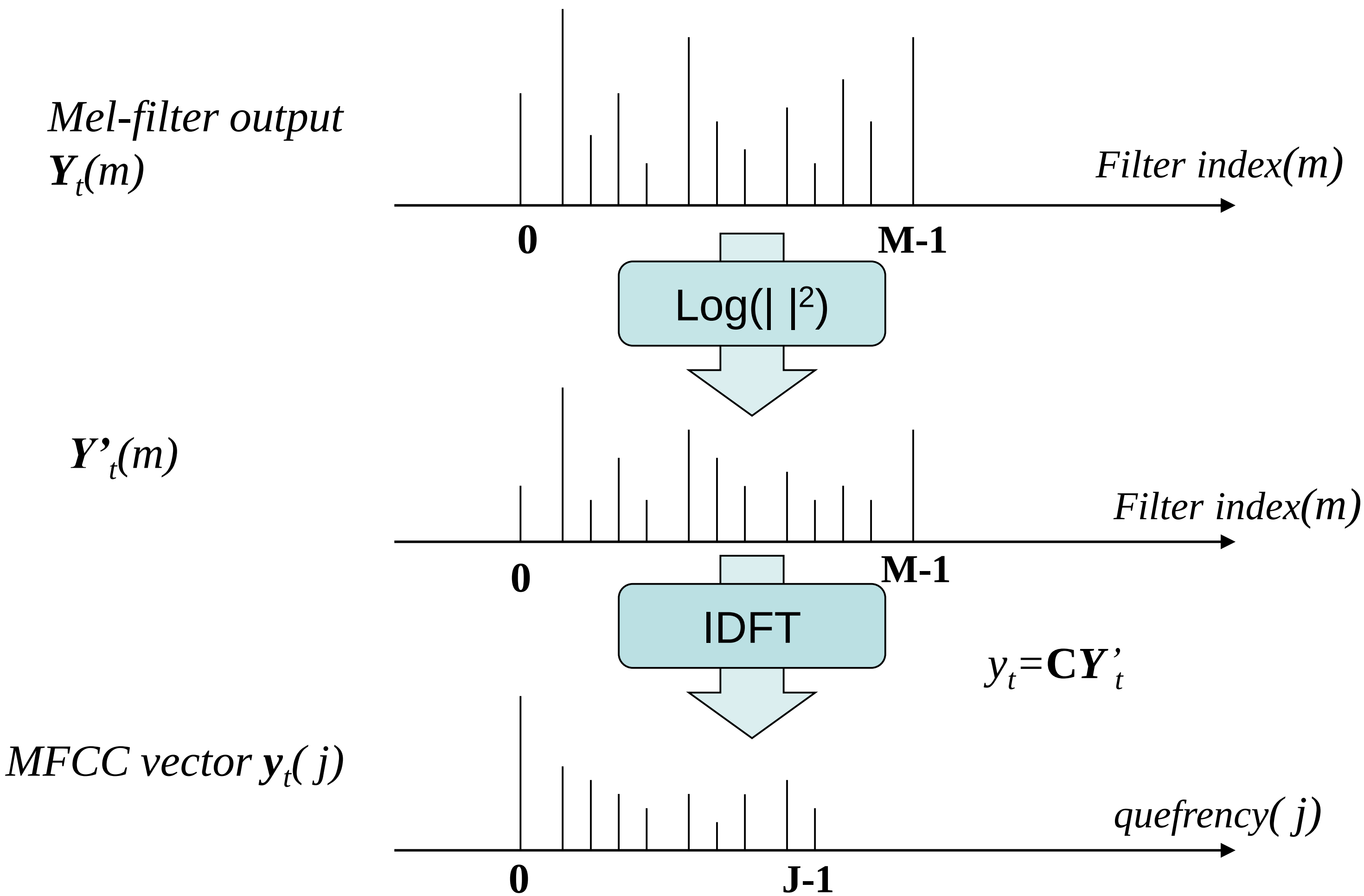
Feature Extraction - MFCC

- **Mel-Frequency Cepstral Coefficients (MFCC)**
  - Most widely used in the speech recognition
  - Has generally obtained a better accuracy at relatively low computational complexity
  - The process of MFCC extraction :



Logarithmic Operation and IDFT

- **The final process of MFCC evaluation : logarithm operation and IDFT**



Why Log Energy Computation?

- **Using the magnitude (or energy) only**
  - Phase information is not very helpful in speech recognition
    - Replacing the phase part of the original speech signal with continuous random phase usually won't be perceived by human ears
- **Using the Logarithmic operation**
  - Human perception sensitivity is proportional to signal energy in logarithmic scale (relative ratios between signal energy values)
  - The logarithm compresses larger values while expands smaller values, which is a characteristic of the human hearing system
  - The dynamic compression also makes feature extraction less sensitive to variations in signal dynamics
  - To make a convolved noisy process additive
    - Speech signal $x(n)$, excitation $u(n)$ and the impulse response of vocal tract $g(n)$

$$x(n)=u(n)*g(n) \Rightarrow X(\omega)=U(\omega)G(\omega)$$

$$\Rightarrow |X(\omega)|=|U(\omega)||G(\omega)| \Rightarrow \log|X(\omega)|=\log|U(\omega)|+\log|G(\omega)|$$

Why Inverse DFT?

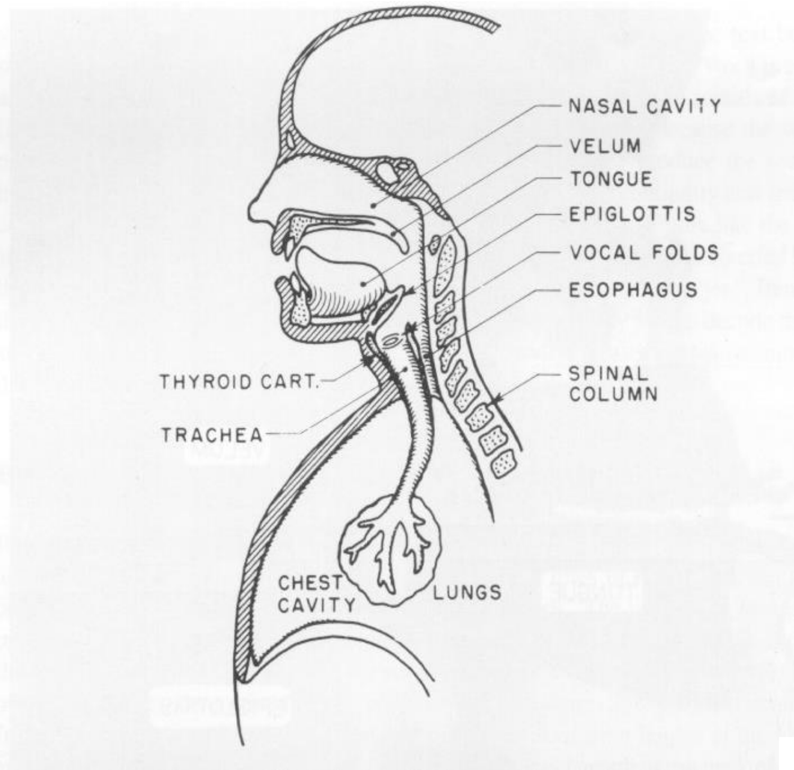
- **Final procedure for MFCC : performing the inverse DFT on the log-spectral power**

$$y_t(j) = \sum_{m=0}^{M-1} \log\left(\left|Y_t(m)\right|^2\right) \cos\left[j\left(m - \frac{1}{2}\right)\frac{\pi}{M}\right], \quad j = 0,1,\ldots, J-1 < M$$

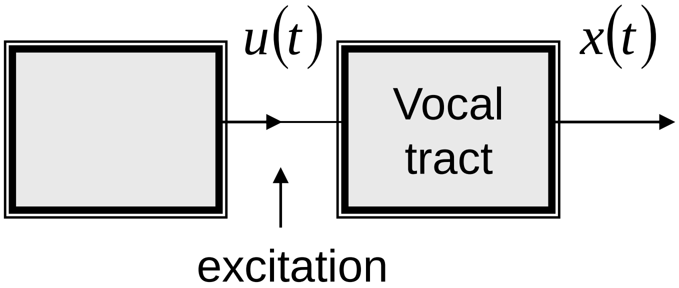
- **Advantages :**
  - Since the log-power spectrum is real and symmetric, the inverse DFT reduces to a Discrete Cosine Transform (DCT). The DCT has the property to produce highly uncorrelated features $\boldsymbol{y}_t$
    - diagonal rather than full covariance matrices can be used in the Gaussian distributions in many cases
  - Easier to remove the interference of excitation on formant structures
    - the phoneme for a segment of speech signal is primarily based on the formant structure (or vocal tract shape)
    - on the frequency scale the formant structure changes slowly over frequency, while the excitation changes much faster

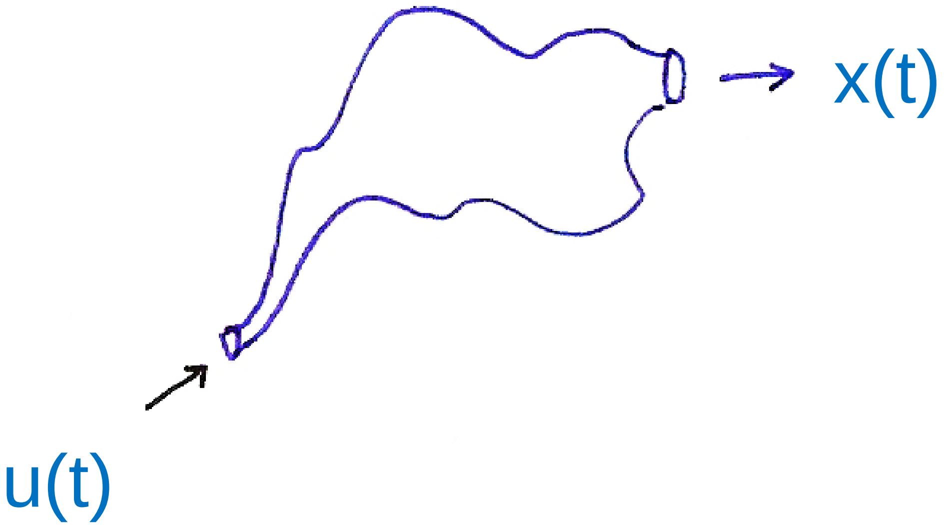
Speech Production and Source Model (P.3 of 7.0)

- Human vocal mechanism

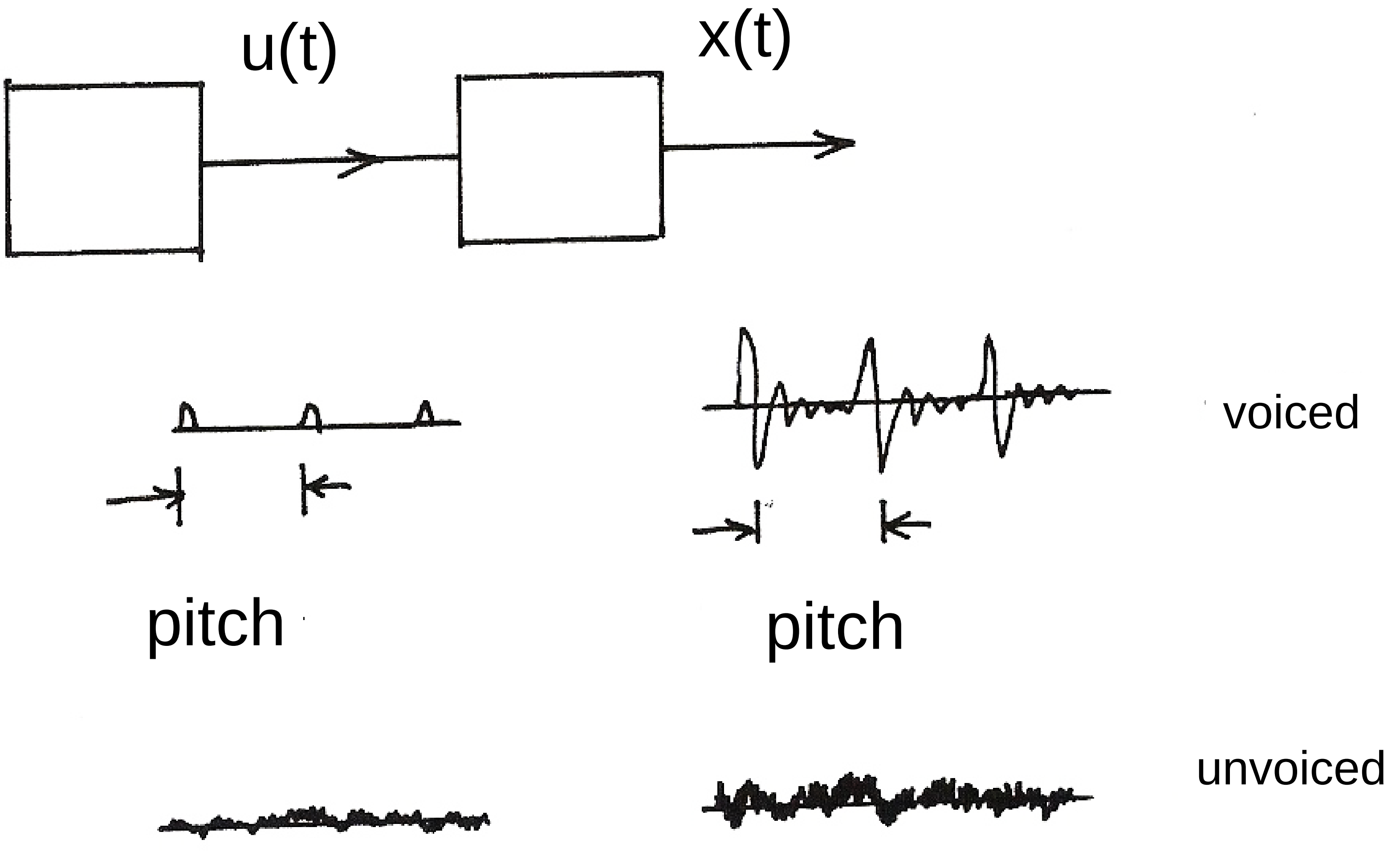


- Speech Source Model



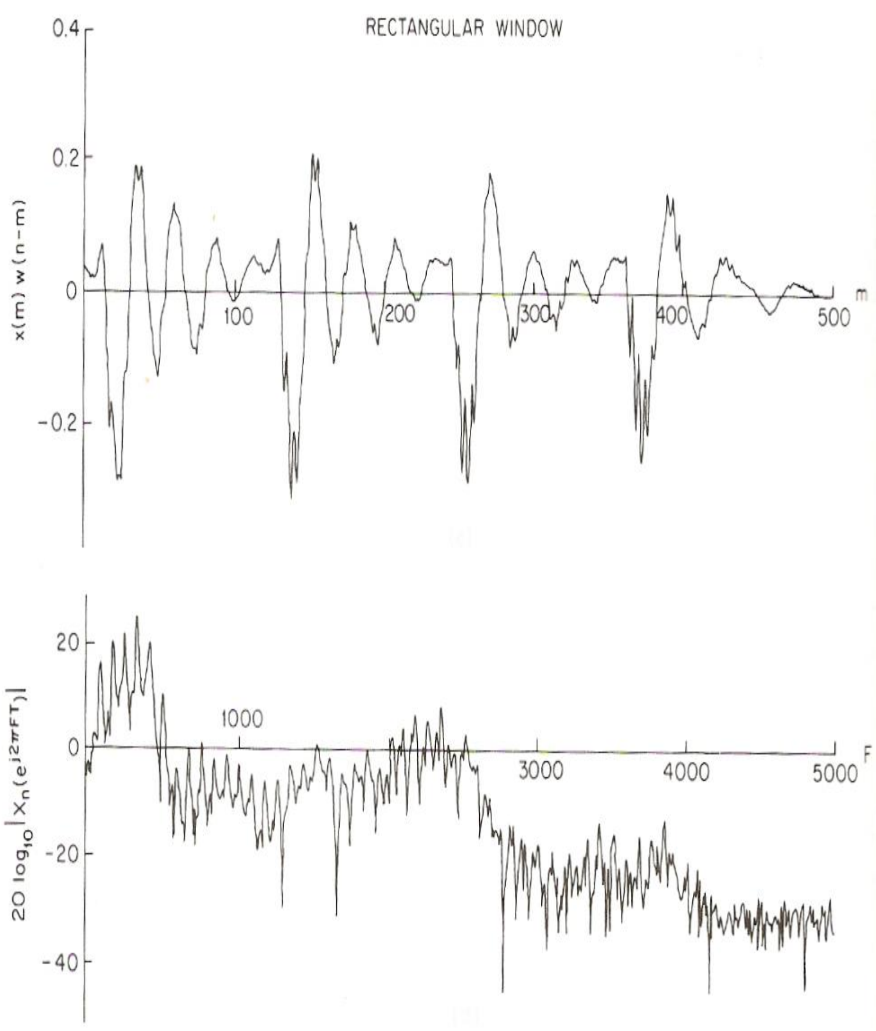


Voiced and Unvoiced Speech (P.4 of 7.0)

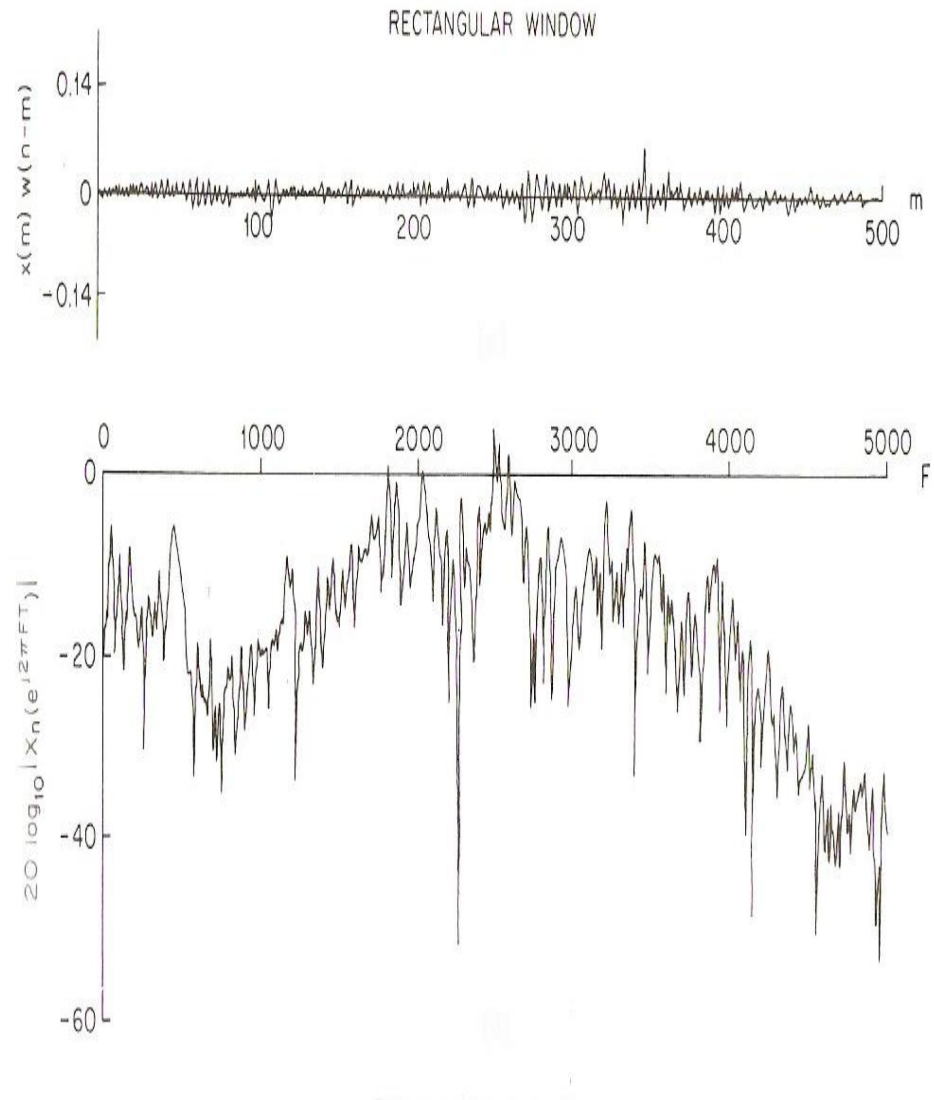


Frequency domain spectra of speech signals (P.8 of 7.0)

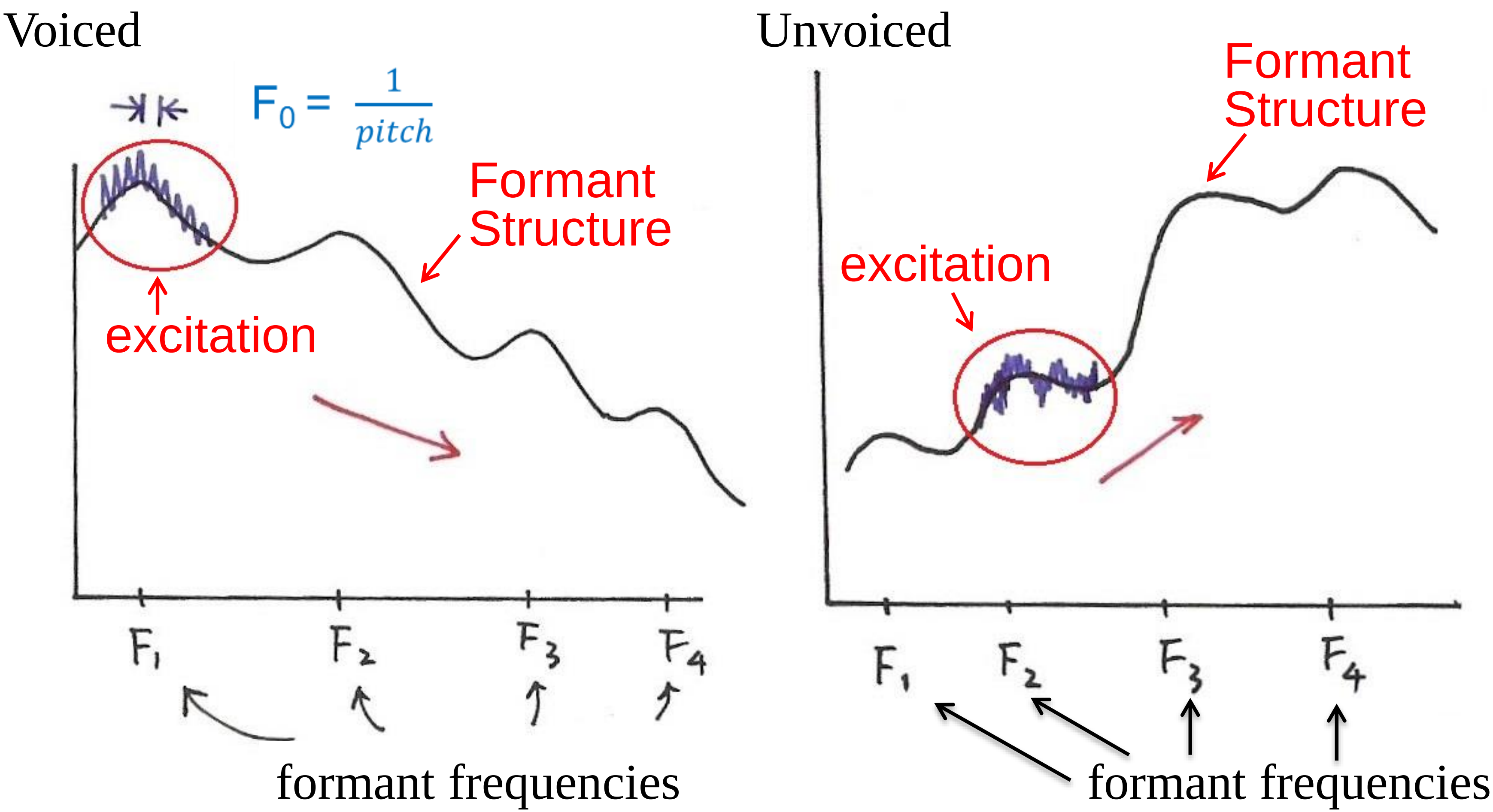
Voiced



Unvoiced

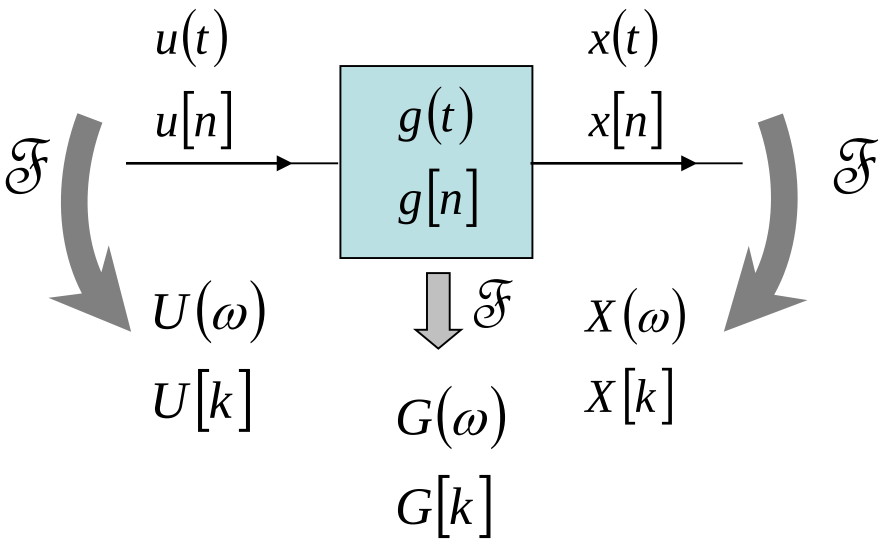


Frequency Domain (P.9 of 7.0)



Input/Output Relationship for Time/Frequency Domains

(P.10 of 7.0)



excitation

formant structure

$$x(t) = u(t) * g(t) = \int_{\tau} u(\tau) g(t-\tau) d\tau$$

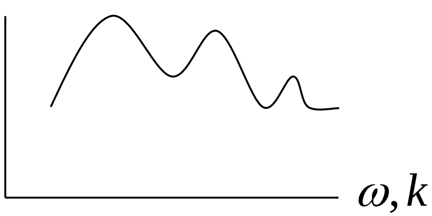
$$x[n] = u[n] * g[n] = \sum_{k} u[k] g[n-k]$$

time domain: convolution

$$X(\omega) = U(\omega) G(\omega)$$

$$X[k] = U[k] G[k]$$

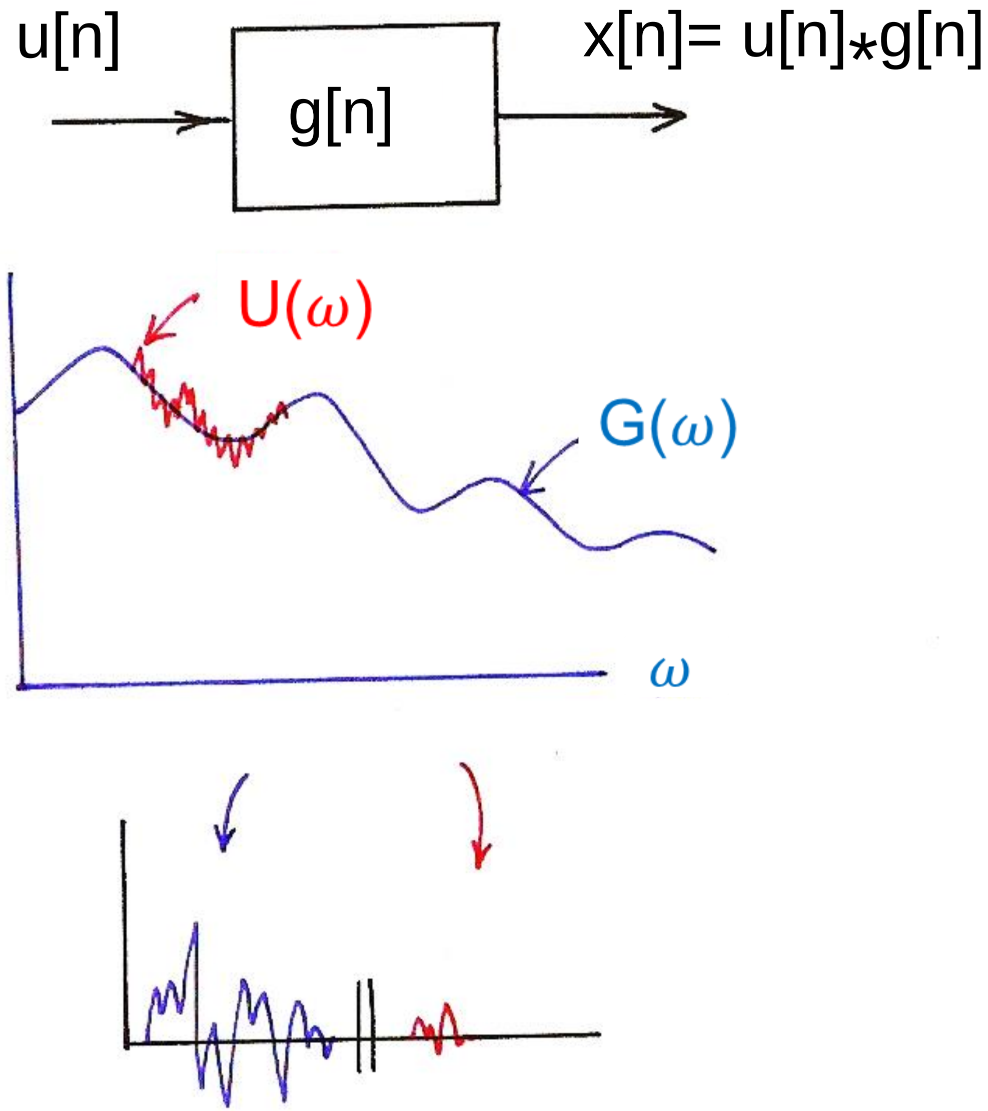
frequency domain: product



$g(t), G(\omega)$: Formant structure: differences between phonemes

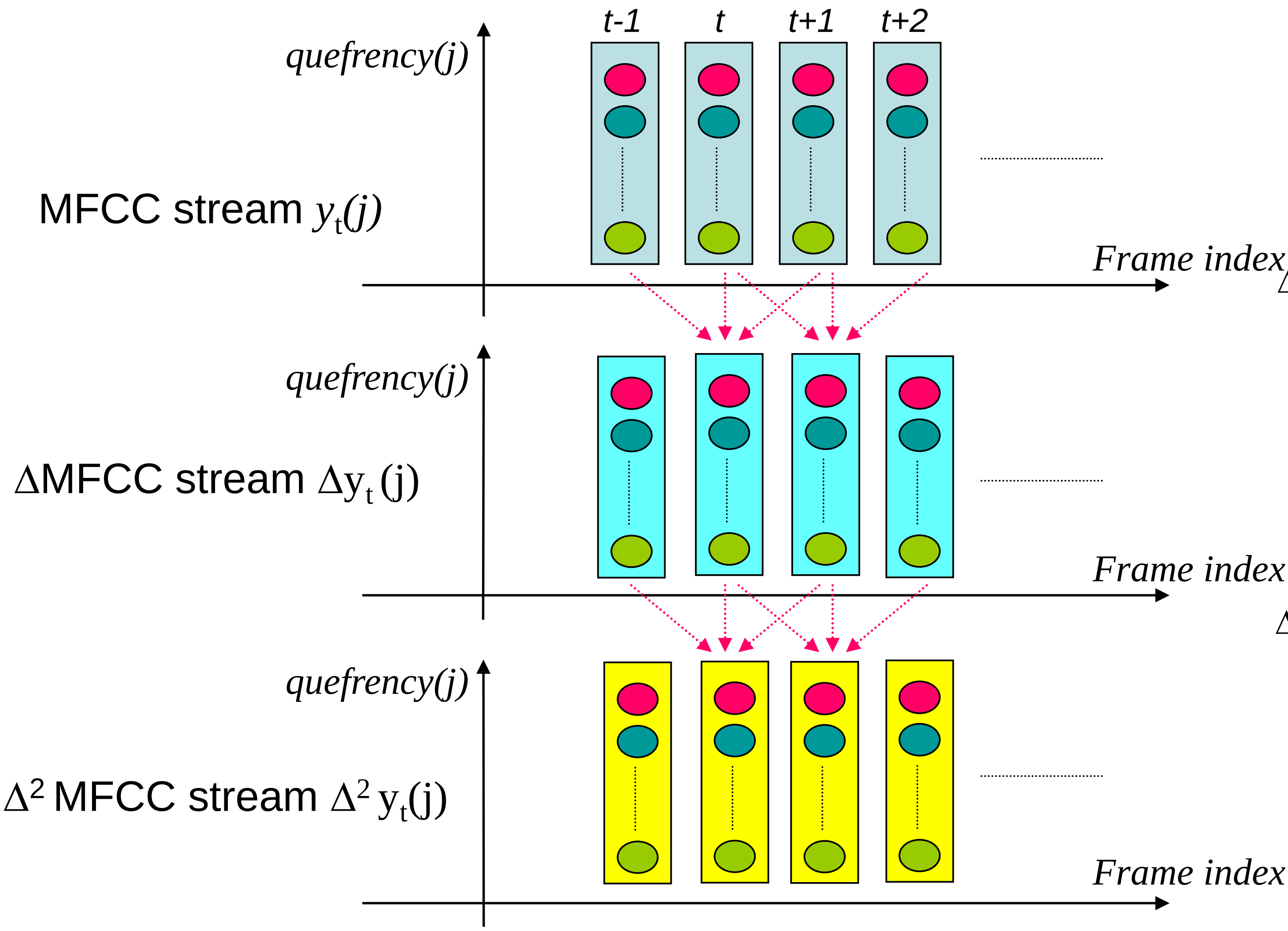
$u(t), U(\omega)$: excitation

Logarithmic Operation



Derivatives

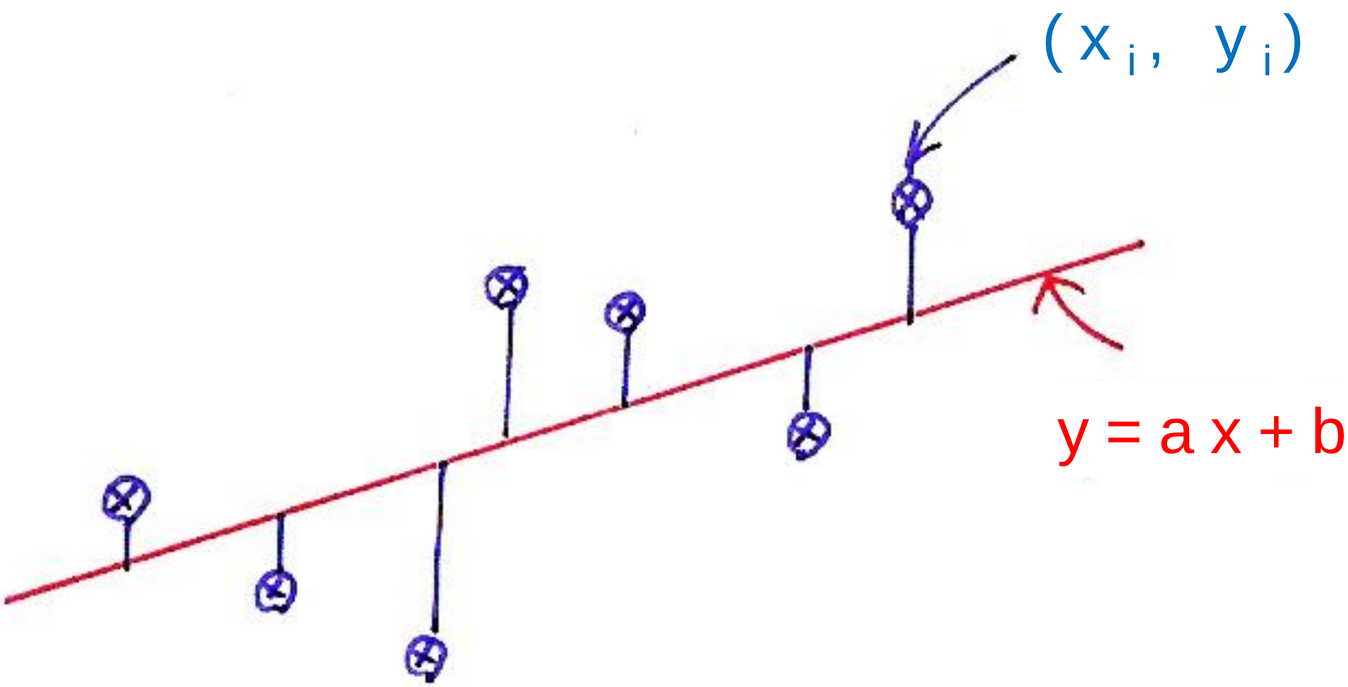
- **Derivative operation : to obtain the change of the feature vectors with time**



$$\Delta y_t(j) = \frac{\sum_{m=-p}^{p} m \bullet y_{t-m}(j)}{\sum_{m=-p}^{p} m^2}$$

$$\Delta^2 y_t(j) = \frac{\sum_{m=-p}^{p} m \bullet \Delta y_{t-m}(j)}{\sum_{m=-p}^{p} m^2}$$

Linear Regression



$$\sum_i \left(ax_i + b - y_i\right)^2 = \min$$

find a, b

Why Delta Coefficients?

- **To capture the dynamic characters of the speech signal**
  - Such information carries relevant information for speech recognition
  - The value of p should be properly chosen
    - The dynamic characters may not be properly extracted if p is too small
    - Too large p may imply frames too far away
- **To cancel the DC part (channel distortion or convolutional noise) of the MFCC features**
  - Assume, for clean speech, an MFCC parameter stream for an utterance is $\{\mathbf{y}(t\text{-}N), \mathbf{y}(t\text{-}N+1), \ldots\ldots, \mathbf{y}(t), \mathbf{y}(t+1), \mathbf{y}(t+2), \ldots\ldots\}$,

    $\mathbf{y}(t)$ is an MFCC parameter at time t,

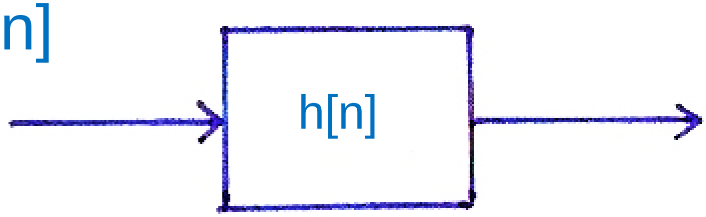
    while after channel distortion, the MFCC stream becomes

    $\{\mathbf{y}(t\text{-}N)+h, \mathbf{y}(t\text{-}N+1)+h, \ldots\ldots, \mathbf{y}(t)+h, \mathbf{y}(t+1)+h, \mathbf{y}(t+2)+h, \ldots\ldots\}$

    the channel effect h is eliminated in the delta (difference) coefficients

Convolutional Noise

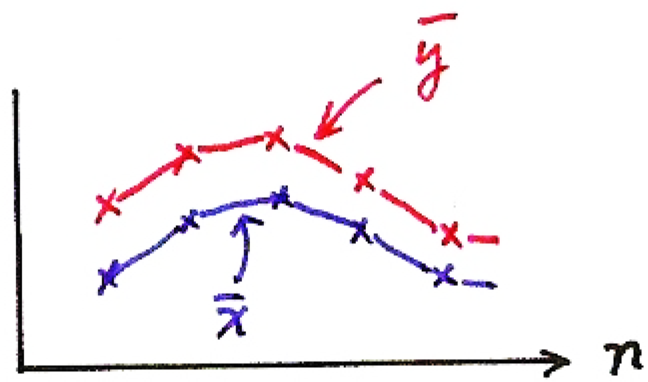
$x[n]$



$$y[n] = x[n] * h[n]$$

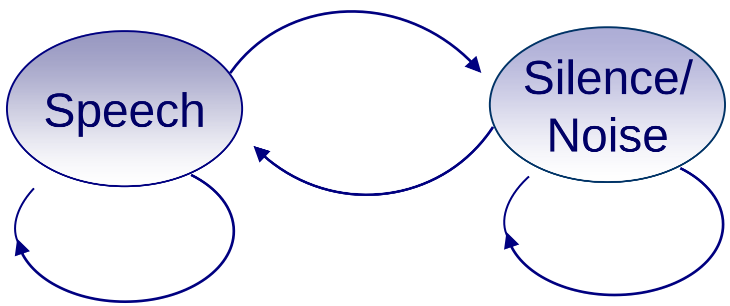
MFCC

$$\bar{y} = \bar{x} + \bar{h}$$



End-point Detection

- **Push (and Hold) to Talk/Continuously Listening**
- **Adaptive Energy Threshold**
- **Low Rejection Rate**
  - false acceptance may be rescued
- **Vocabulary Words Preceded and Followed by a Silence/Noise Model**
- **Two-class Pattern Classifier**



  - Gaussian density functions used to model the two classes
  - log-energy, delta log-energy as the feature parameters
  - dynamically adapted parameters

End-point Detection