數位語音處理概論
Introduction to Digital Speech Processing

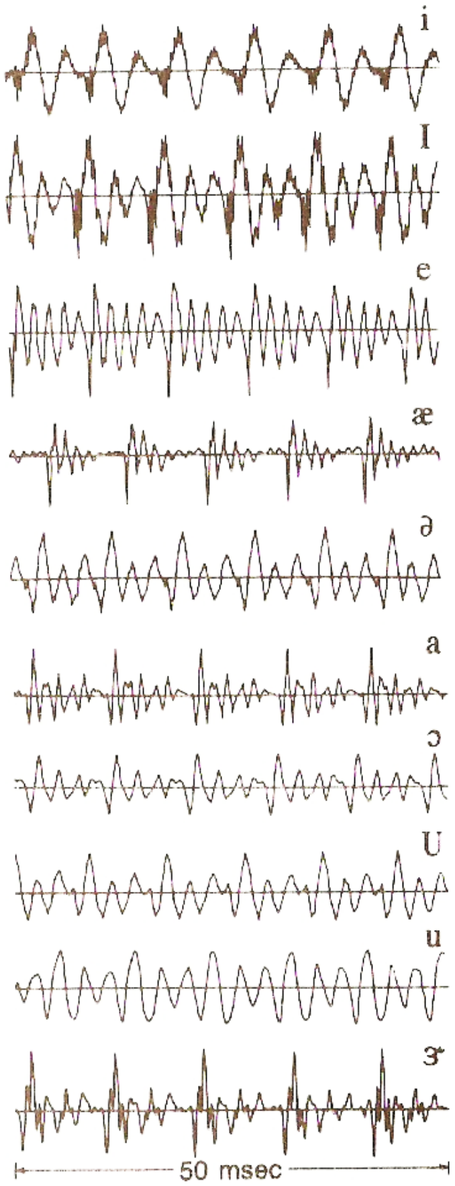
7.0 Speech Signal and Front-end Processing

References for 7.0

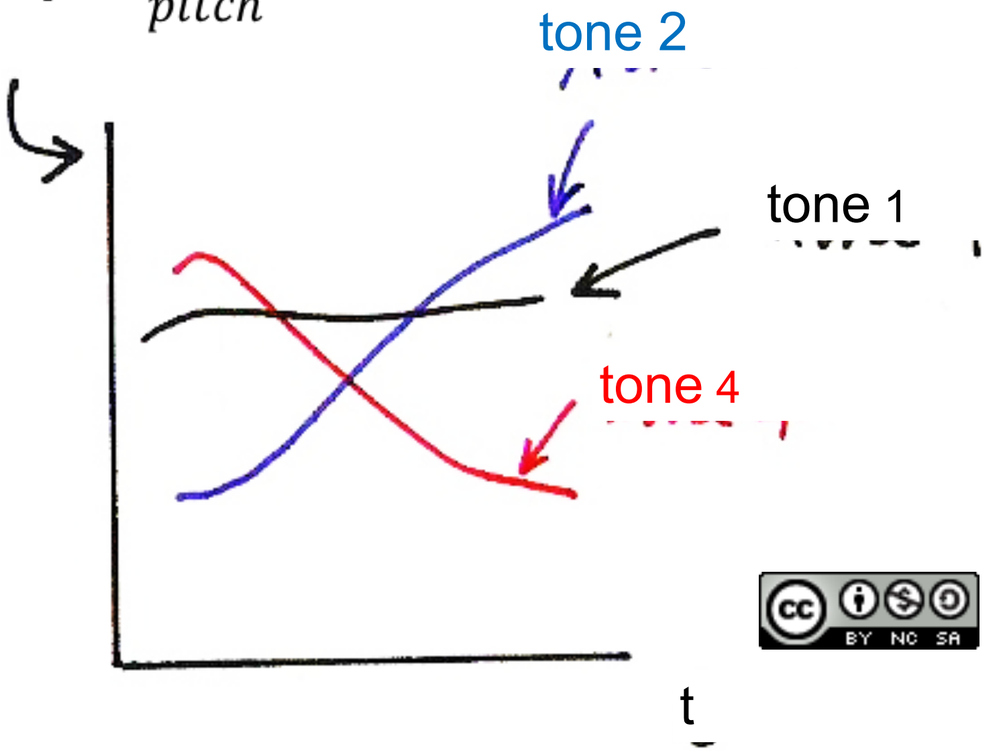
1. 3.3, 3.4 of Becchetti 2. 9.3 of Huang

授課教師：國立臺灣大學 電機工程學系 李琳山 教授

Waveform plots of typical vowel sounds - Voiced（濁音）

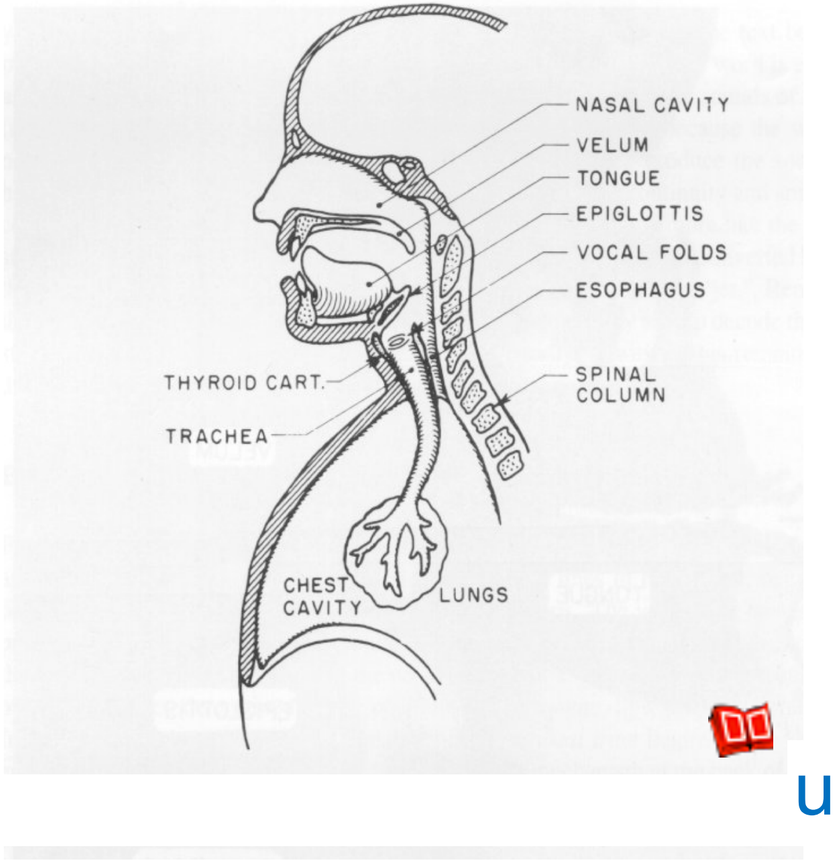


$$F_0 = \frac{1}{pitch}\text{(音高)}$$

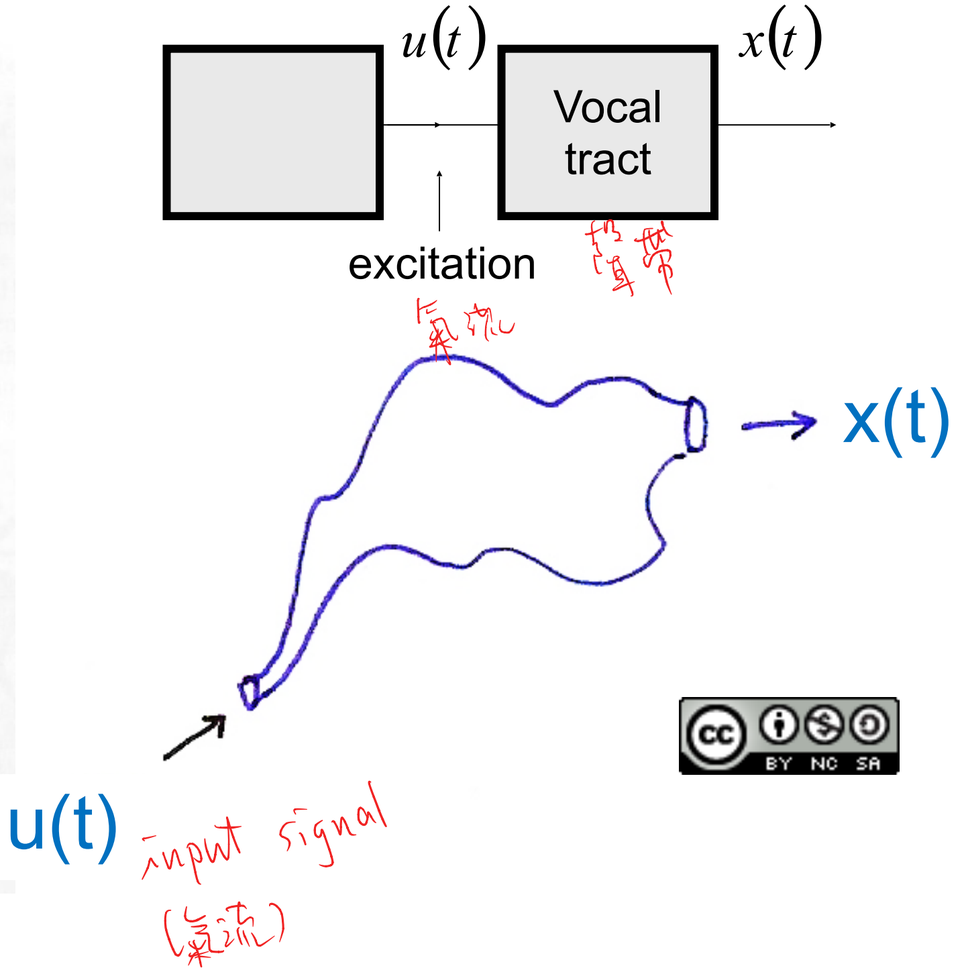


Speech Production and Source Model

- Human vocal mechanism

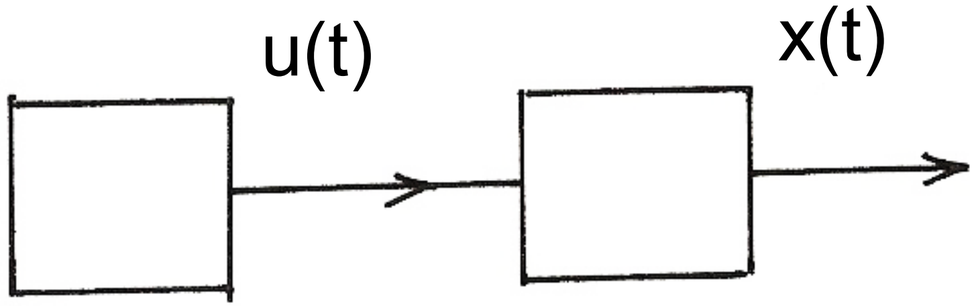


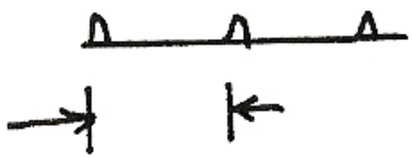
- Speech Source Model



Voiced and Unvoiced Speech

一個振動生一個 function





pitch

pitch

voiced

濁音子母音為 voiced

/sh/

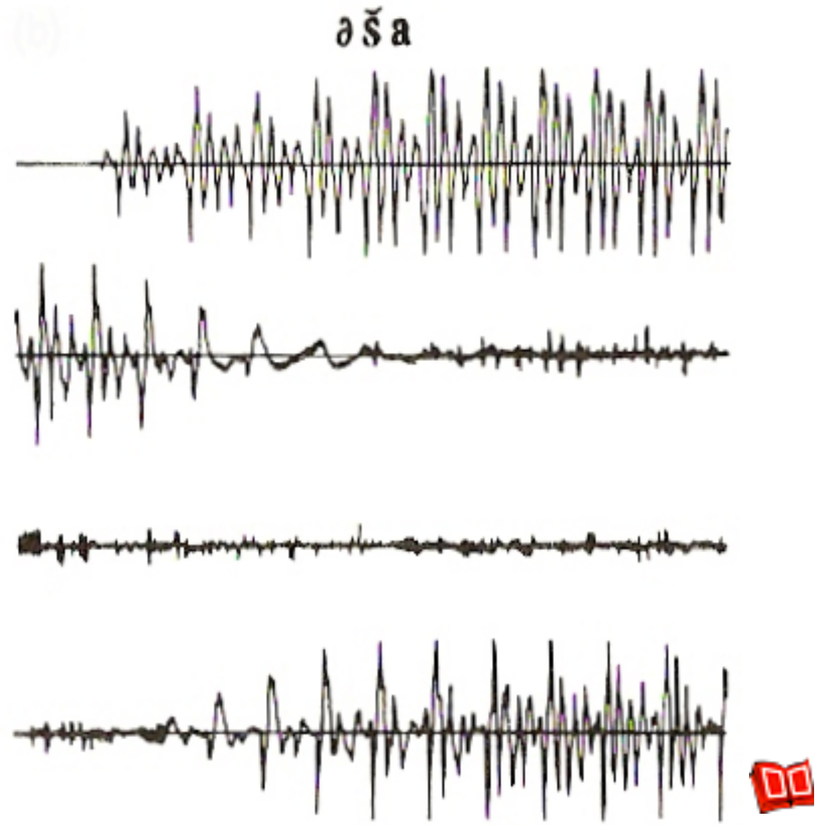
unvoiced 子音為 unvoiced

但也有 voiced 的子音

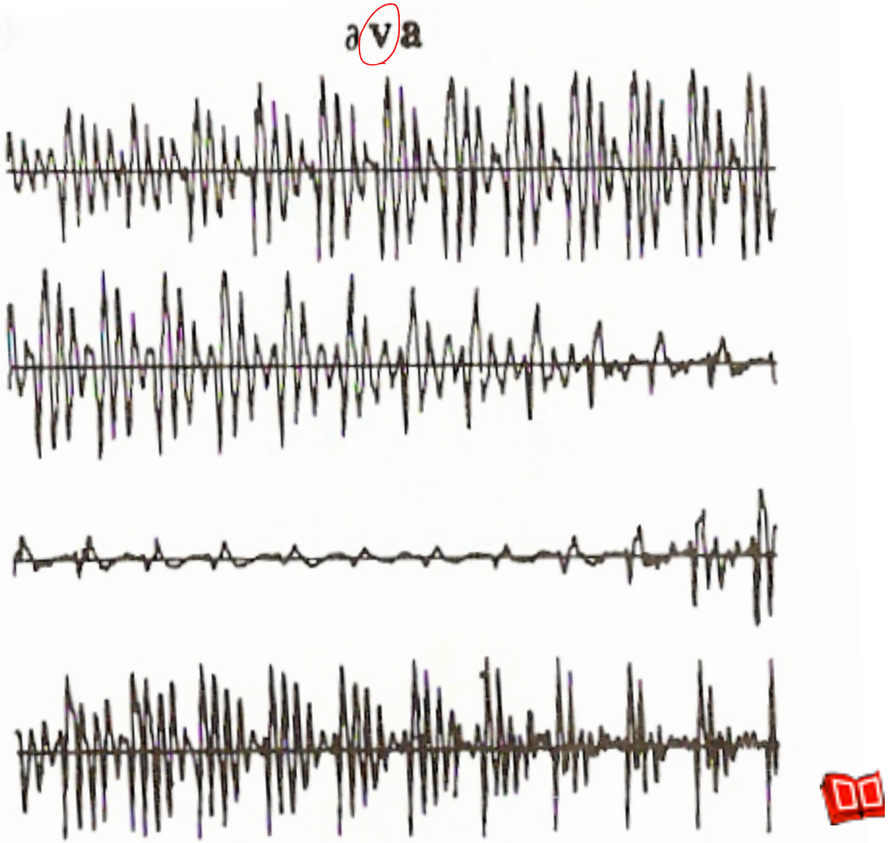
Waveform plots of typical consonant sounds

聲帶沒有振動 e.g. /sh/

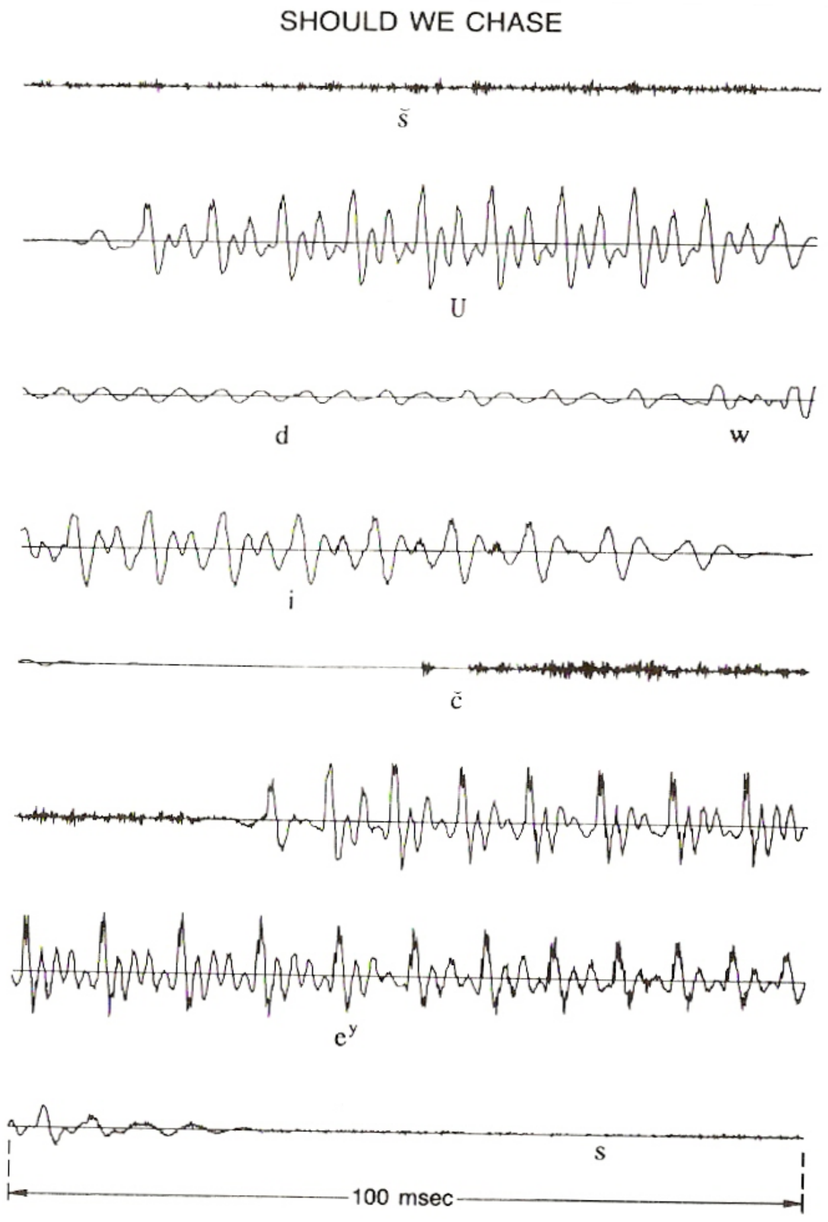
Unvoiced （清音）



Voiced （濁音）

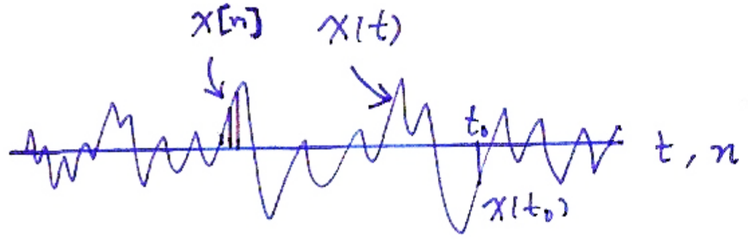


Waveform plot of a sentence



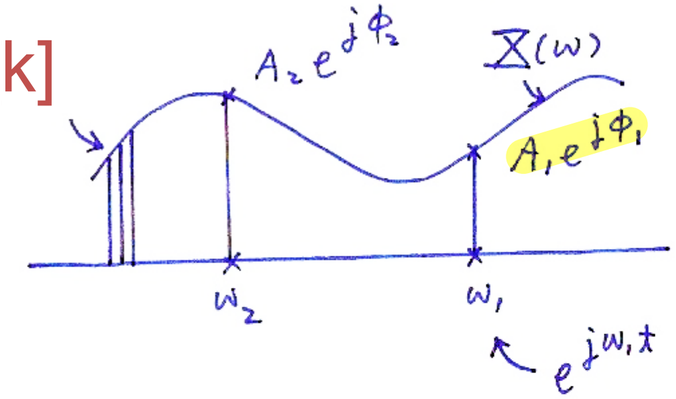
Time and Frequency Domains (P.12 of 2.0)

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



time domain

X[k]



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

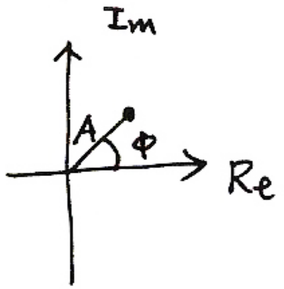
frequency domain

$e^{jw_1 t}$ 在複數平面上與原點之距離

w, f, k

Frequency domain

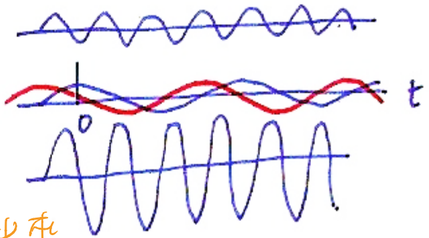
$$R_e\left\{e^{j\omega_1 t}\right\} = \cos(\omega_1 t)$$



$$R_e\left\{(A_1 e^{j\phi_1})(e^{j\omega_1 t})\right\} = A_1\cos(\omega_1 t + \phi_1)$$

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

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

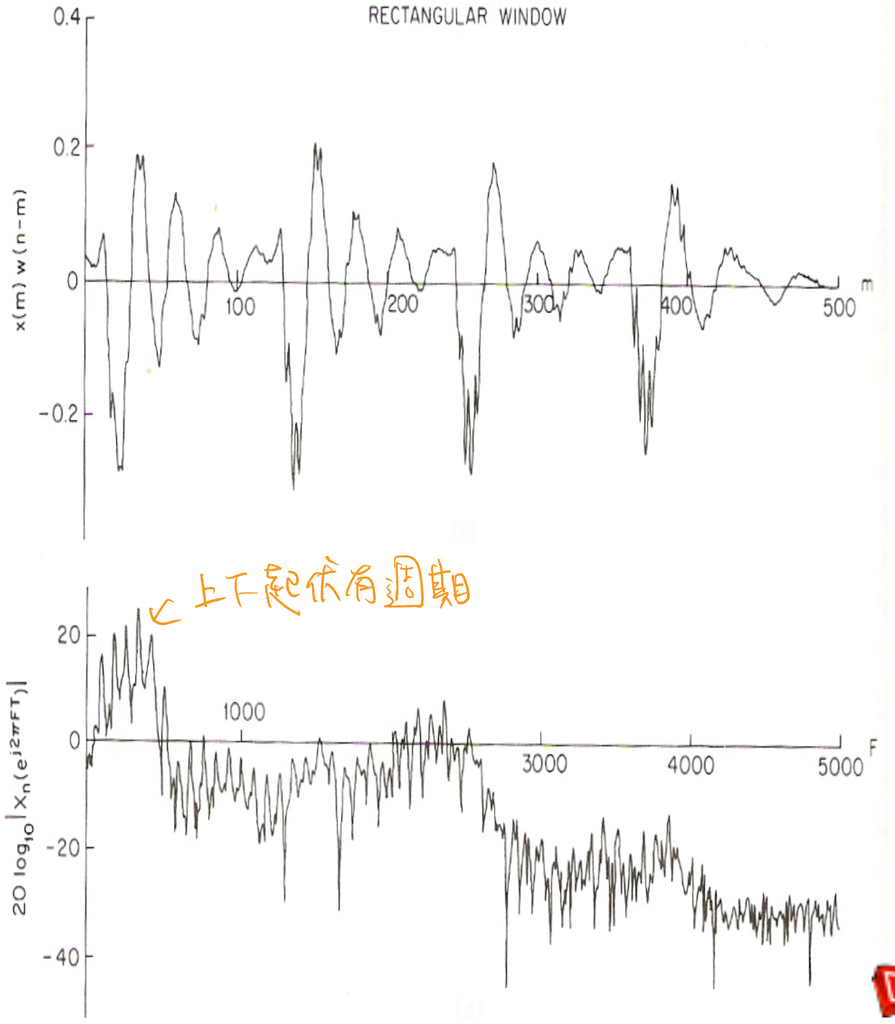


$$x(t) = \sum_i a_i \; x_i(t)$$

把訊號表達出來

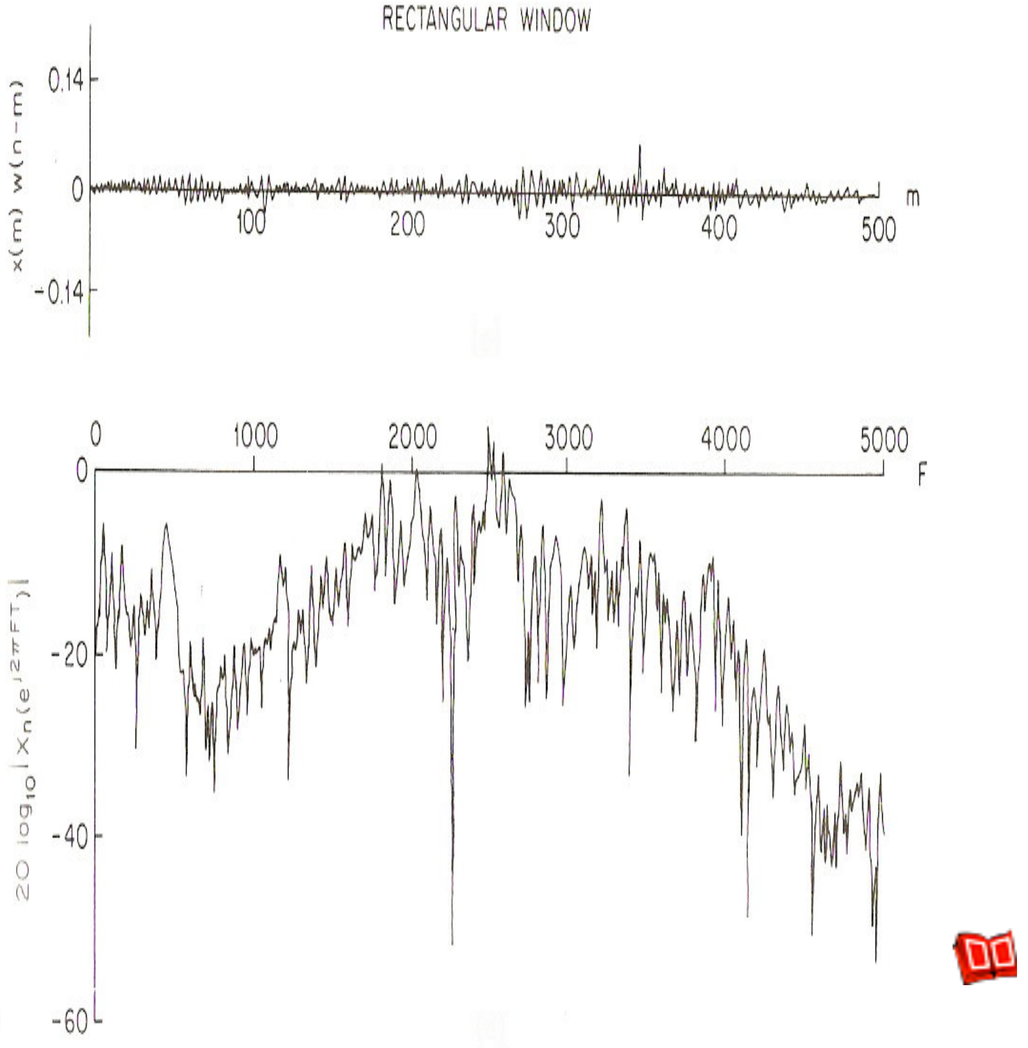
Frequency domain spectra of speech signals

Voiced 有週期

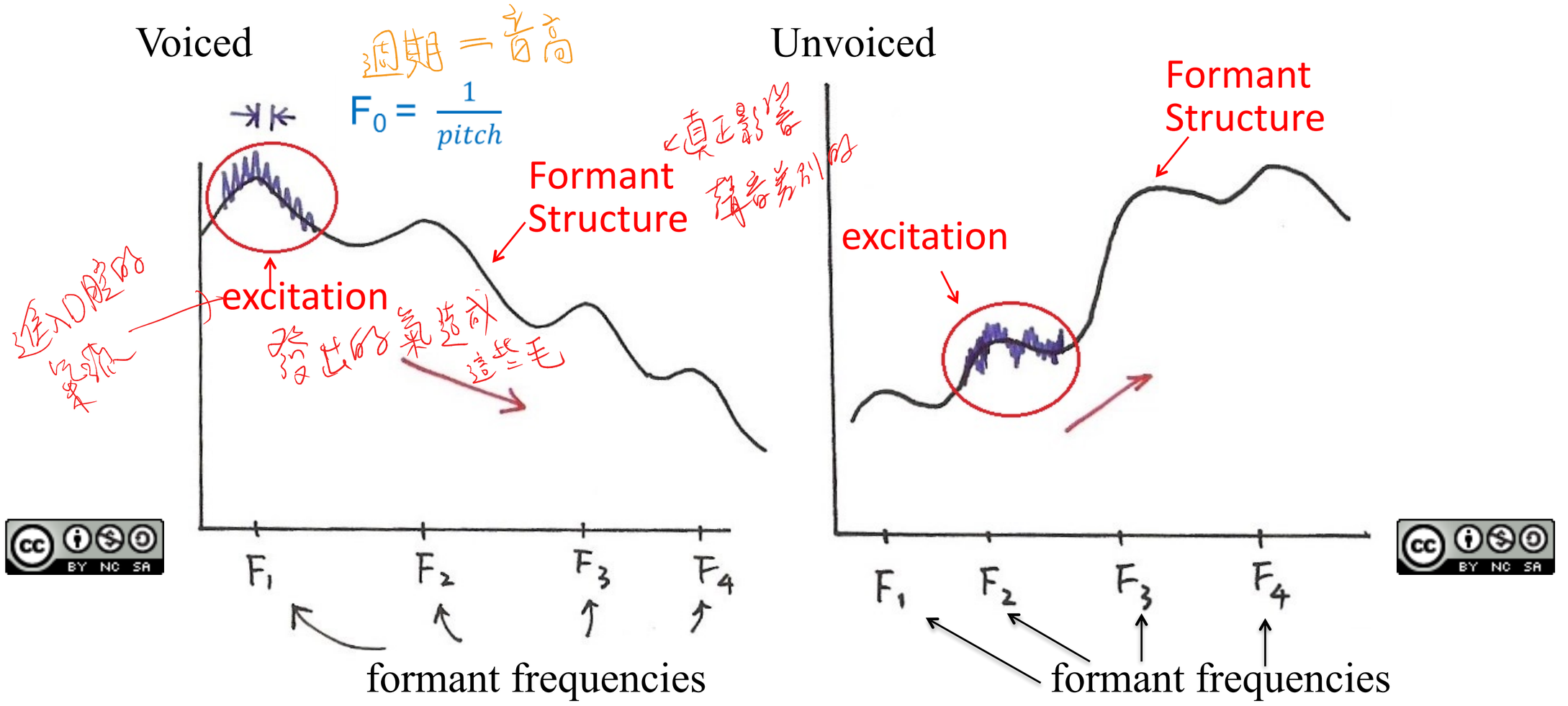


上下起伏有週期

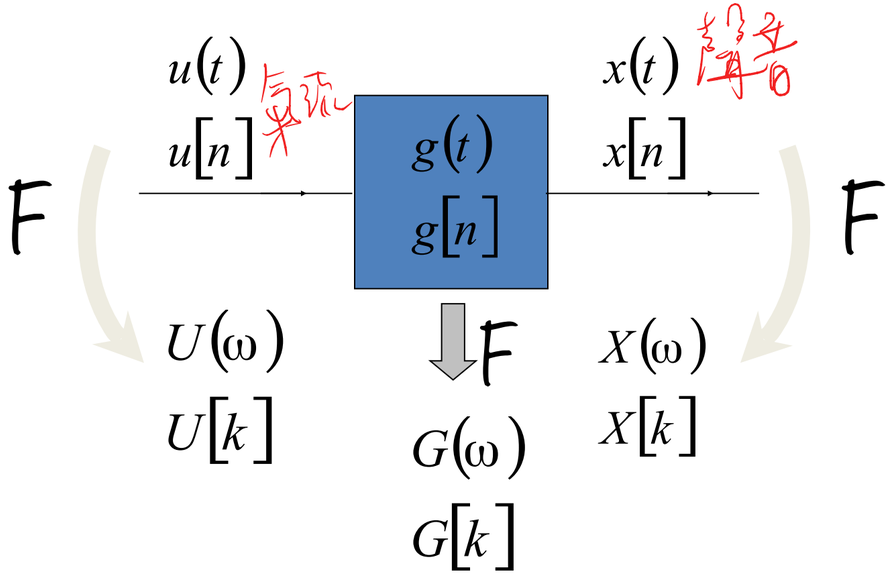
Unvoiced 無週期



Frequency Domain



Input/Output Relationship for Time/Frequency Domains



excitation

formant structure

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

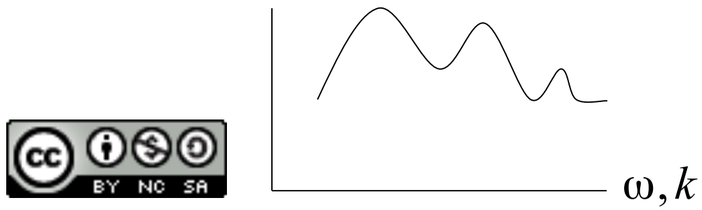
$$x[n] = u[n] * g[n] = \sum_{k} x[k] g[n-k]$$

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

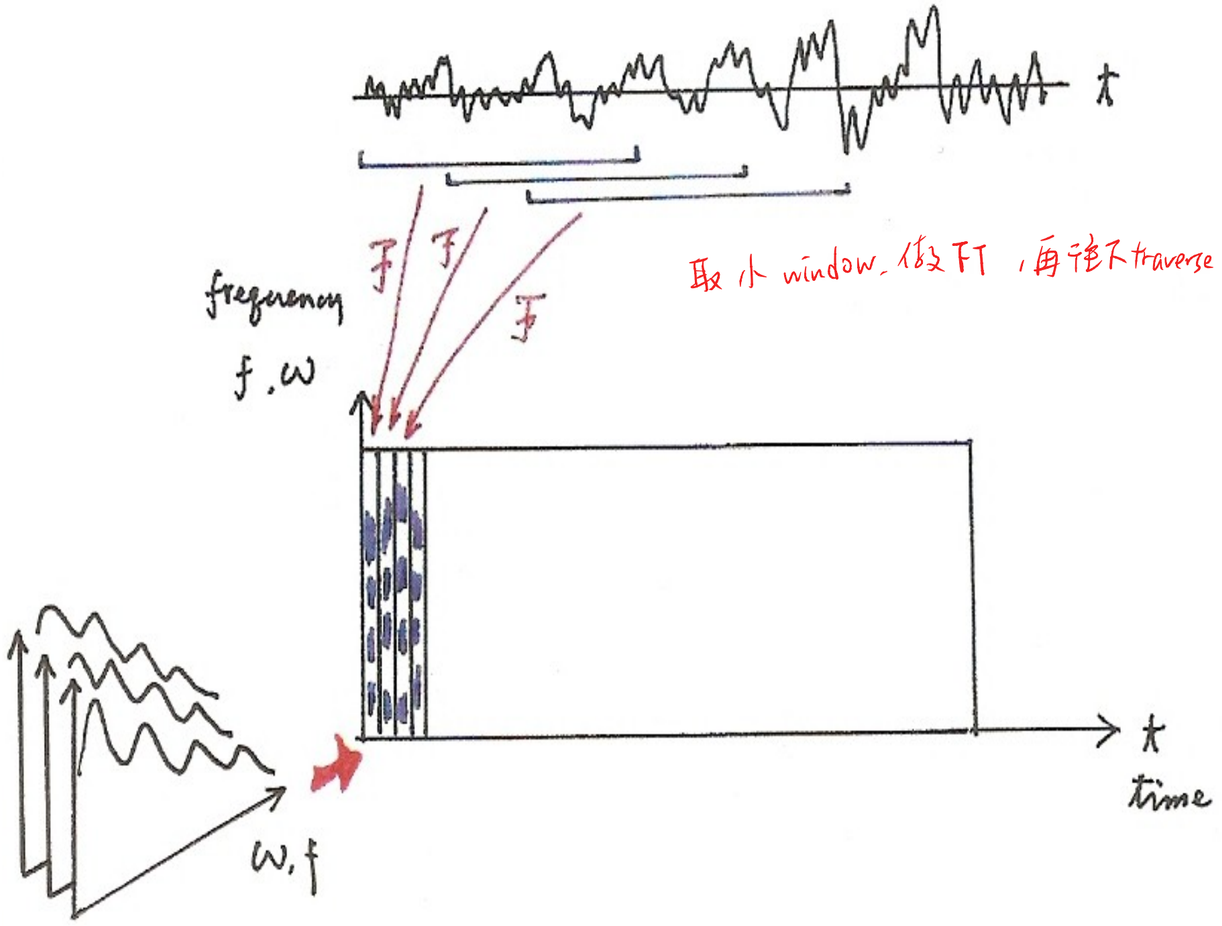
$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt$$

$$= \sum_{n=-\infty}^{\infty} x[n] e^{j\omega n}$$

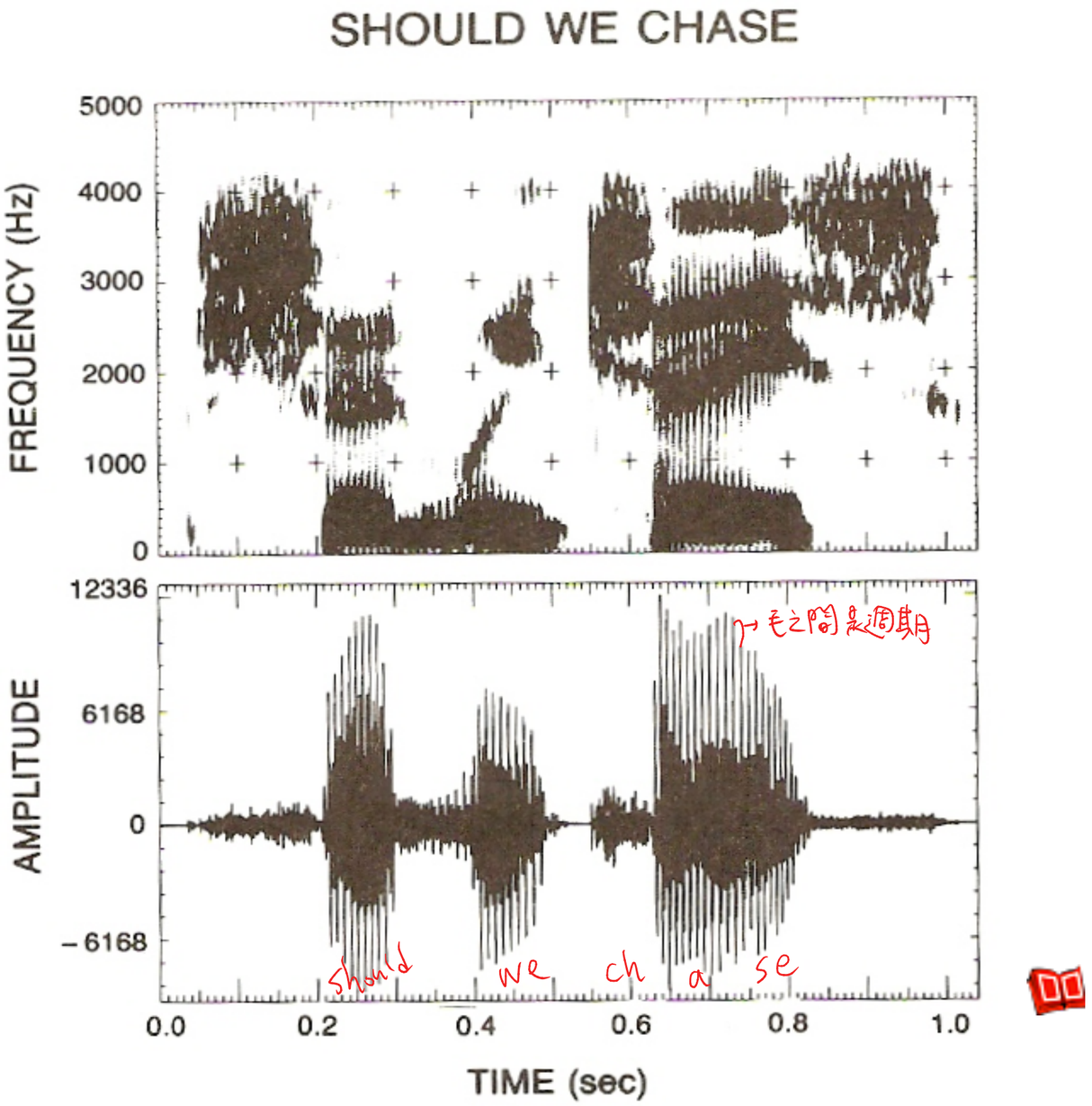
取小 window $\Rightarrow X(\omega) = \int_0^T x(t) e^{j\omega t} dt$

↓

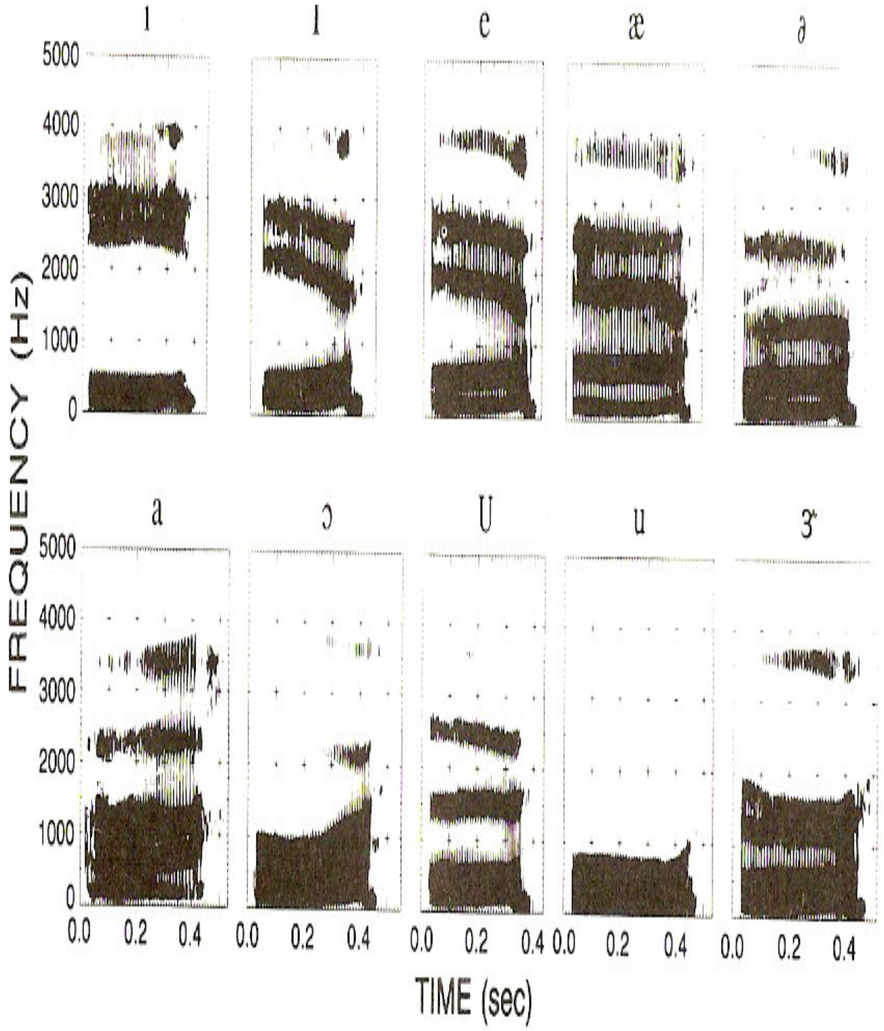
short-time FT

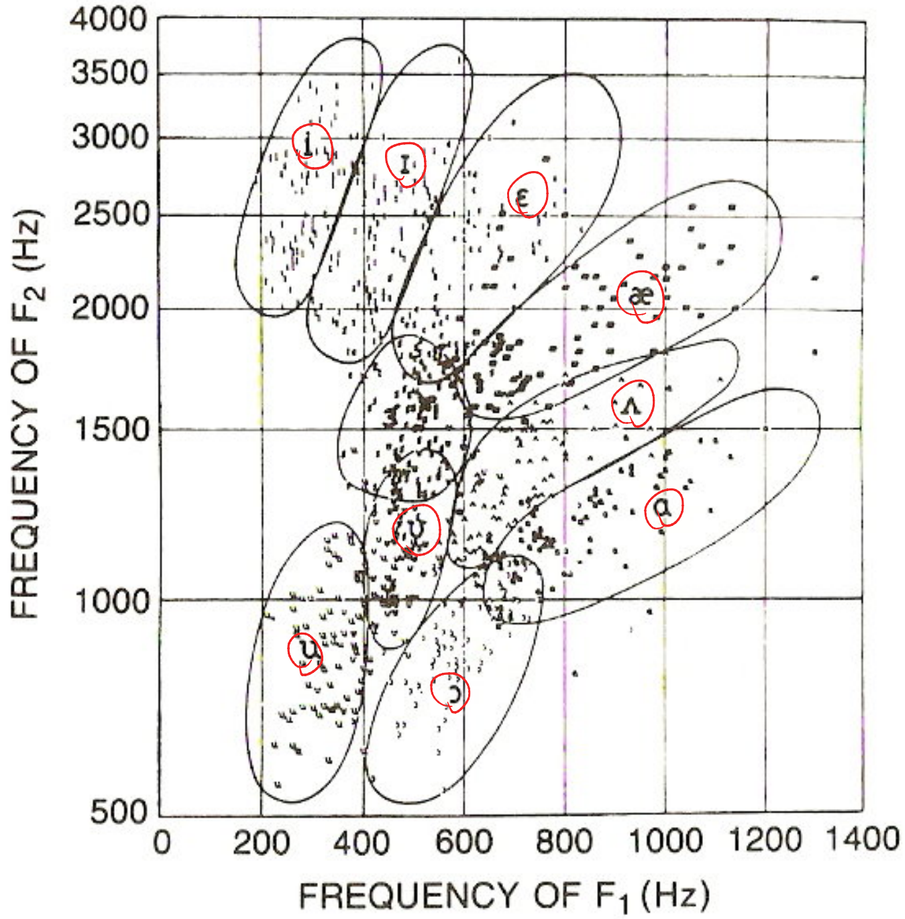


Spectrogram

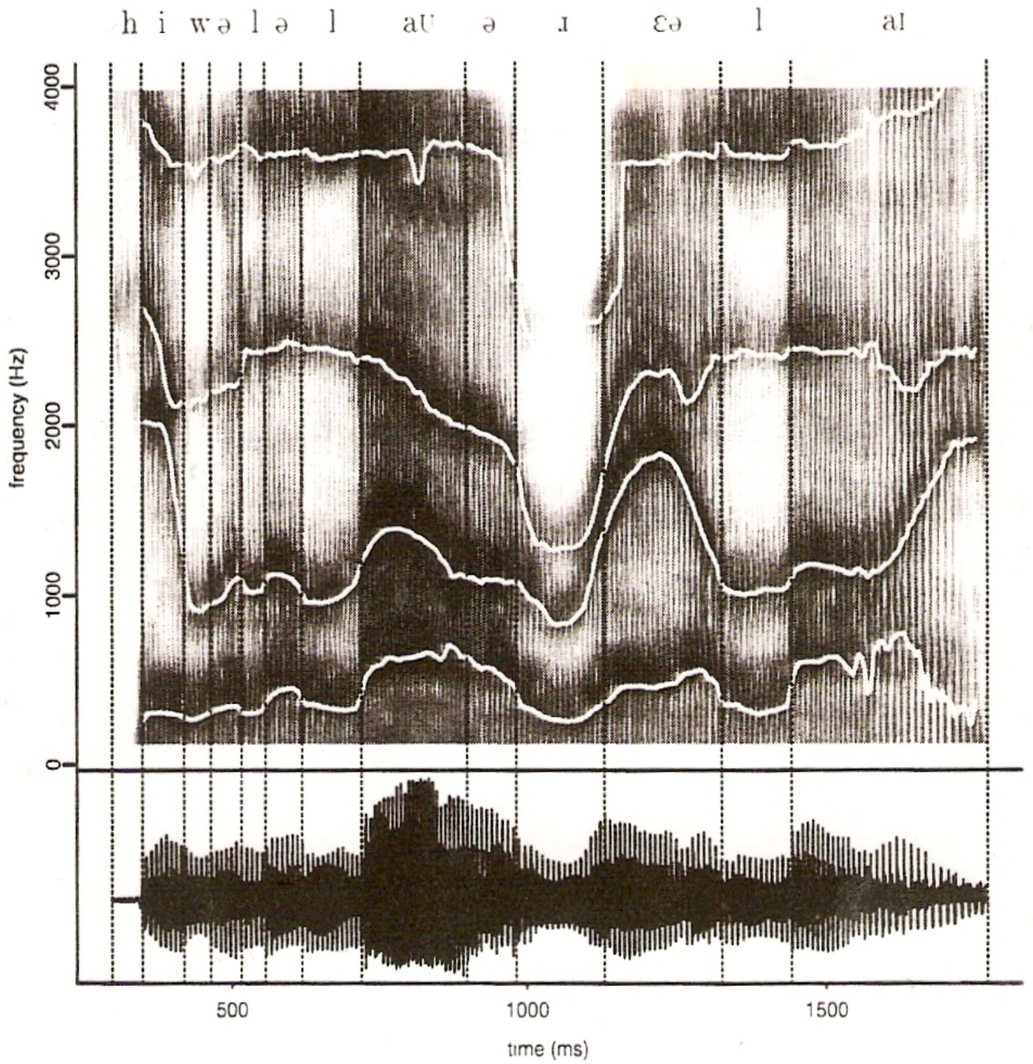


Formant Frequencies





Formant frequency contours

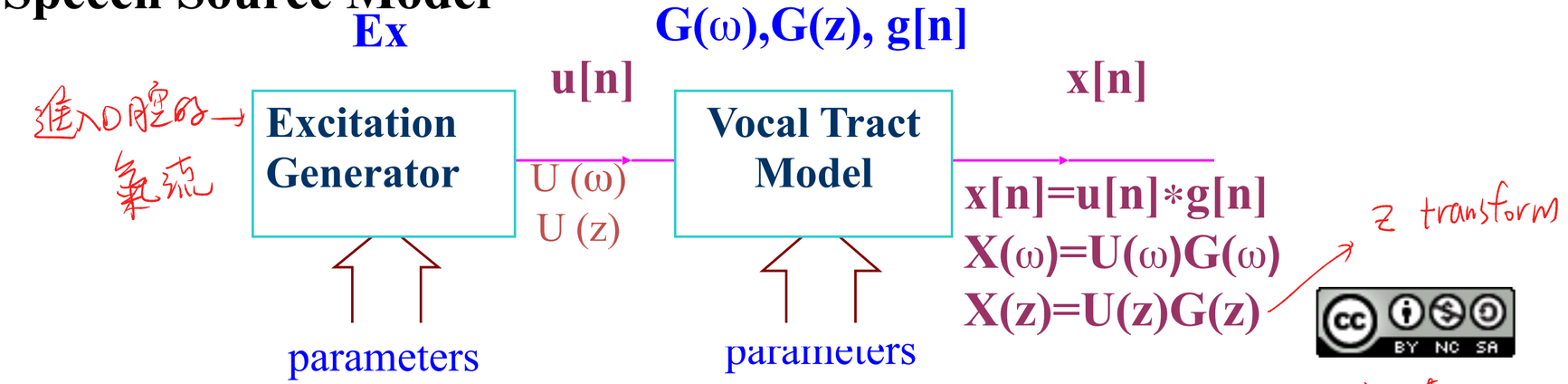


He will allow a rare lie.

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

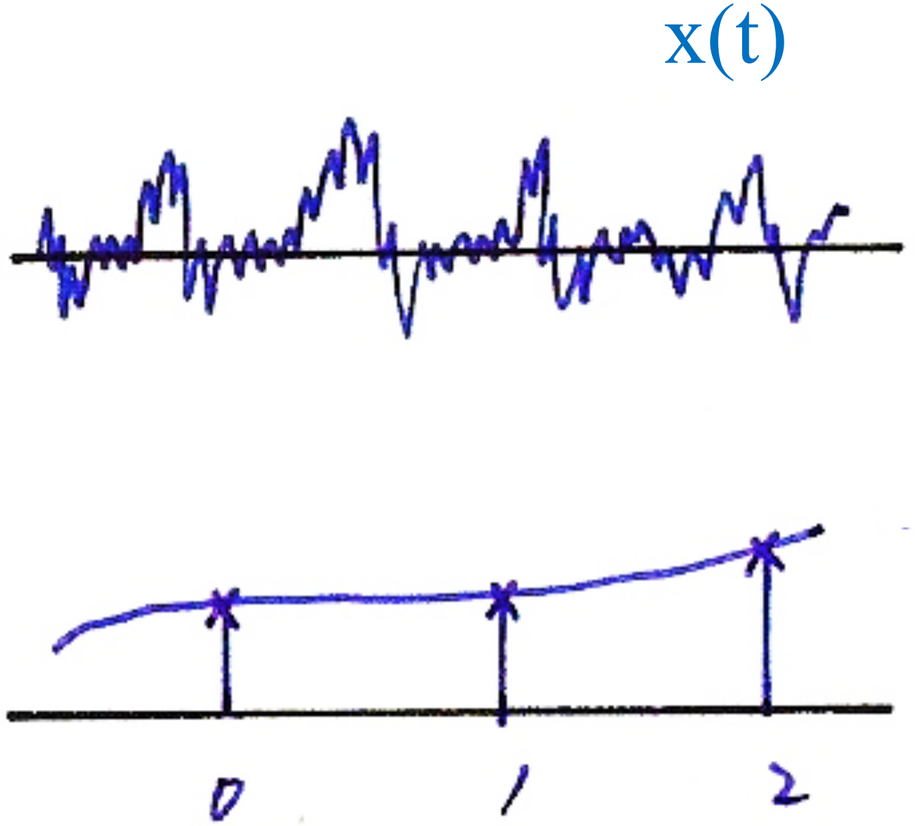
Speech Signals

- **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**



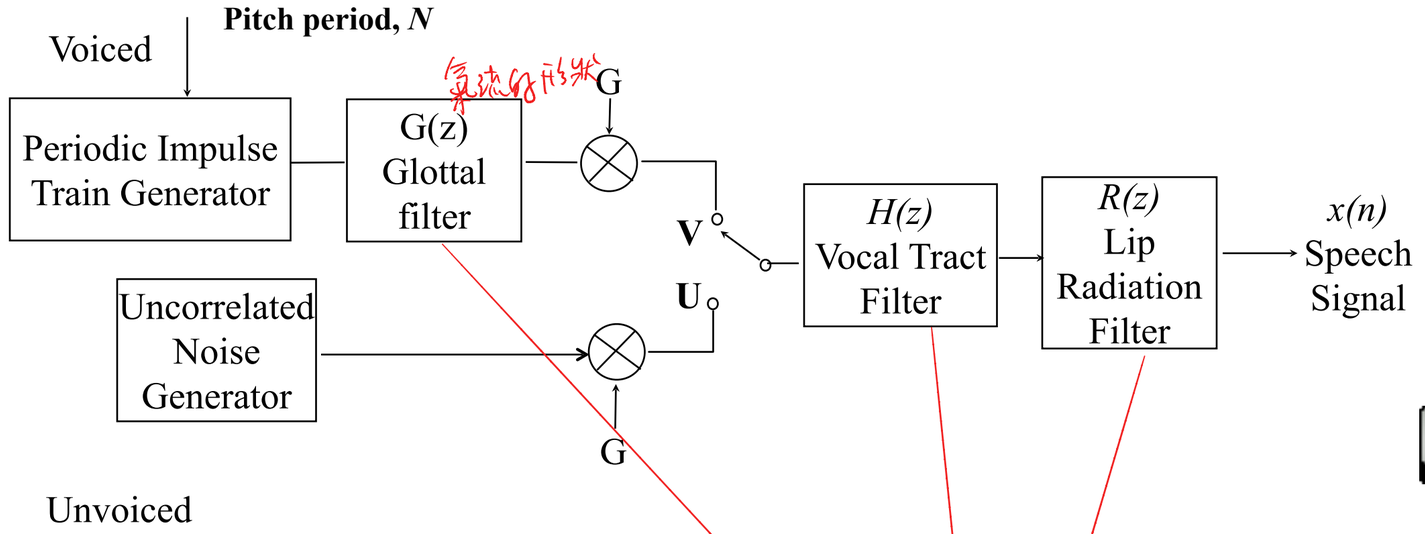
– digitization and transmission of the parameters will be adequate 就傳 parameter 即可
– at receiver the parameters can produce x[n] with the model
– much less parameters with much slower variation in time lead to much less bits required
– the key for low bit rate speech coding

Speech Source Model

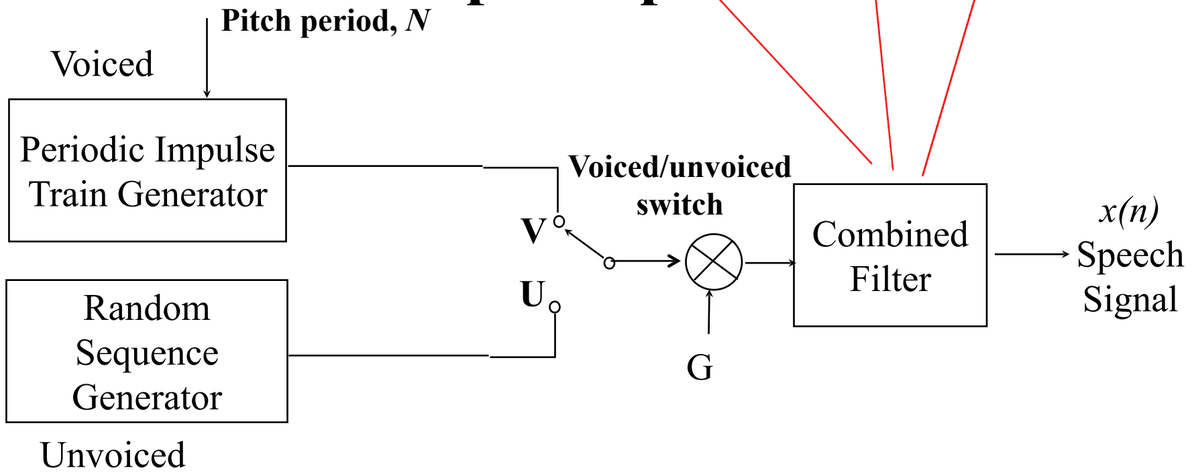


Speech Source Model

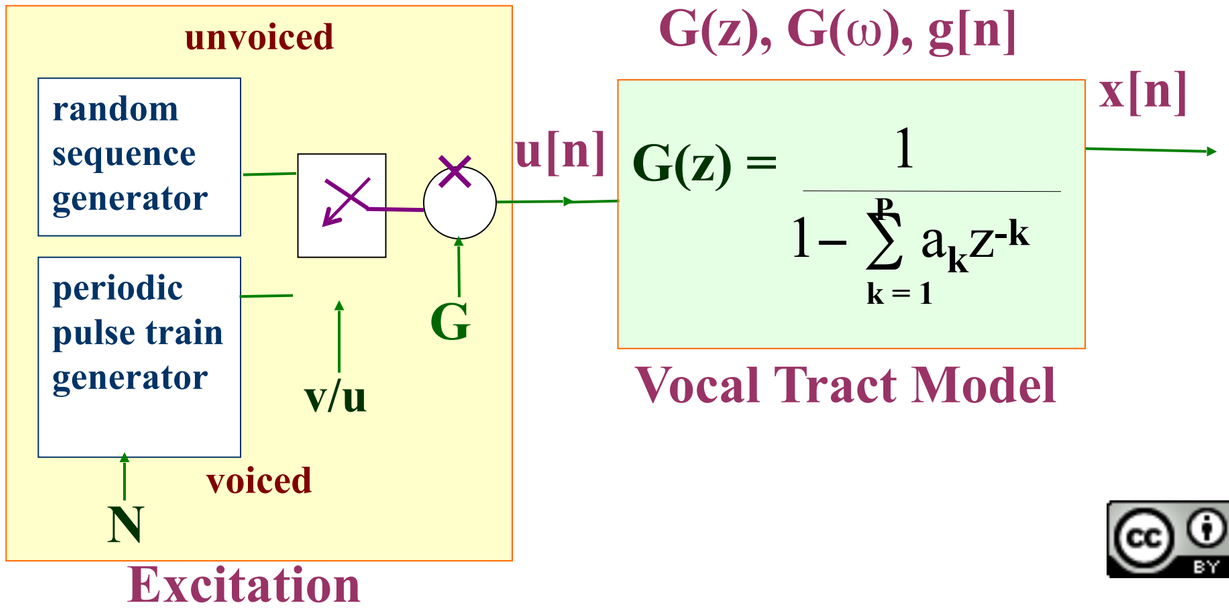
- **Sophisticated model for speech production**



- **Simplified model for speech production**



Simplified Speech Source Model



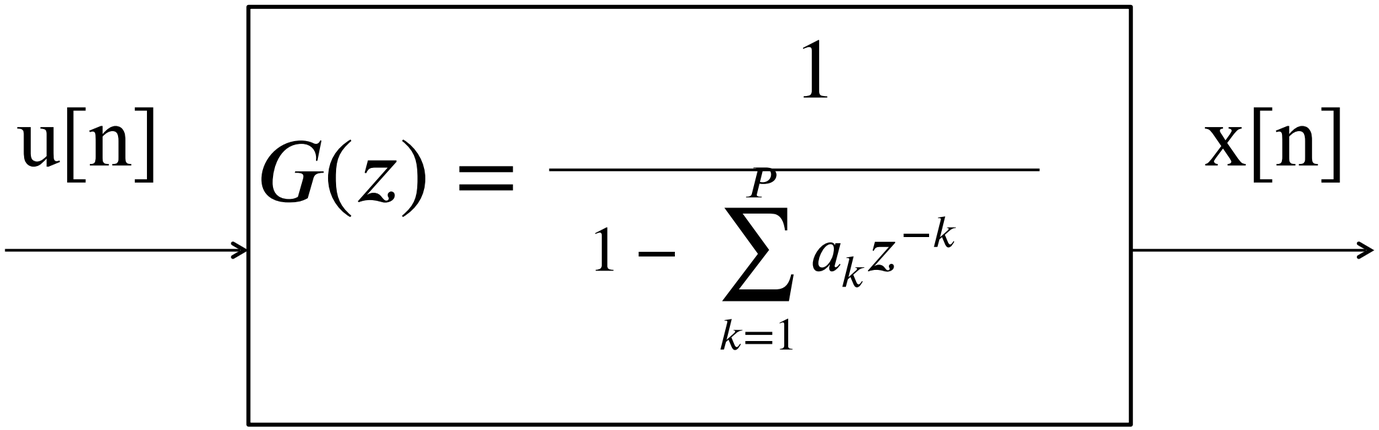
– Excitation parameters
  v/u : voiced/ unvoiced
  N : pitch for voiced
  G : signal gain
  → excitation signal u[n]

–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

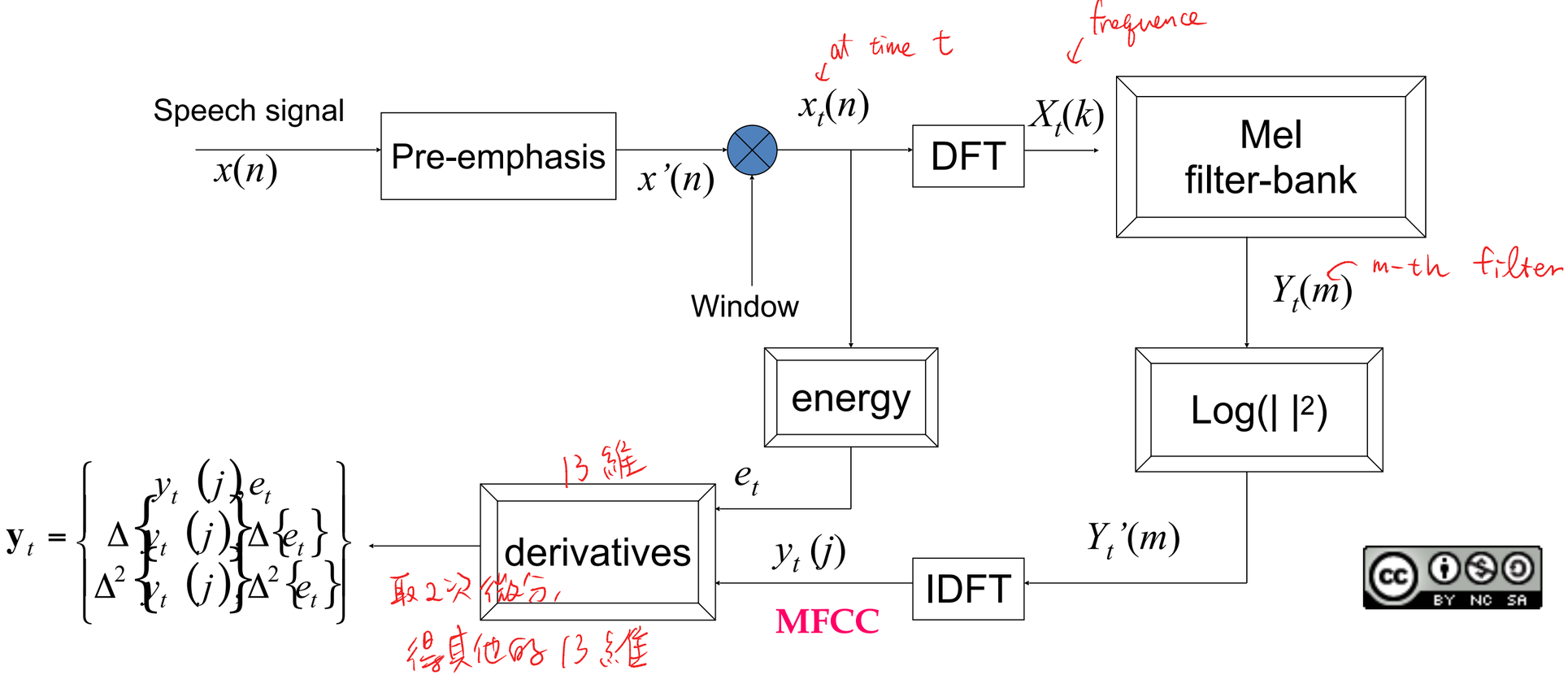
Speech Source Model



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

Feature Extraction - MFCC

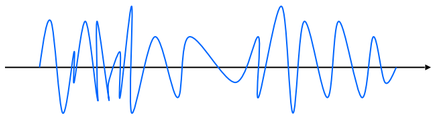
- **Mel-Frequency Cepstral Coefficients (MFCC)** ← 39維的 parameter
  - Most widely used in the speech recognition
  - Has generally obtained a better accuracy at relatively low computational complexity
  - The process of MFCC extraction :



Pre-emphasis

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

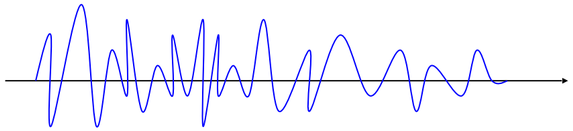
Speech signal $x(n)$

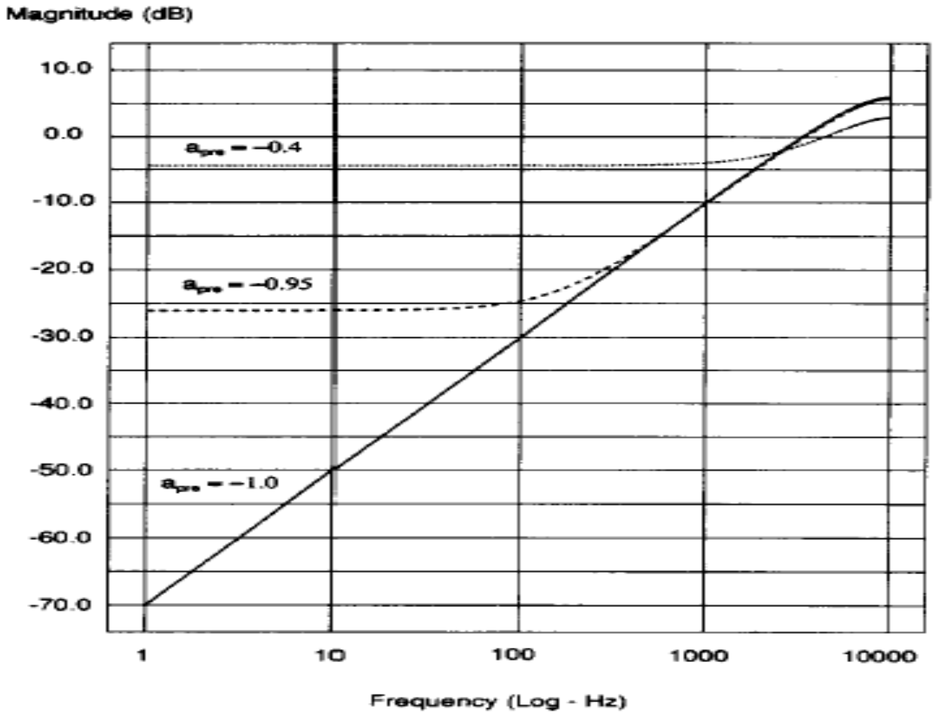


$H(z)=1-a \cdot z^{-1} \quad 0<a\leq 1$

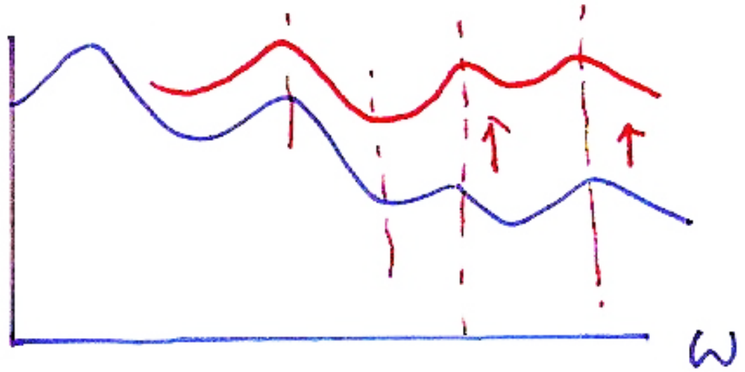
$a \sim 1$

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





$X(w)$



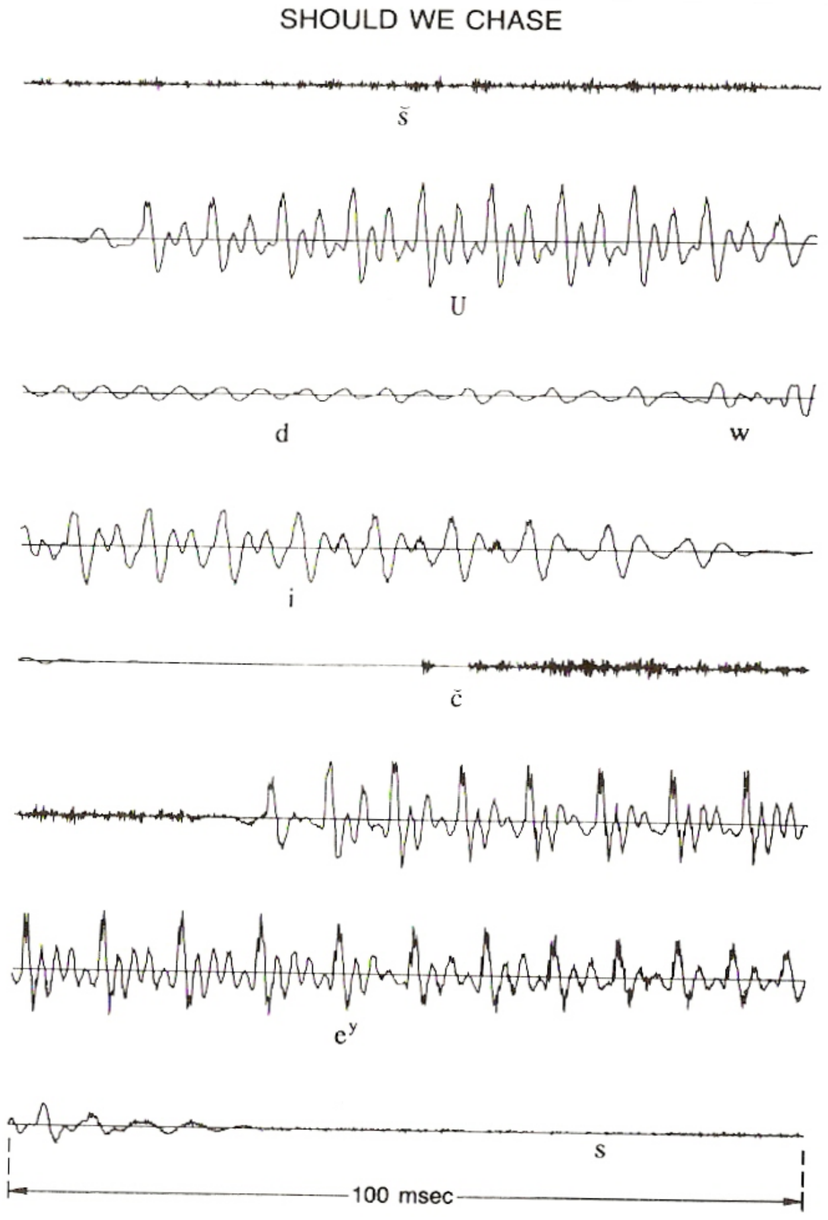
Why pre-emphasis?

- **Reason :** ∵ 聲音頻率會大幅下降在低頻拉高
  - 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?

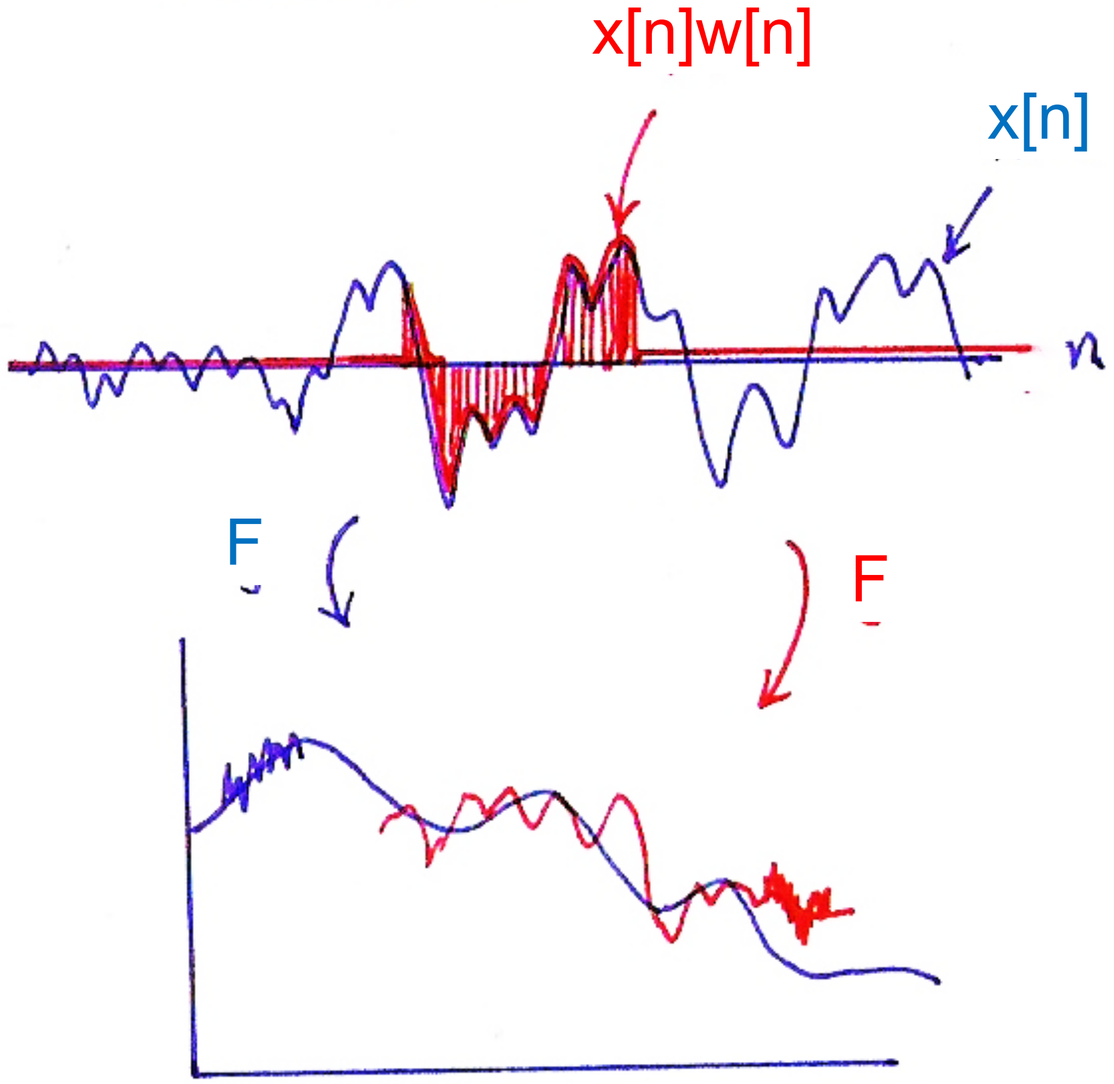
- **Why dividing the speech signal into successive and overlapping frames?**
  - Voice signals change their characteristics from time to time. The characteristics remain unchanged only in short time intervals (short-time stationary, short-time Fourier transform)
- **Frames** = window
  - **Frame Length :** 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 重疊 overlap
  - **Frame Rate:** number of frames per second

Waveform plot of a sentence



Hamming

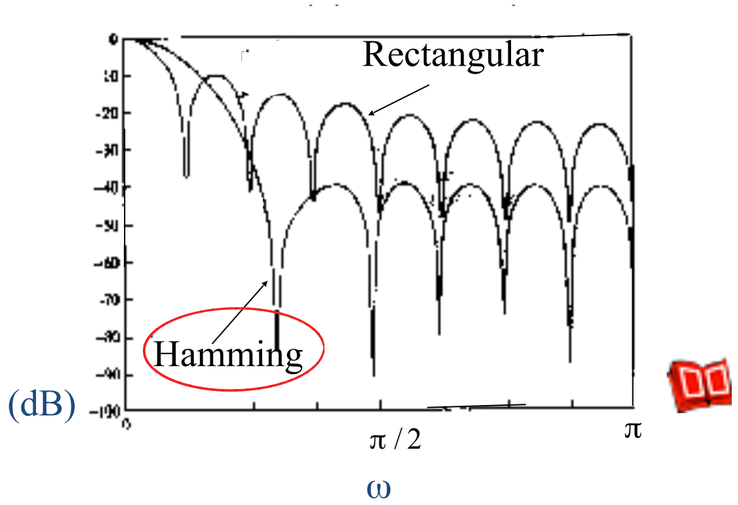
Rectangular



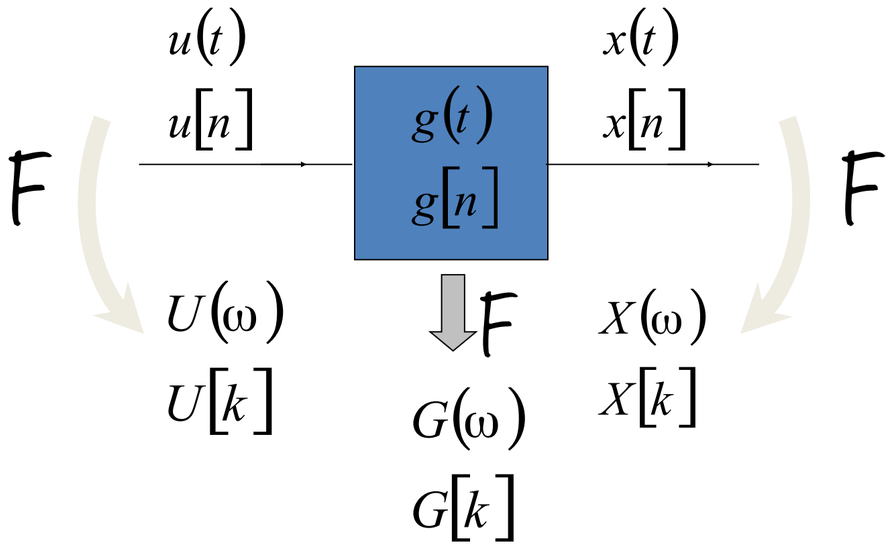
windowing 後會使
訊號變圓

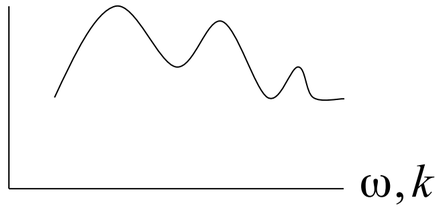
Effect of Windowing (1)

- **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

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

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

time domain: convolution

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

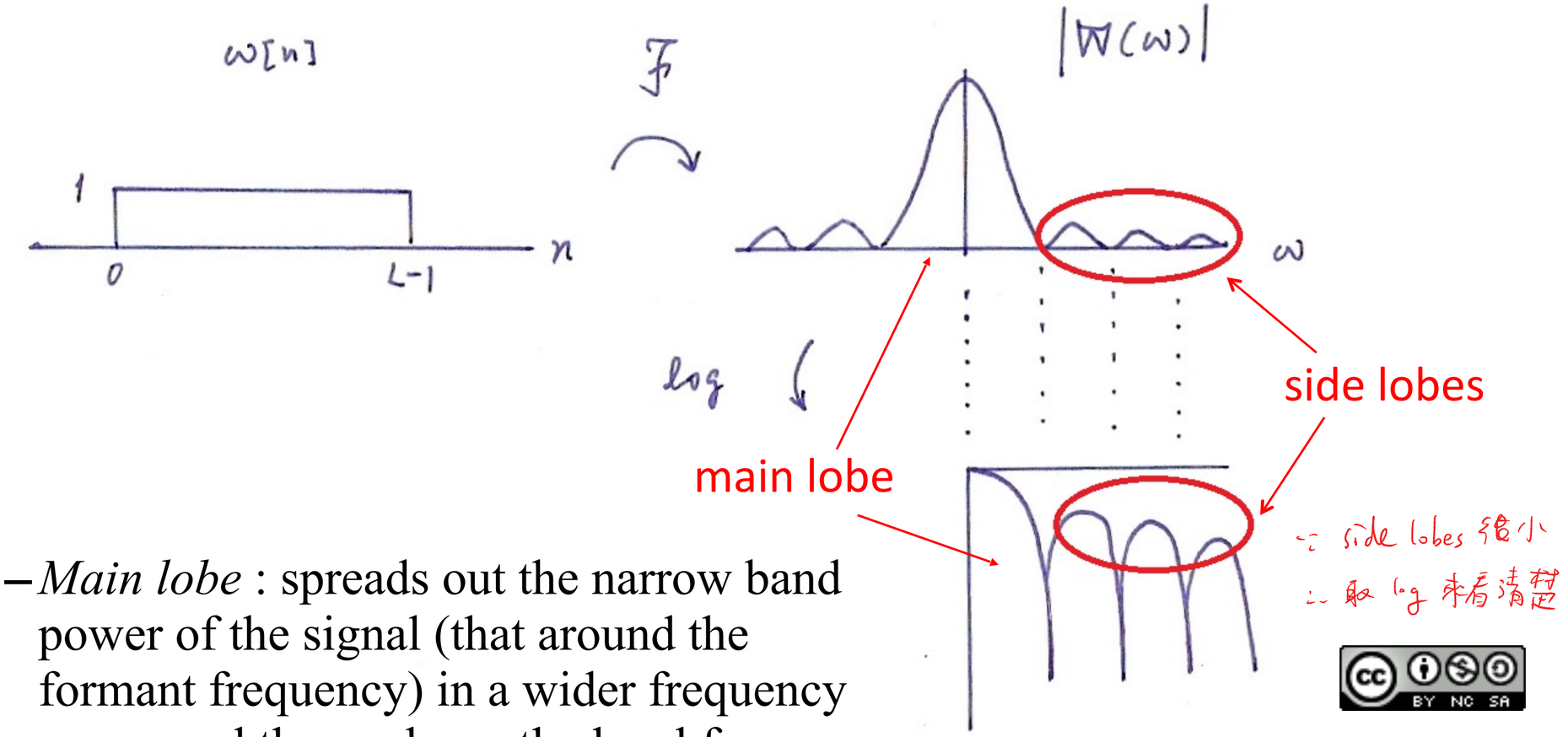
$$X[k] = U[k]\, G[k]$$

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

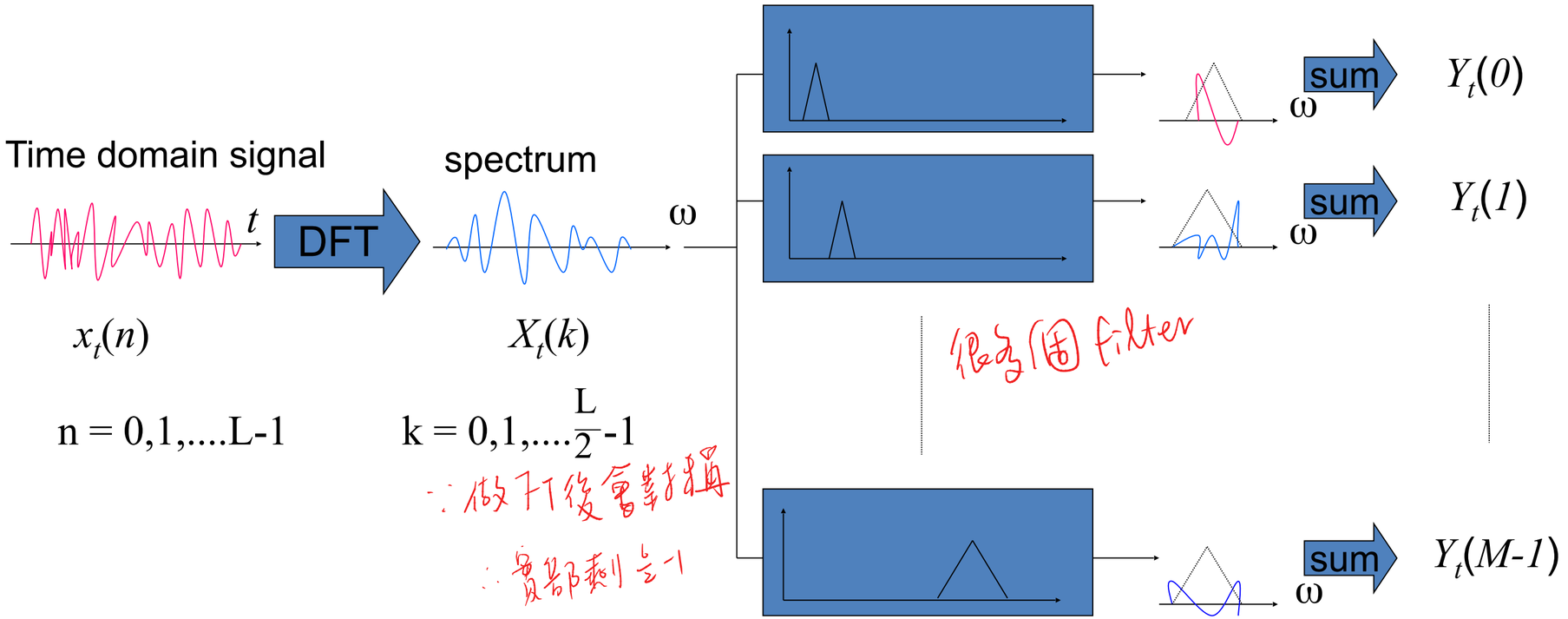
Effect of Windowing (2)

- **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

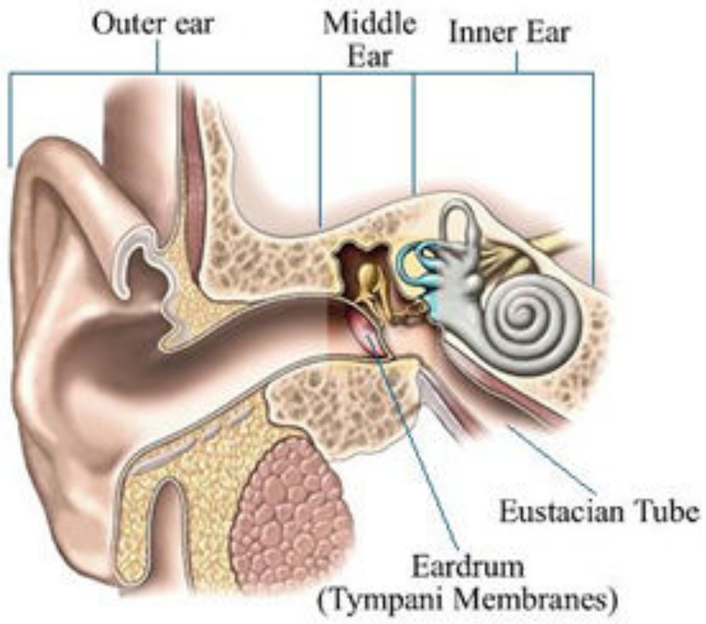
$$w(n)=\begin{cases}0.54-0.46\cos\left(\dfrac{2\pi n}{L-1}\right), & n=0,1,\ldots\ldots,L-1\\ 0 & \text{otherwise}\end{cases}$$

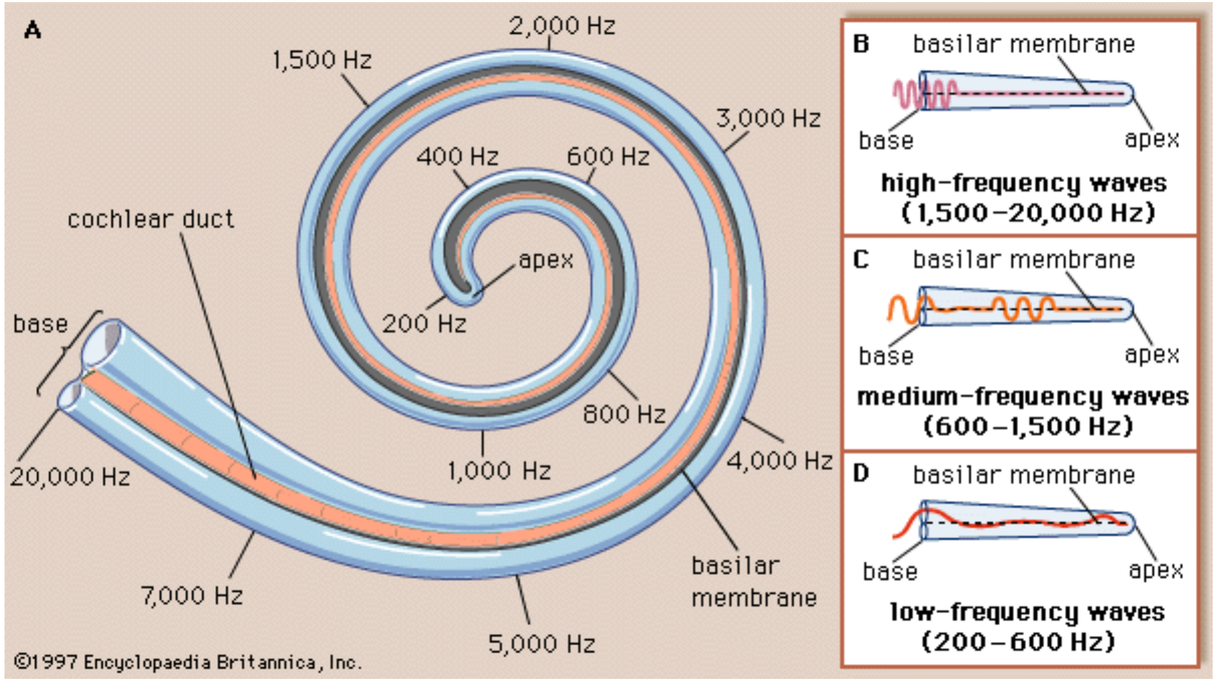
DFT and Mel-filter-bank Processing

- **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)

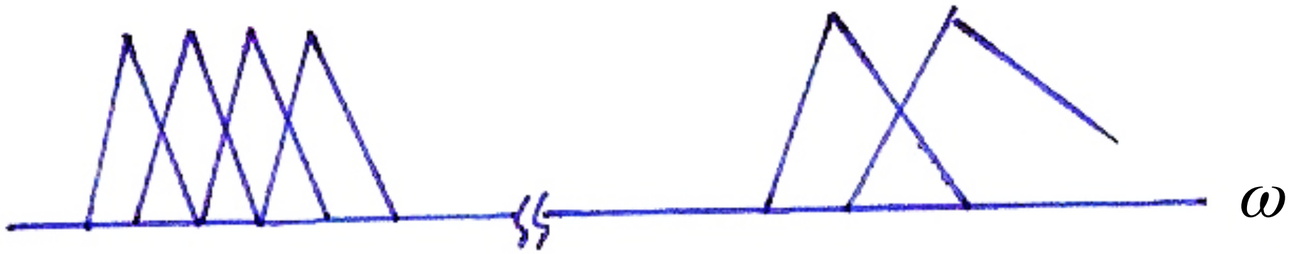


Peripheral Processing for Human Perception

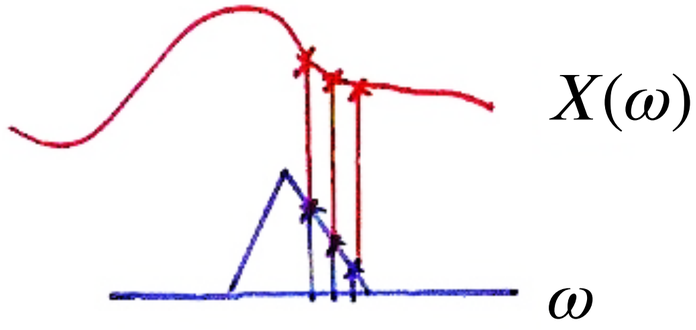


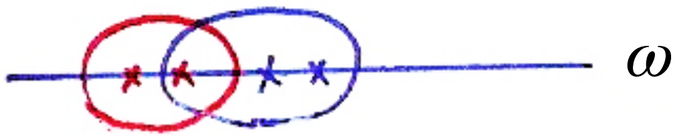


Mel-scale Filter Bank



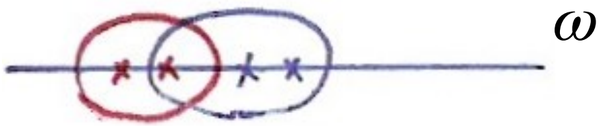
工程師常用很粗糙的想法來分，用 △

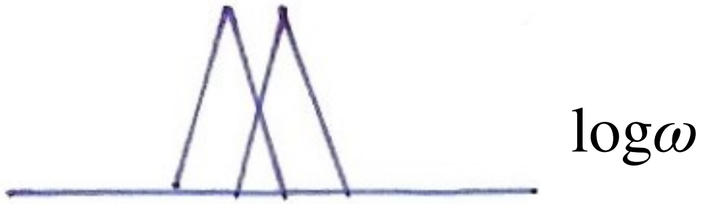




Why Filter-bank Processing?

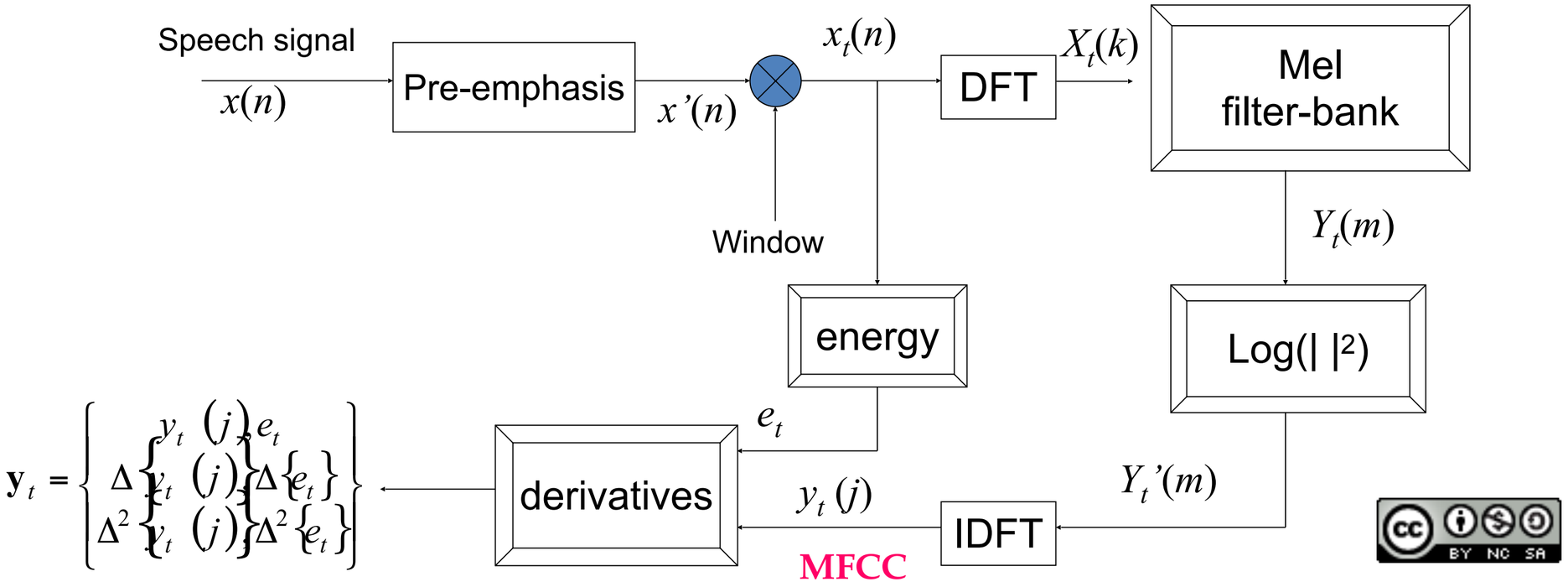
- **The filter-bank processing simulates human ear perception**
  - Frequencies of a complex sound within a certain frequency band cannot be individually identified. 耳朵分不出兩者太相近的 frequency.
  - When one of the components of this sound falls outside this frequency band, it can be individually distinguished.
  - 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)





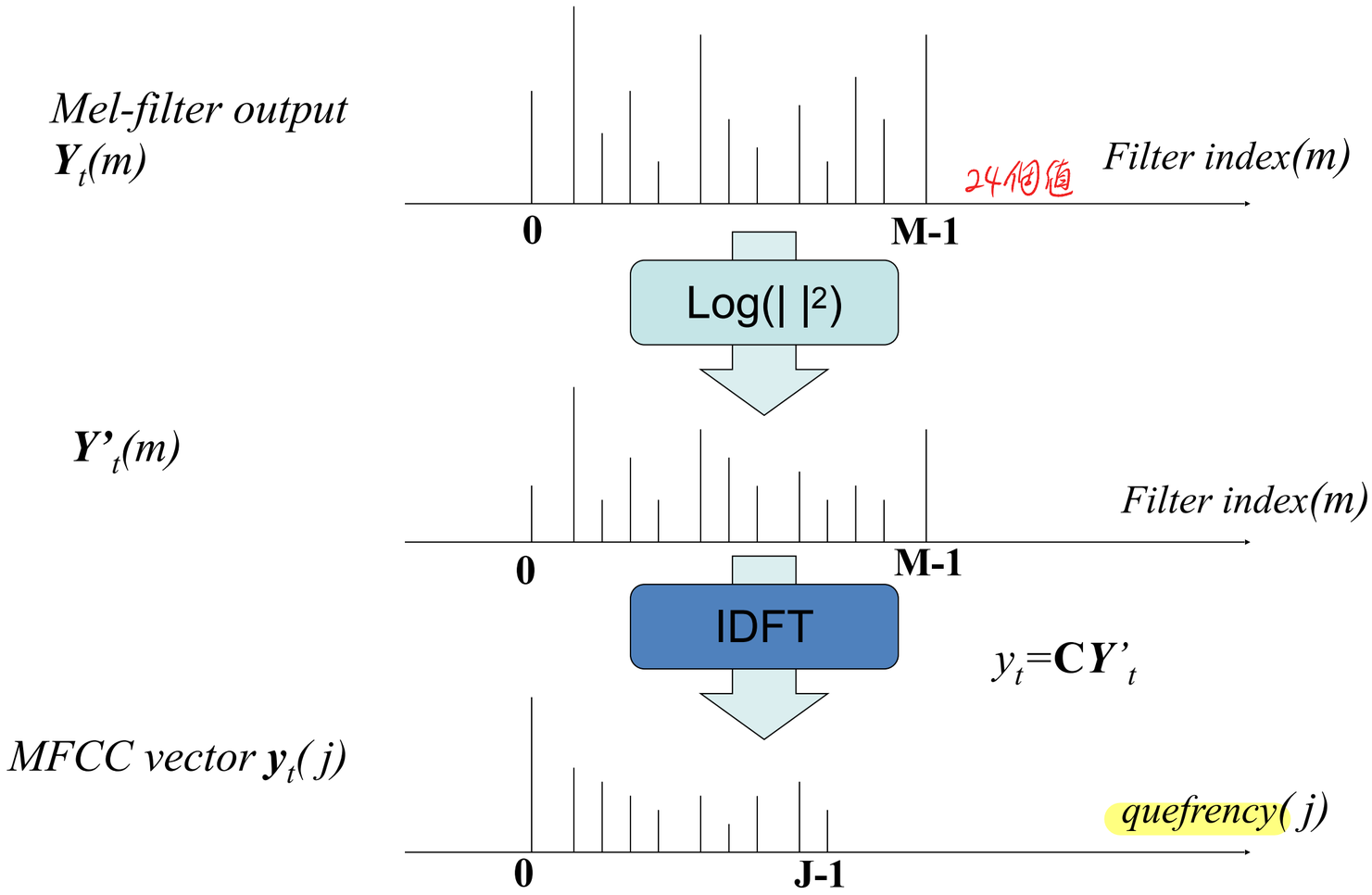
Feature Extraction - MFCC

- **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?

frequency → time domain

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

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

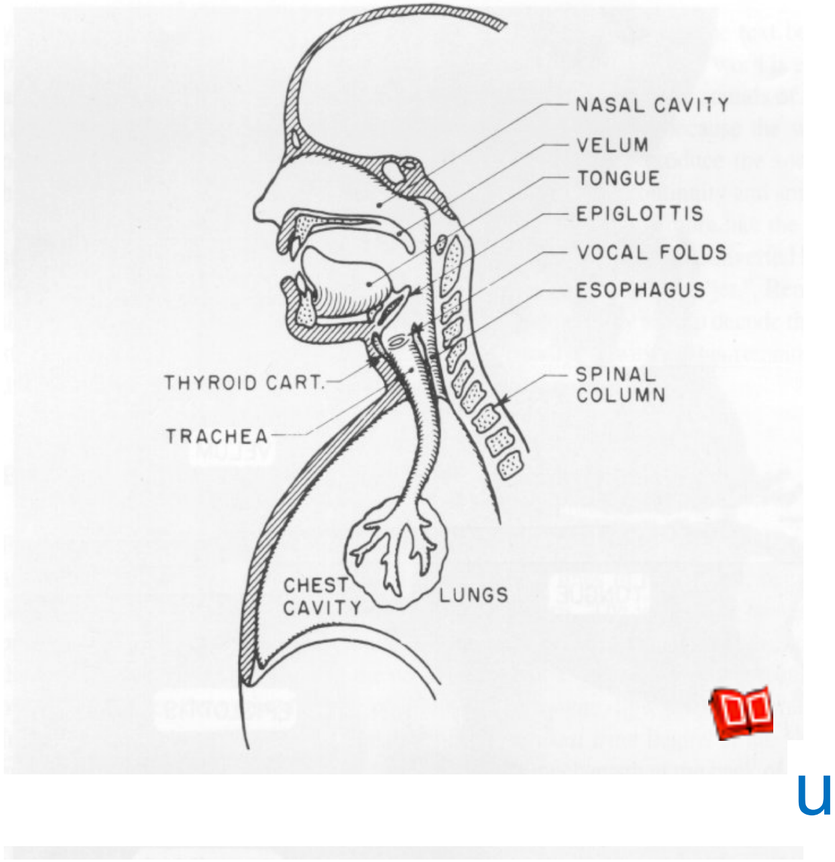
- **Advantages :**

轉成 cosine transform

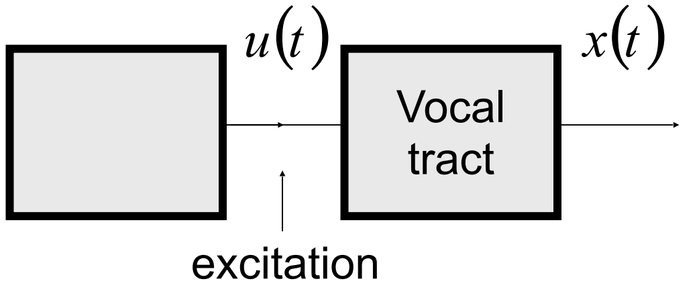
  - Since the log-power spectrum is real and symmetric, the inverse DFT reduces to a Discrete Cosine Transform (DCT). The DCT has the property to produce highly uncorrelated features $\boldsymbol{y}_t$
    - diagonal rather than full covariance matrices can be used in the Gaussian distributions in many 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

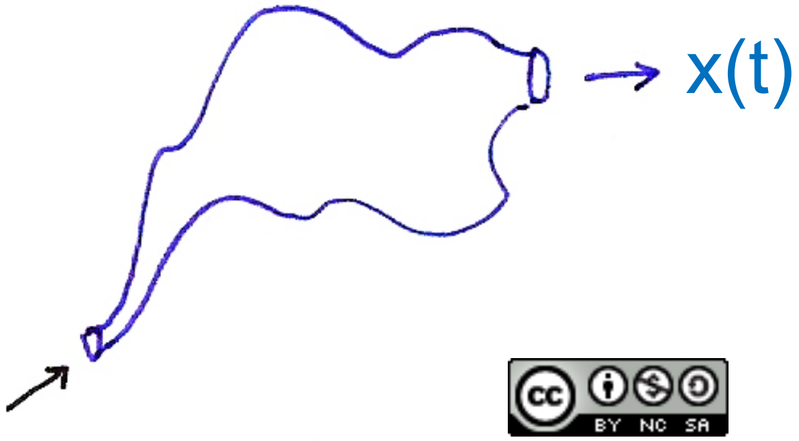
Speech Production and Source Model (P.3 of 7.0)

- Human vocal mechanism



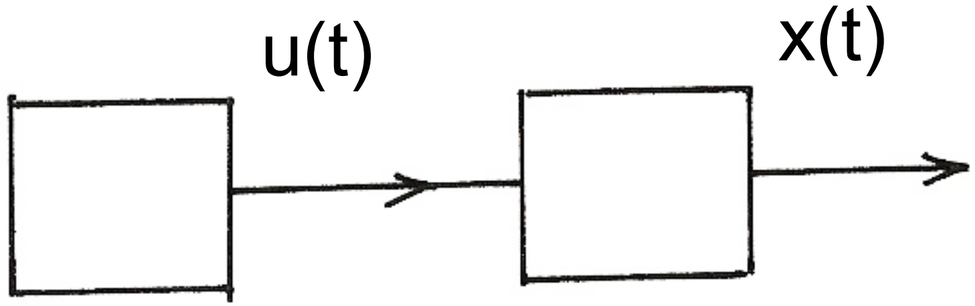
- Speech Source Model

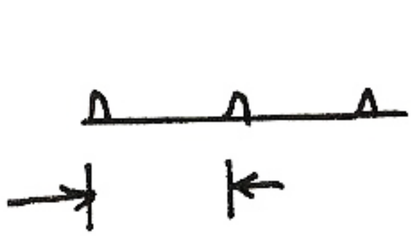




u(t)

Voiced and Unvoiced Speech (P.4 of 7.0)





pitch

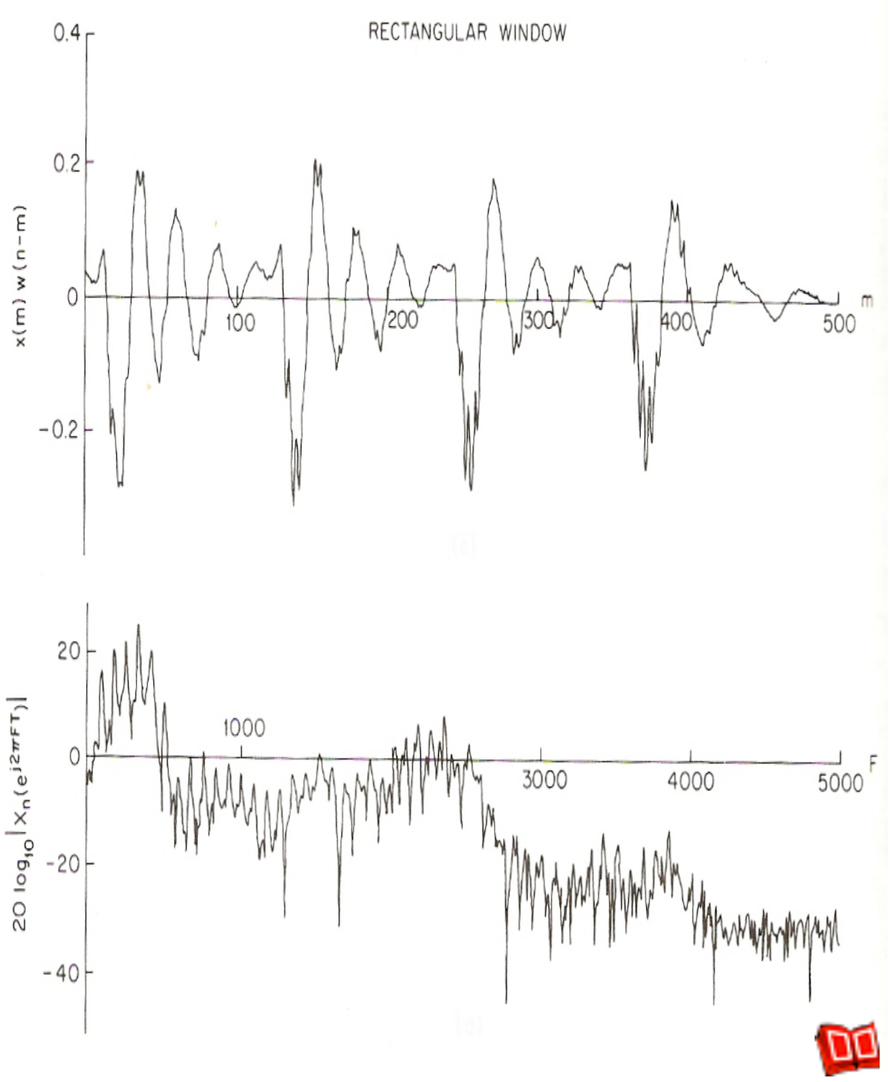
voiced

pitch

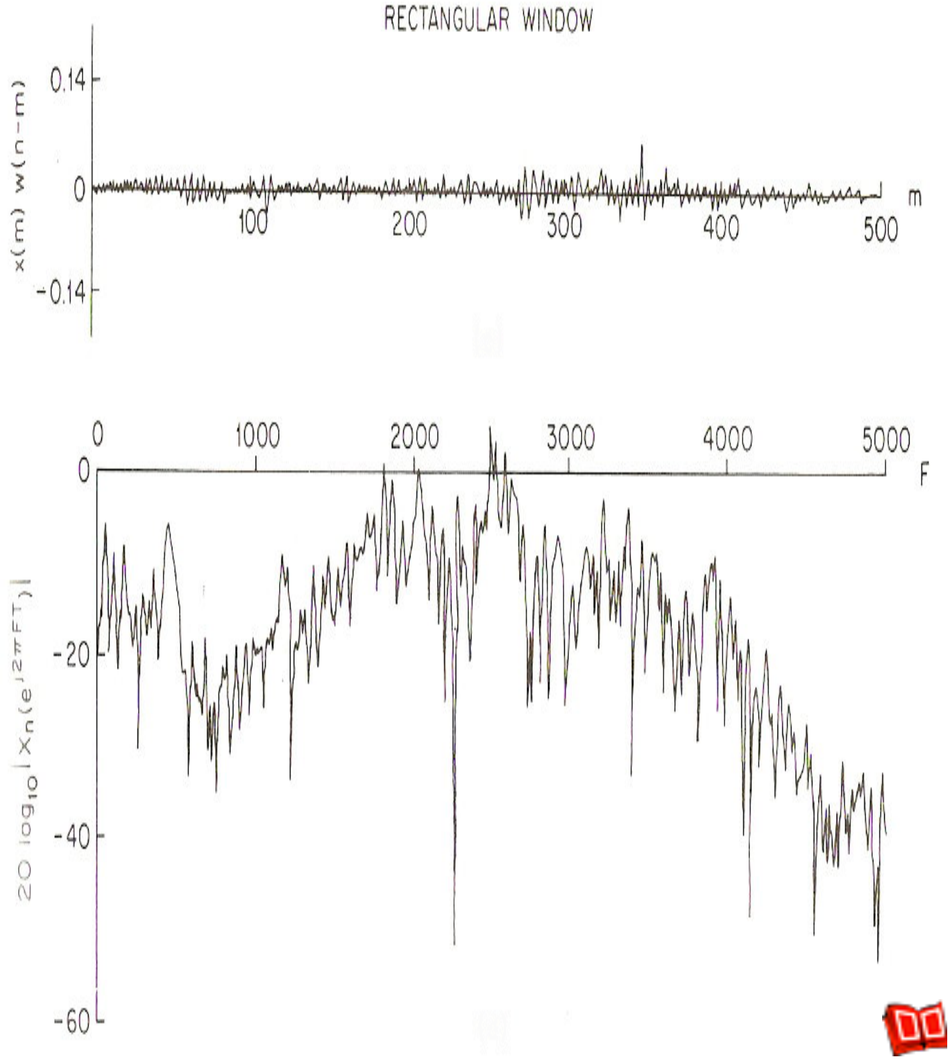
unvoiced

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

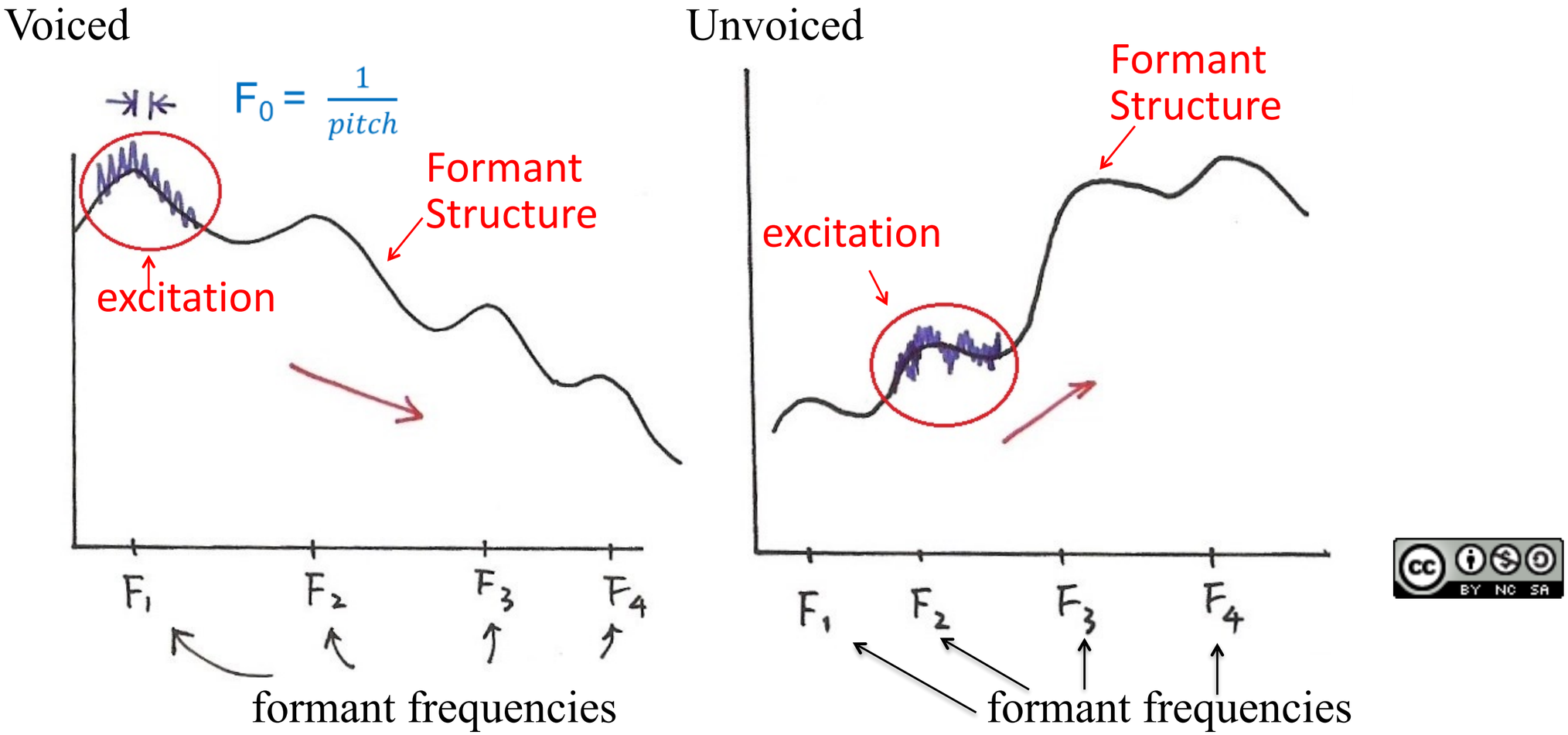
Voiced



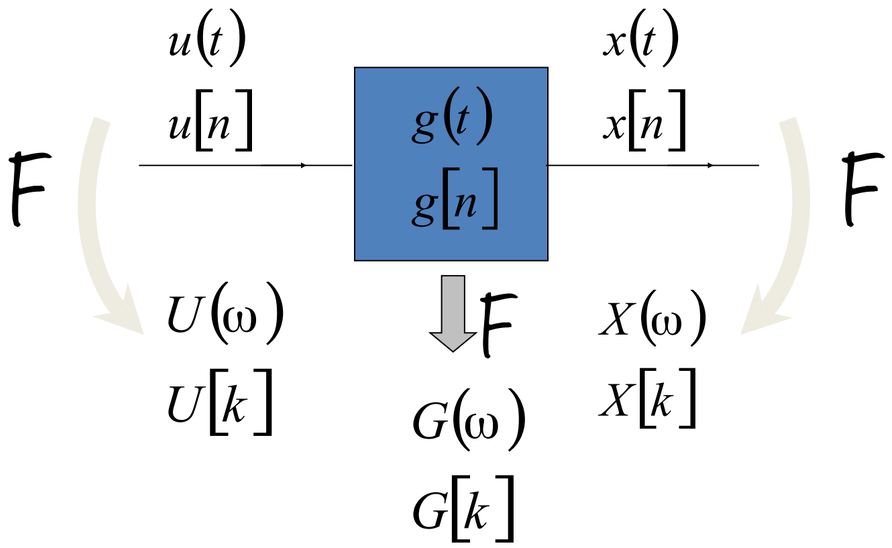
Unvoiced



Frequency Domain (P.9 of 7.0)



Input/Output Relationship for Time/Frequency Domains



excitation

formant structure

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

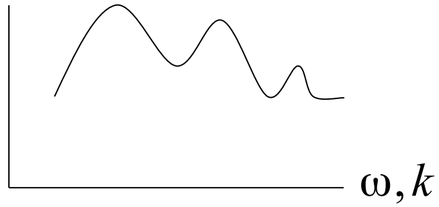
$$x[n] = u[n] * g[n] = \sum_{k} x[k]\, g[n-k]$$

time domain: convolution

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

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

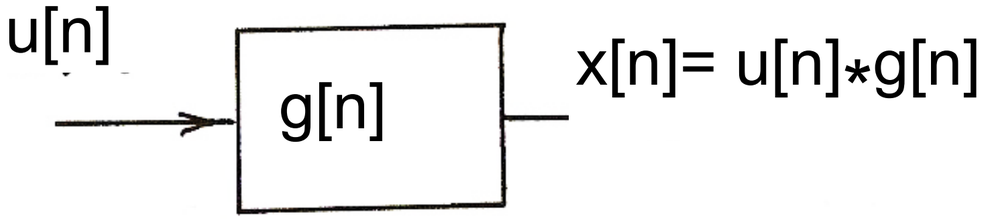
frequency domain: product

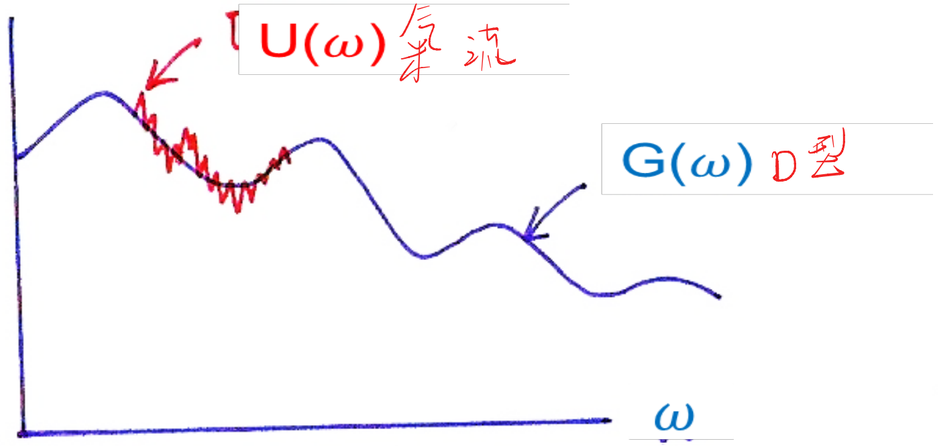


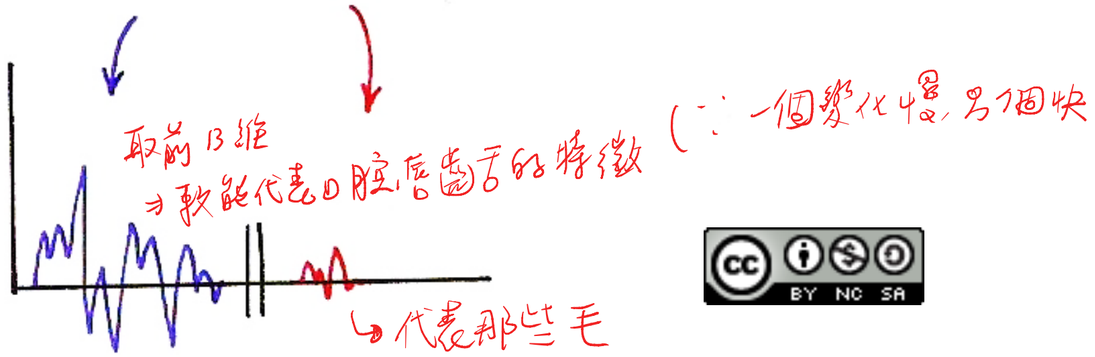
$g(t)$, $G(\omega)$: Formant structure: differences between phonemes

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

Logarithmic Operation

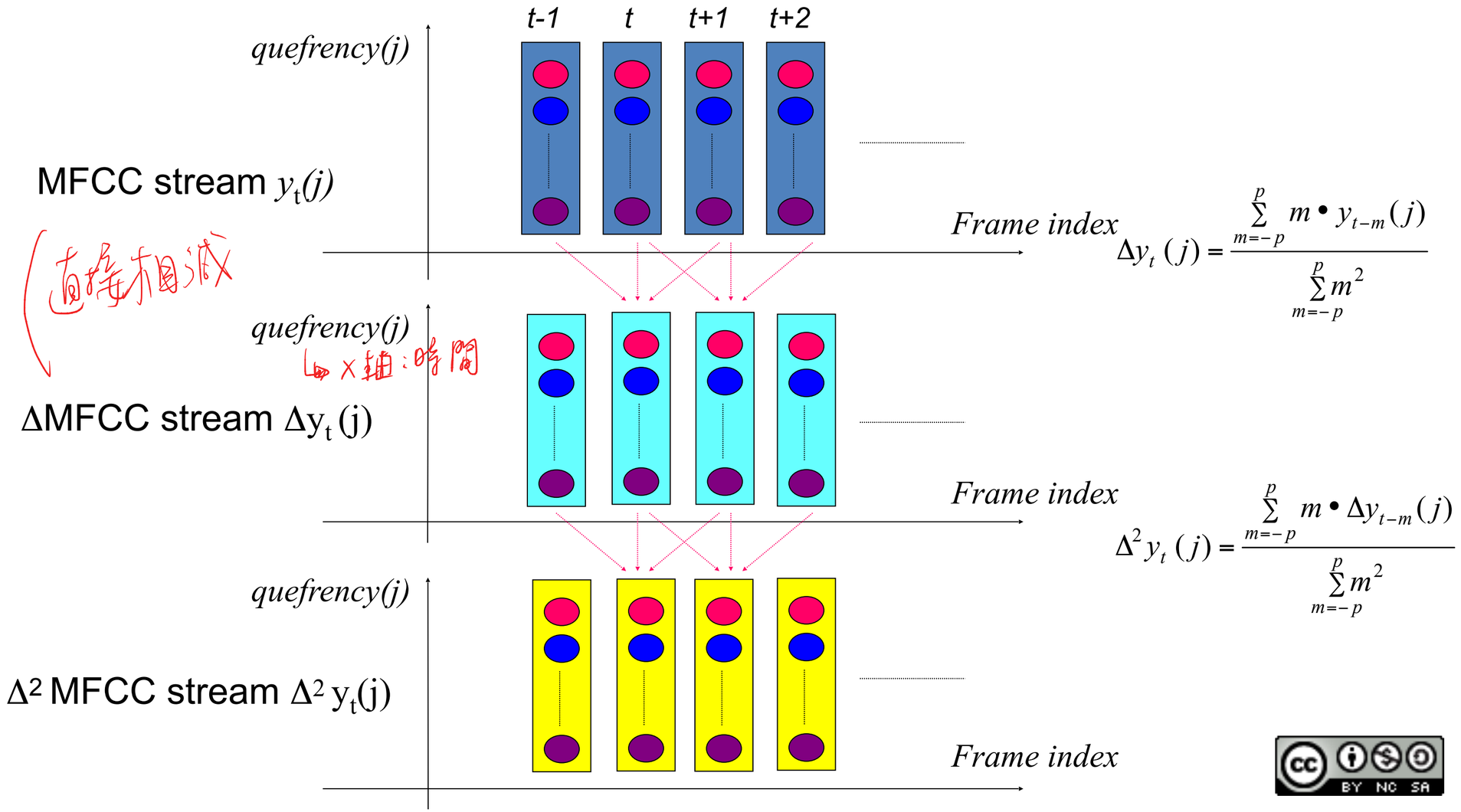




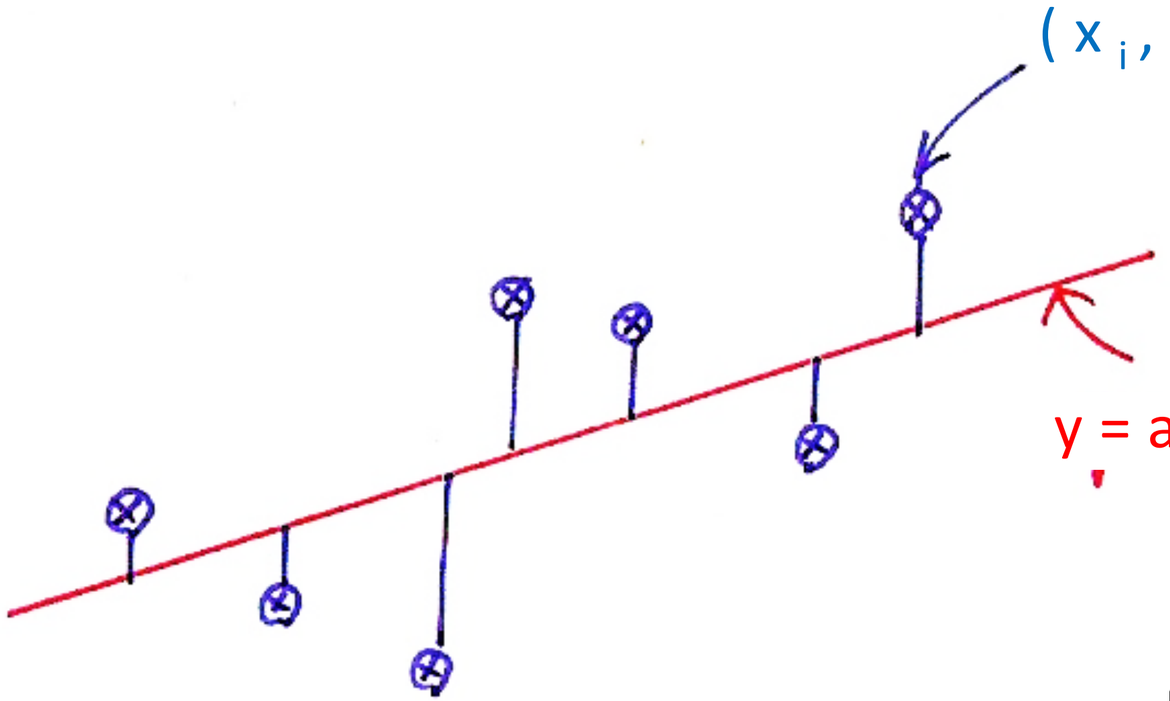


Derivatives

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



Linear Regression



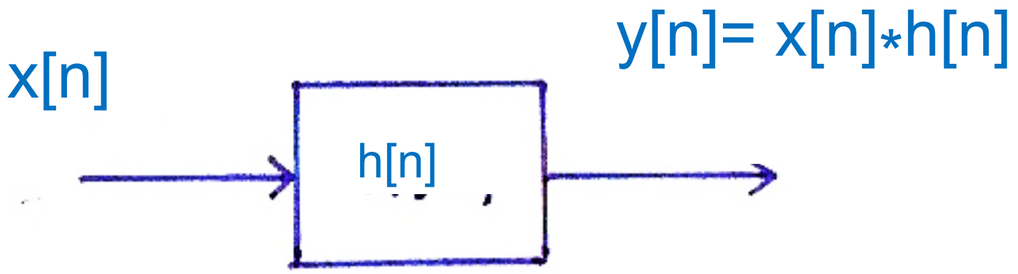
$$\sum_i \left(ax_i + b - y_i\right)^2 = \min$$

find a, b

Why Delta Coefficients?

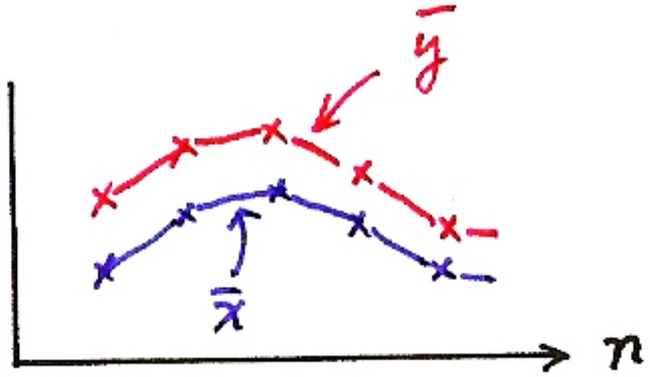
- **To capture the dynamic characters of the speech signal**
  - Such information carries relevant information for speech recognition
  - The value of p should be properly chosen
    - The dynamic characters may not be properly extracted if p is too small
    - Too large P may imply frames too far away
- **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



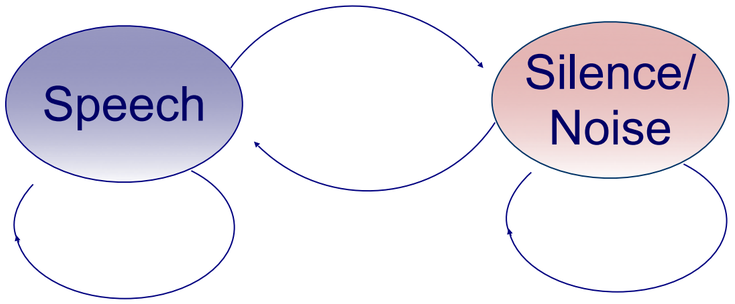
$$\bar{y} = \bar{x} + \bar{h}$$

MFCC
把 convolution 變成加法
=>雜訊容易 eliminate



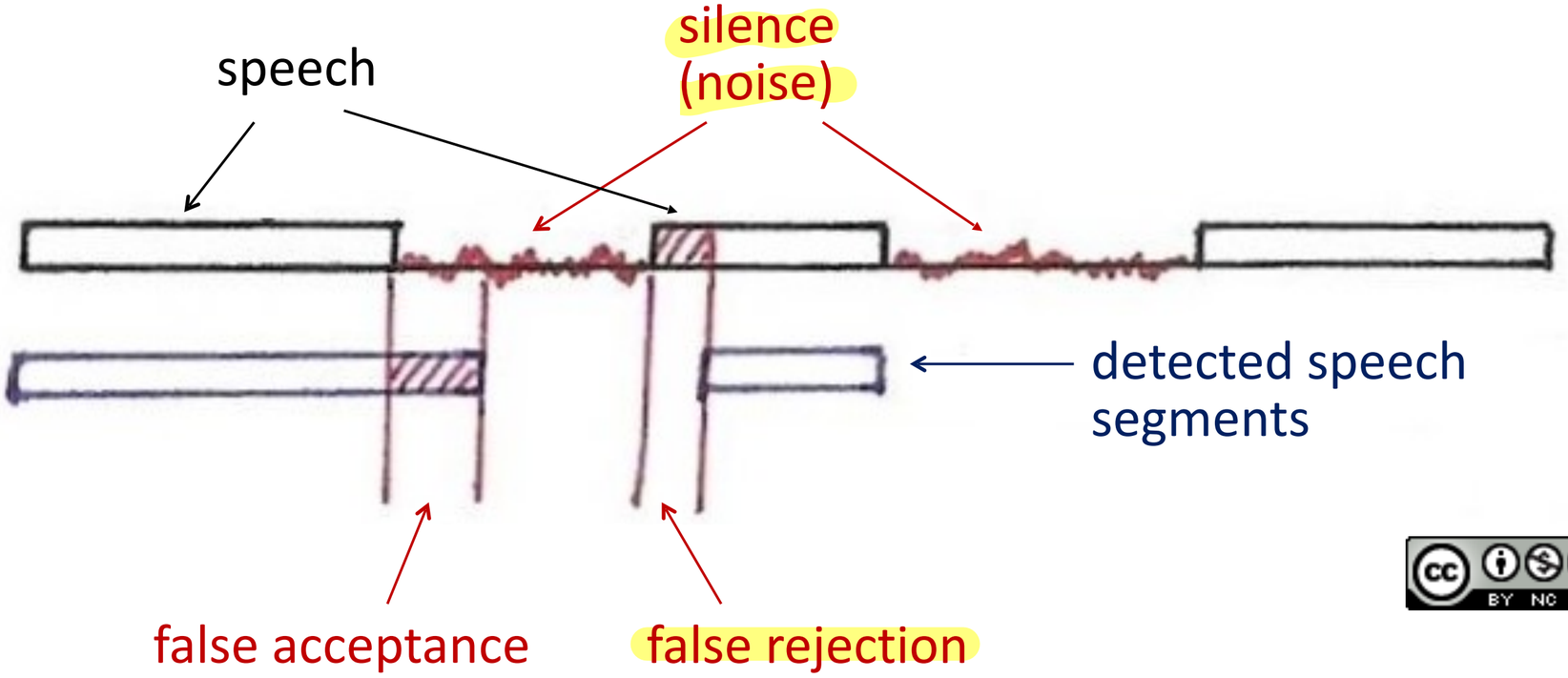
End-point Detection

- **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



比較嚴重(與 f- acceptance 比)