Course Information Lecture1 Introduction Dr Nisachon Tangsangiumvisai Lecturer ดร. นิศาชล ตั้งเสงี่ยมวิสัย Contact office 02-2186909 2102874 **Speech Processing** E-mail: Nisachon.T@Chula.ac.th webpage : www.ee.eng.chula.ac.th/~ntang Dr Nisachon Tangsangiumvisai N. Tangsangiumvisai Lecture1 : Introduction 2 **Course Information (II) Books** ■ Speech and Audio Signal Processing : Time Wednesday 9.00 – 12.00 pm Processing and perception of speech and music as given in the course outline B. Gold and N. Morgan Schedule Wiley, 2000. Evaluation Assignments 30 % Mid-term Examination 40 % Digital Speech : Coding for low bit rate Project 30 % communication systems A. M. Kondoz Wiley, 2000. N. Tangsangiumvisai Lecture1 : Introduction N. Tangsangiumvisai Lecture1 · Introduction 4

Course Contents

Part I : Speech Processing

- Fundamentals of the course
- Speech Modeling
- Speech Analysis and Synthesis
- Speech Coding
- Human Recognition
- Speaker Verification
- Text-to-Speech Synthesis
- Speech Prosody

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Overview

Course Contents (II)

Part II : Speech Enhancement

Noise Reduction Techniques

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Speech Communication

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■ What is speech communication ?

The transfer of information from one person to another via *speech*, which consists of variations in pressure coming from the mouth of a speaker.

■ What is sound ?

Sound is an acoustic *wave* that results when a vibrating source (e.g vocal cords) disturbs an elastic medium (e.g air).

Speech Communication (II)

When a sound wave reaches a listener's ear drum, the vibrations are transmitted to the inner ear (or cochlea), where mechanical displacements are converted to neural pulses that are sent to the brain and result in the sensation of sound.

Speech chain consists of speech mechanism in the speaker, transmission through medium, and a speech perception process in the ear and brain of the listener.

In many applications of speech processing, part of the speech chain is implemented by a simulation device.
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Speech Processing

- Speech Analysis
 - Speech Recognition
 - Speaker Verification
 - Speaker Identification

- Speech Synthesis
 - Text-to-speech (TTS)
- Speech Codec

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Factors

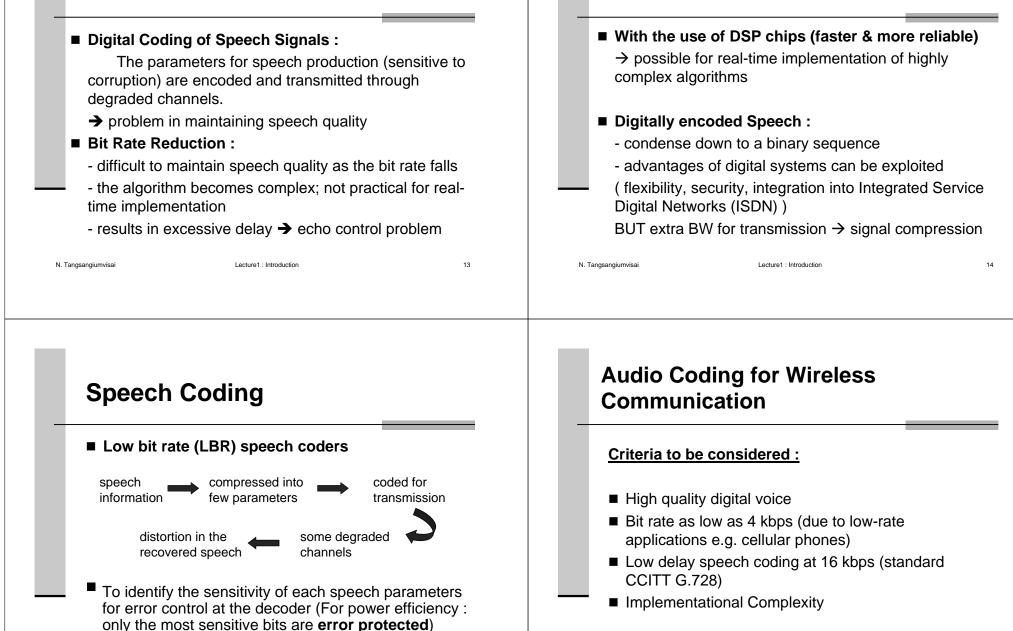
- Analogue form of Speech for Telecommunication
 - transmission power
 - spectral utilization
- Digital Transmission of Speech
 - low cost
 - consistent quality
 - security
 - spectral efficiency

Digitization of Speech Signals

- Sampling : Nyquist Criterion
- Quantization : Number of quantizer levels is proportional to reconstruction at the receiver
- Speech Transmission Systems
 In mobile communication systems
 for reduction in PCM bit rate

(64 kbps; restricts the desired spectral efficiency)

Digitization of Speech Signals (II)

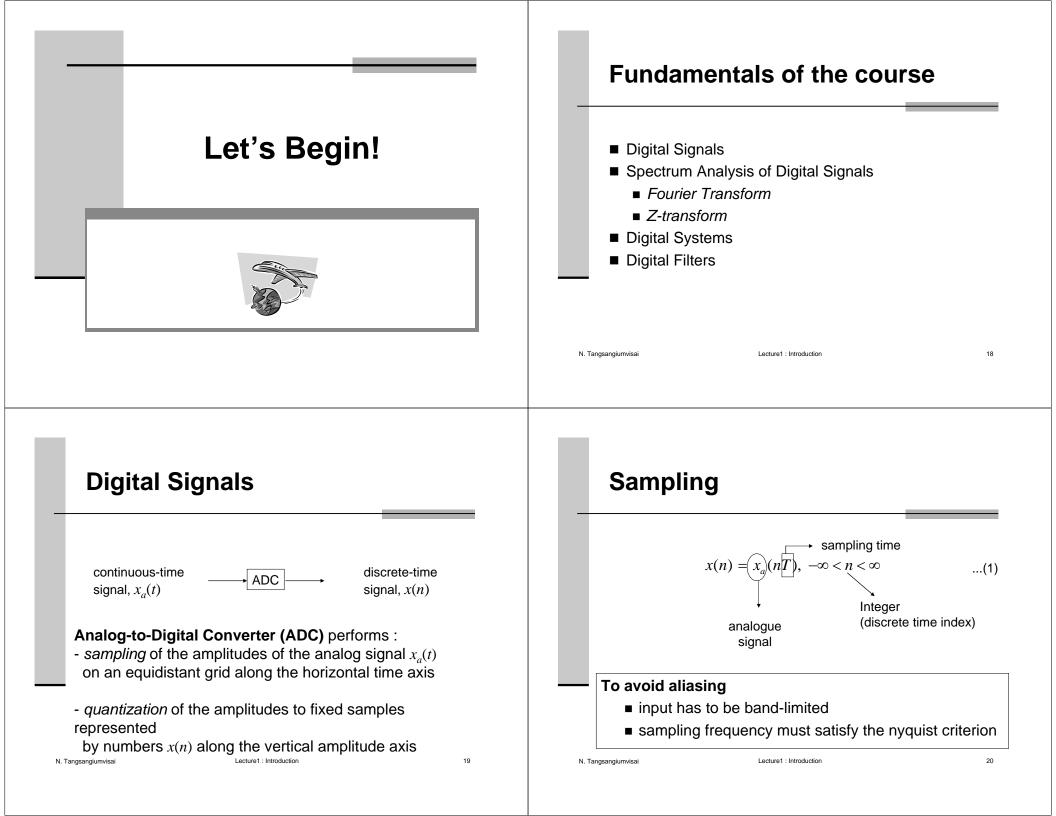


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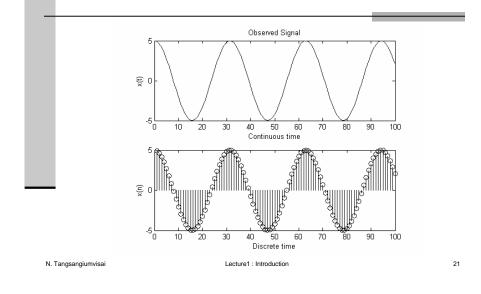
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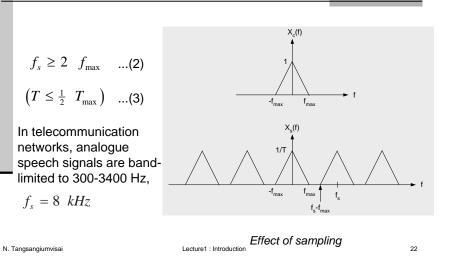
Digitization of Speech Signals (III)



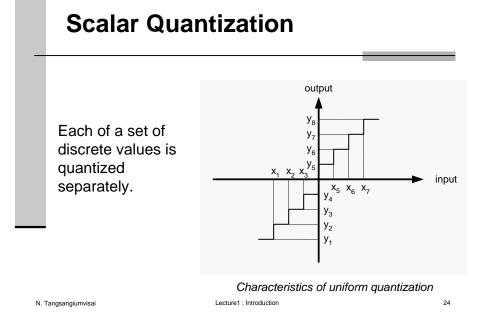
Example of signals







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Scalar Quantization (II)

- Quantisation step-size (∆)

 : distance between the finite sets of amplitude levels

 Each Δ_n is represented by a <u>code-word</u> for transmission.
- At digital receiver → De-quantizer
 - : indicate which discrete amplitude to be used.
- Channel transmission bit rate :



(bit/sec)

...(4)

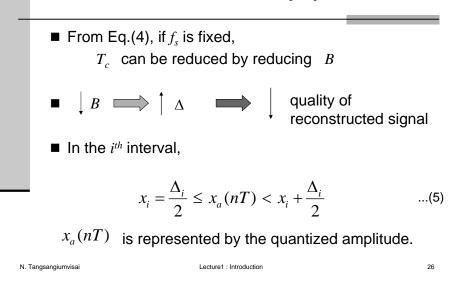
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B : number of bits representing the discrete amplitudes. (length of c(n))

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Scalar Quantization (III)



Scalar Quantization (IV)

- The quantization of the amplitudes to fixed numbers in the range between -32768 ... 32767 is based on a 16-bit representation of the sample amplitudes.
- It allows 2¹⁶ quantized values in the range of -2¹⁵ to 2¹⁵-1.
- Thus, for *B*-bit representation, the number range is $-2^{(B-1)}$ to $2^{(B-1)}$ -1.

Scalar Quantization (V)

Instantaneous squared error is $\left(x_a(nT) - x_i\right)^2 \qquad \dots(6)$ Mean Squared Error of the signal $E_i^2 = \int_{x_i - \frac{\Delta i}{2}}^{x_i + \frac{\Delta i}{2}} (x - x_i)^2 p(x) dx \qquad \dots(7)$ Assume fine resolution (small \$\Delta_i\$), \$p(x)\$ is flat within \$\left[x_i - \frac{\Delta}{2}, x_i + \frac{\Delta}{2}\right]\$ → use its center value \$p(x_i)\$

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Scalar Quantization (VI) Scalar Quantization (VII) ■ Hence, MSE becomes Assume uniform quantisation step-size $E_i^2 = \frac{\Delta_i^3}{12} p(x_i)$...(8) $E^2 = \frac{\Delta^2}{12}$...(12) Prob. of signal falling in this interval is ■ For *B*-bit binary code words $\Gamma_i = \int_{x_i - \frac{\Delta_i}{2}}^{x_i + \frac{\Delta_i}{2}} p(x) dx = p(x_i) \Delta_i$...(9) $N=2^{B}$...(13) • Substituting for $p(x_i)$ in Eq.(8), $E_i^2 = \frac{\Delta_i^2}{12} \Gamma_i$...(10) • Assuming $|x| \le X_{\text{max}}$ and p(x) is symmetrical • Hence, total MSE is $E^2 = \frac{1}{12} \sum_{i=1}^{N} \Gamma_i \Delta_i^2$...(11) $2X_{\rm max} = \Delta 2^B$...(14) (N = no. of levels in the quantizer) N. Tangsangiumvisai Lecture1 : Introduction 29 N. Tangsangiumvisai Lecture1 : Introduction 30

Scalar Quantization (VIII)

Thus, the step-size can be found from
 $\frac{2X_{\max}}{2^B} = \Delta \qquad ...(15)$ Quantization error *e_q(n)* is bounded by
 $-\frac{\Lambda}{2} \leq e_q(n) \leq \frac{\Lambda}{2} \qquad ...(16)$ Uniform quantizer assumes uniform pdf. of constant height $\frac{1}{2X_{\max}}$.

Scalar Quantization (IX)

■ Hence, input power is given by

$$P_{x} = \int_{-X_{\text{max}}}^{X_{\text{max}}} \frac{x^{2}}{2X_{\text{max}}} p(x)dx \qquad \dots (17)$$

SNR

$$\frac{P_x}{P_n} = \frac{X_{\text{max}}^2/3}{\Delta^2/12} = 2^{2B} \implies 6.02B \text{ (dB)} \dots (18)$$

Vector Quantization

To characterize the spectrum of a speech signal (**spectral analysis**), consider the following example :

- Uncompressed Signal
- Compressed Signal
- 10 kHz sampled speech with 16-bit speech amplitudes
- Information rate is 160,000 bps (required for storage of speech analysis)
- spectral vector v_l, l=1,2,...,L
 vectors of dimension p=10 using 100 spectral vectors/s.
- by representing each spectral component to 16-bit precision, the required storage is 100x10x16 bps

10 times reduction

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Vector Quantization (III)

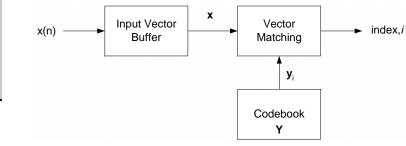
•So, if we require to a codebook with 1024 unique spectral vectors, then we need a 10-bit number.

•Assume a rate of 100 spectral vectors/s, a total bit rate of <u>1 kbps</u> is required to represent the spectral vectors of a speech signal. (this is 1/16 time the rate required by the continuous spectral vectors.)

•So, the VQ method is an **efficient** representation of the spectral information in the speech signal.

Vector Quantization (IV)

- Block Quantization / Pattern Matching Quantization
- Signals are quantized as a single vector.



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Block diagram showing a vector quantization
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Vector Quantization (II)

It is needed a **single** spectral representation for each basic speech unit.

A finite number of **unique** spectral vectors.

(each vector corresponds to one of the basic speech units.)

impossible, due to time-varying properties of the spectra of the signal.

build a codebook of **distinct** analysis vectors. (common techniques for vector quantization (VQ) methods)

Vector Quantization (V)

Advantages

reduced storage

reduced computation for determining similarity of spectral analysis vectors (use of a table lookup) discrete representation of speech sounds (use of codebook) N. Tangsangiumvisai Lecture1 : Introduction 37 N. Tangsangiumvisai Comparison **Vector Quantization (VII)** Scalar Quantization - different cells have same shape cell C Vector Quantization ٠ - different cells have different shapes

- at very low bit rate, performs better than the scalar

method, but at computational and storage costs.

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Partitioning a 2-dimensional space into 18 cells

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Vector Quantization (VI)

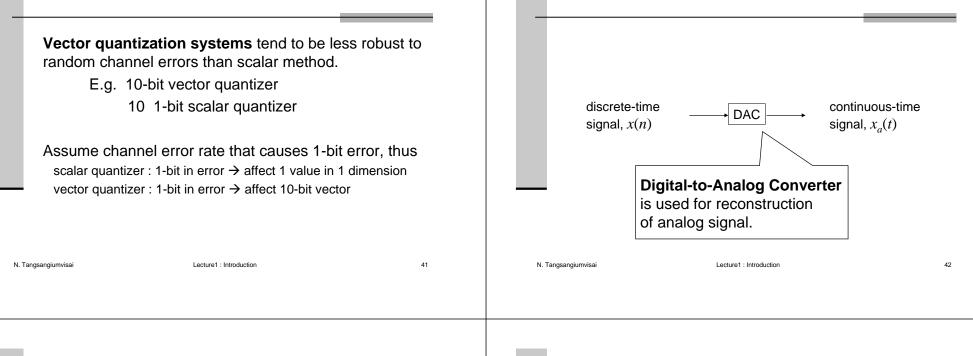
Disadvantages

 since there is a *finite* number of codebook vectors, the "best" representation of a given spectral vector is obtained with a certain level (non-zero) of quantization error.

(As the size of the codebook increases, the size of the quantization error decreases.)

• To reduce the quantization error, larger codebook is needed more storage!!

Comparison (II)



Spectrum Analysis of Digital Signals

■ Discrete-time Fourier Transform (DTFT)

$$X(e^{j\omega}) = F[x(n)] = \sum_{n=-\infty}^{\infty} x(n) e^{-j\omega n} \qquad \dots (19)$$

a function of continuous ω

$$\mathbf{x}(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\omega}) e^{jn\omega} d\omega \qquad \dots (20)$$

Spectrum Analysis (II)

Signal Reconstruction

■ Discrete Fourier Transform (DFT)

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi k n/N}, \quad k = 0, 1, \dots, N-1 \qquad \dots (21)$$

for digital computation

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{j2\pi kn/N}, \quad n = 0, 1, \dots, N-1 \qquad \dots (22)$$

Spectrum Analysis (III)

■ The fast version of the DFT is called the Fast Fourier Transform (FFT).

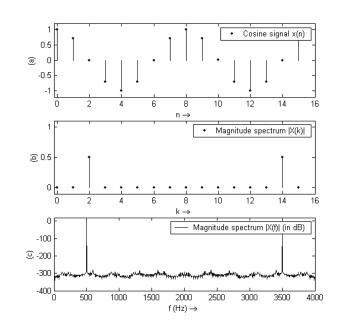
>> Xmag = abs(fft(x,N)); Xphase = angle(fft(x,N));

■ From Eq.(21),

 $X(k) = X_R(k) + jX_I(k), \quad k = 0, 1, \dots, N-1$

Magnitude spectrum :
$$|X(k)| = \sqrt{X_R^2(k) + X_I^2(k)}$$
 ... (23)
Phase : $\varphi(k) = \arctan\left(\frac{X_I(k)}{X_R(k)}\right)$... (24)

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Spectrum Analysis (V)

Time-frequency representation → Spectrogram

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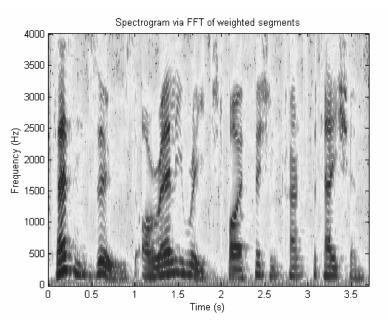
■ It is an estimate of the short-time, time-localized frequency content of the signal.

- The signal is split into segments of length N
- and are multiplied by a window
- and an FFT is performed
- An overlap of the weighted segment is used to increase the time-localization of the short-time spectra.

>> [B,F,T] = specgram(x,NFFT,Fs,WINDOW,NOVERLAP);

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Spectrum Analysis (VII) Digital Systems ■ z-transform ... (25) X(z) = Z[x(n)] $T\{\cdot\}$ x(n) → y(n) $=\sum_{n=-\infty}^{\infty}x(n)z^{-n}$... (26) $y(n) = T\{x(n)\}$...(29) therefore $x(n) = \frac{1}{2\pi i} \iint_C X(z) z^{n-1} dz$ Properties of discrete-time systems: ... (27) linearity shift-invariance $X(z)\Big|_{z=e^{j\omega}} = X(e^{j\omega}) = \sum_{n=1}^{\infty} x(n)e^{-j\omega n}$... (28) causality invertibility

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Digital Systems (II)

■ Linearity

$$T\{ax_1(n) + bx_2(n)\} = aT\{x_1(n)\} + bT\{x_2(n)\} \quad ...(30)$$

a, b are constants.

Shift-invariance

 $x(n) \rightarrow y(n)$

then

lf

$$x(n-n_0) \rightarrow y(n-n_0)$$

Digital Systems (III)

Causality

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For any n_0 , the response of the system at time n_0 depends only upon the values of the input for $n < n_0$. *Examples* :

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y(n) = x(n) + x(n-1) ...(33)

$$y(n) = x(n) + x(n+1)$$
 ...(34)

Invertibility

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The input to the system maybe uniquely determined by observing the output.

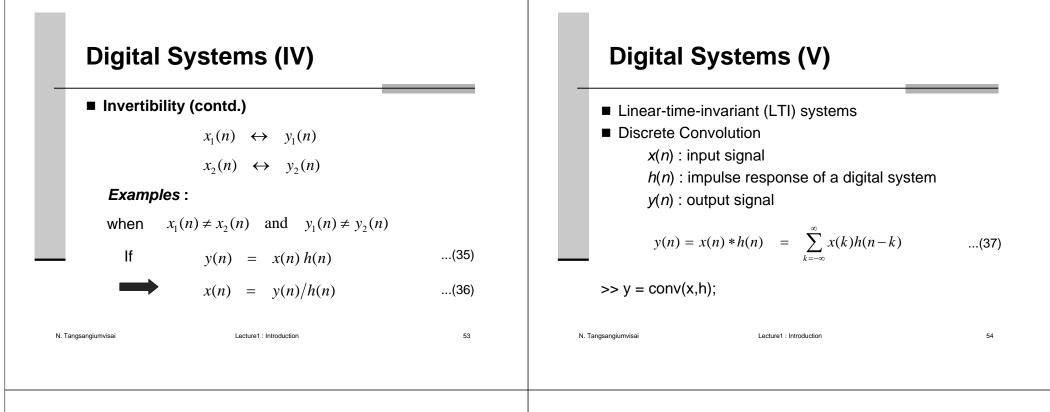
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...(31)

...(32)

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Digital Systems (VI)

■ FIR system : a system with a finite impulse response

$$H(z) = \frac{Y(z)}{X(z)} = 1 + b_1 z^{-1} + b_2 z^{-2} \qquad \dots (38)$$

IIR system : a system with an infinite impulse response

$$H(z) = \frac{Y(z)}{X(z)} = \frac{1}{1 + a_1 z^{-1} + a_2 z^{-2}}$$
...(39)

>> y = filter(B,A,x); >> [H,W] = freqz(B,A,N);

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Digital Filters

- Lowpass filter (LPF)
 - select low frequencies up to the cutoff frequency $f_{\rm c}$
 - Attenuate frequencies higher than f_c

■ Highpass filter (HPF)

- select frequencies higher than f_c
- attenuate frequencies below f_c

Bandpass filter (BPF)

- select frequencies between a lower f_{c1} and a higher f_{c2}
- attenuate frequencies outside this range

Digital Filters (II)

Bandreject filter

- attenuate frequencies between a lower f_{c1} and a higher f_{c2}
- frequencies outside this range are passed

Notch filter

■ attenuate frequencies in a narrow bandwidth around the cutoff frequency *f*_c

Allpass filter

pass all frequencies but modify the phase of the input signal
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and a Introduction to the course Fundamentals of the course Next Lecture Lecture 2 : Speech Modeling

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