

ESE 531: Digital Signal Processing

Lec 11: February 20, 2020
Polyphase Decomposition and Multi-rate
Filter Banks



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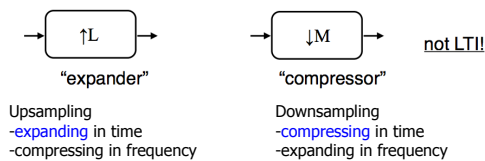
Lecture Outline

- Review: Interchanging Operations
- Polyphase Decomposition
- Multi-Rate Filter Banks

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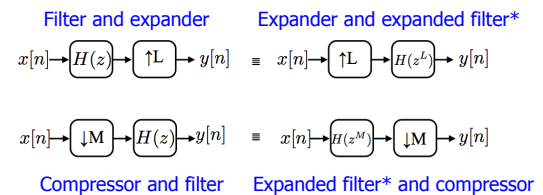
Expander and Compressor



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Interchanging Operations - Summary



*Expanded filter = expanded impulse response, compressed freq response

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Polyphase Decomposition

- The polyphase decomposition of a sequence is obtained by representing it as a superposition of M subsequences, each consisting of every Mth value of successively delayed versions of the sequence.
- When this decomposition is applied to a filter impulse response, it can lead to efficient implementation structures for linear filters in several contexts.

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Polyphase Decomposition

- We can decompose an impulse response (of our filter) to:

$$h[n] = \sum_{k=0}^{M-1} h_k[n-k]$$

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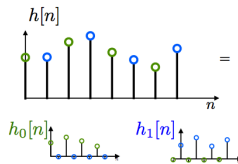
6

Polyphase Decomposition

- We can decompose an impulse response (of our filter) to:

$$h[n] = \sum_{k=0}^{M-1} h_k[n-k]$$

M=2



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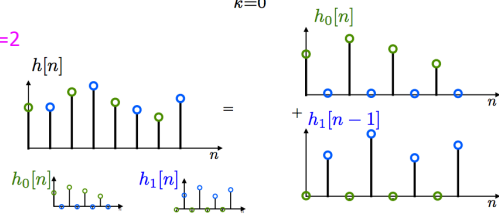
7

Polyphase Decomposition

- We can decompose an impulse response (of our filter) to:

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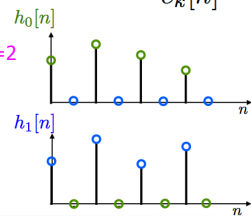
8

Polyphase Decomposition

$$h_k[n] \rightarrow \downarrow M \rightarrow e_k[n]$$

$$e_k[n] = h_k[nM]$$

M=2



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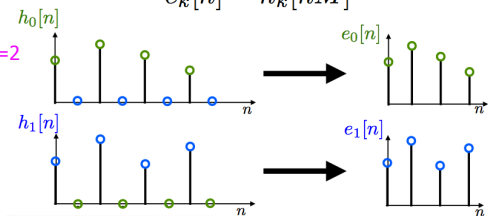
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Polyphase Decomposition

$$h_k[n] \rightarrow \downarrow M \rightarrow e_k[n]$$

$$e_k[n] = h_k[nM]$$

M=2



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Polyphase Decomposition

$$e_k[n] \rightarrow \uparrow M \rightarrow h_k[n]$$

recall upsampling $\Rightarrow$ scaling

$$H_k(z) = E_k(z^M)$$

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Polyphase Decomposition

$$e_k[n] \rightarrow \uparrow M \rightarrow h_k[n]$$

recall upsampling $\Rightarrow$ scaling

$$H_k(z) = E_k(z^M)$$

Also, recall:

$$h[n] = \sum_{k=0}^{M-1} h_k[n-k]$$

So,

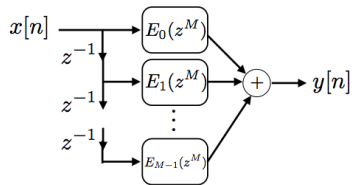
$$H(z) = \sum_{k=0}^{M-1} E_k(z^M) z^{-k}$$

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Polyphase Decomposition

$$H(z) = \sum_{k=0}^{M-1} E_k(z^M) z^{-k}$$



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Polyphase Implementation of Decimation

$$x[n] \rightarrow H(z) \rightarrow y[n] \rightarrow \downarrow M \rightarrow w[n] = y[nM]$$

□ Problem:

- Compute all $y[n]$ and then throw away -- wasted computation!

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Polyphase Implementation of Decimation

$$x[n] \rightarrow H(z) \rightarrow y[n] \rightarrow \downarrow M \rightarrow w[n] = y[nM]$$

□ Problem:

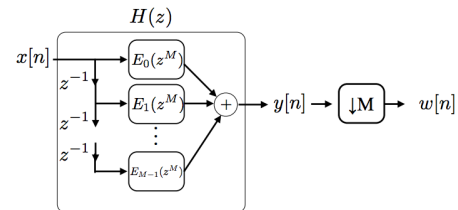
- Compute all $y[n]$ and then throw away -- wasted computation!
- For FIR length $N \rightarrow N$ multiplications/unit time

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Polyphase Implementation of Decimation

$$x[n] \rightarrow H(z) \rightarrow y[n] \rightarrow \downarrow M \rightarrow w[n] = y[nM]$$

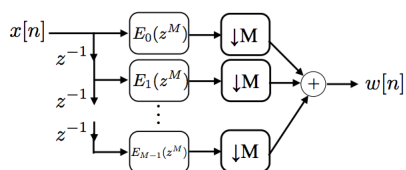


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Polyphase Implementation of Decimation

$$x[n] \rightarrow H(z) \rightarrow y[n] \rightarrow \downarrow M \rightarrow w[n] = y[nM]$$

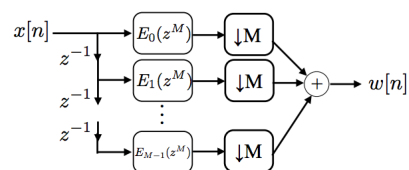


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Polyphase Implementation of Decimation

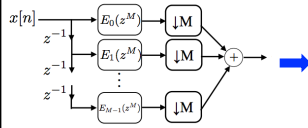
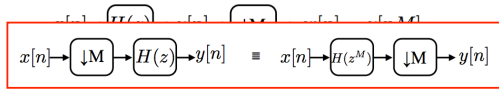
$$x[n] \rightarrow \downarrow M \rightarrow H(z) \rightarrow y[n] = x[n] \rightarrow H(z^M) \rightarrow \downarrow M \rightarrow y[n]$$



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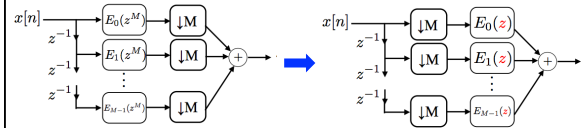
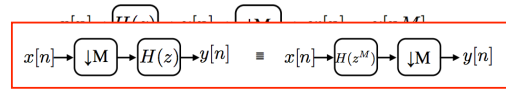
Polyphase Implementation of Decimation



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Polyphase Implementation of Decimation

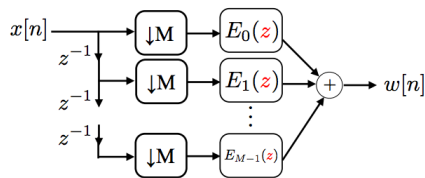


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Polyphase Implementation of Decimation

$$x[n] \rightarrow H(z) \rightarrow y[n] \rightarrow \downarrow M \rightarrow w[n] = y[nM]$$

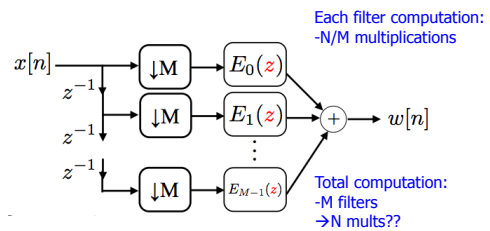


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Polyphase Implementation of Decimation

$$x[n] \rightarrow H(z) \rightarrow y[n] \rightarrow \downarrow M \rightarrow w[n] = y[nM]$$

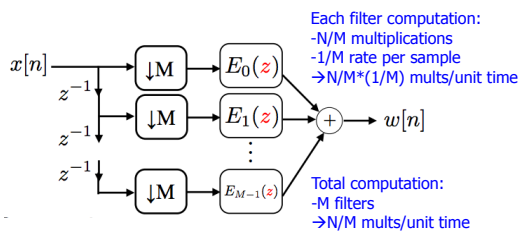


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Polyphase Implementation of Decimation

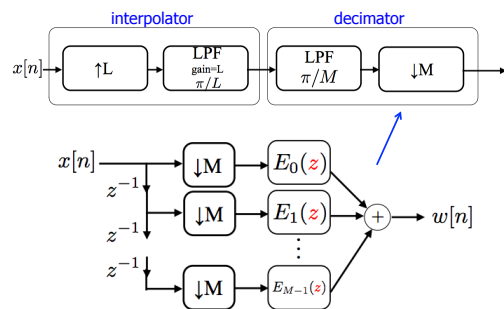
$$x[n] \rightarrow H(z) \rightarrow y[n] \rightarrow \downarrow M \rightarrow w[n] = y[nM]$$



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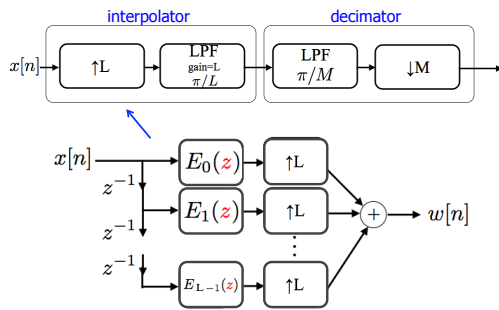
Polyphase Implementation of Decimator



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Polyphase Implementation of Interpolation



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Multi-Rate Filter Banks

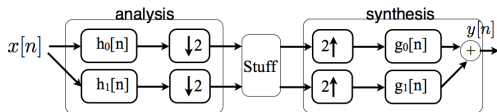
- Use filter banks to operate on a signal differently in different frequency bands
- To save computation, reduce the rate after filtering

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Multi-Rate Filter Banks

- Use filter banks to operate on a signal differently in different frequency bands
- To save computation, reduce the rate after filtering
- $h_0[n]$ is low-pass, $h_1[n]$ is high-pass
- Often $h_1[n] = e^{j\pi n} h_0[n]$ ← shift freq resp by π

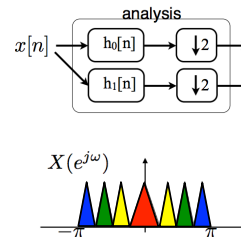


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Multi-Rate Filter Banks

- Assume h_0, h_1 are ideal low/high pass with $\omega_c = \pi/2$

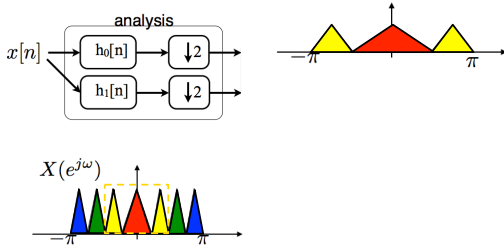


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Multi-Rate Filter Banks

- Assume h_0, h_1 are ideal low/high pass with $\omega_c = \pi/2$

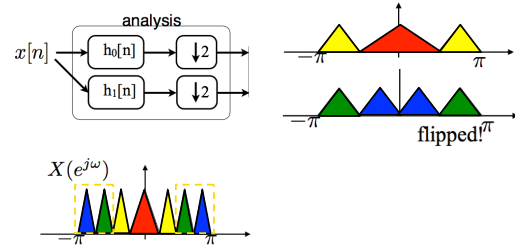


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Multi-Rate Filter Banks

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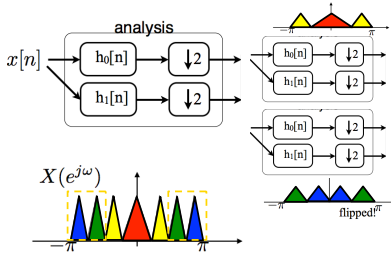


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Multi-Rate Filter Banks

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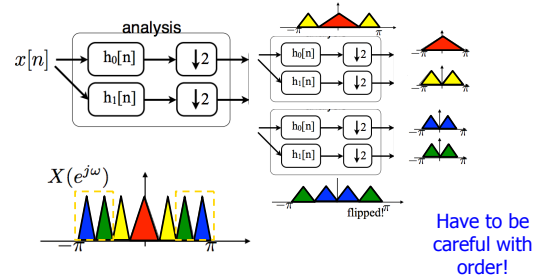


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Multi-Rate Filter Banks

- Assume h_0, h_1 are ideal low/high pass with $\omega_c = \pi/2$

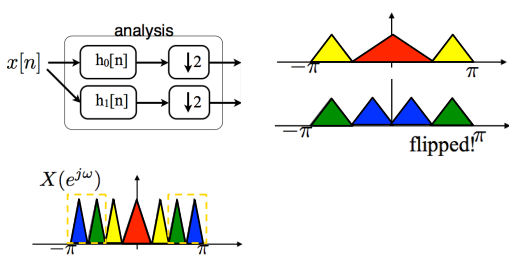


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Multi-Rate Filter Banks

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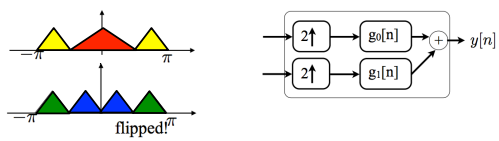


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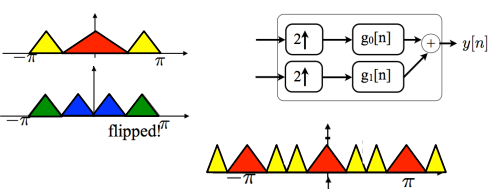


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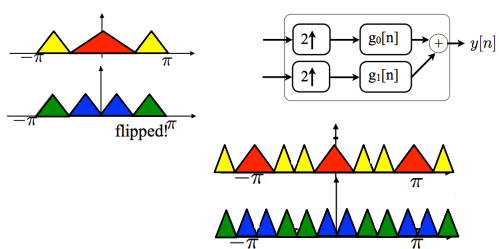


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Multi-Rate Filter Banks

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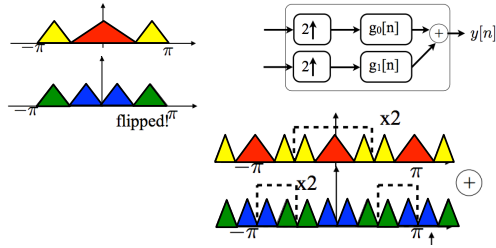


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Multi-Rate Filter Banks

- Assume h_0, h_1 are ideal low/high pass with $\omega_c = \pi/2$

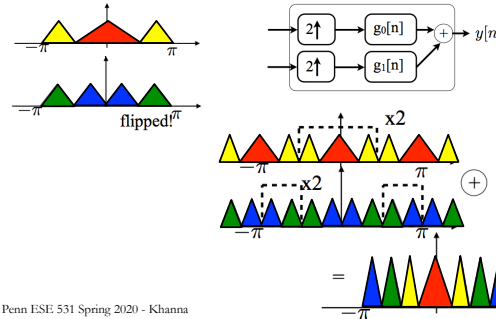


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Multi-Rate Filter Banks

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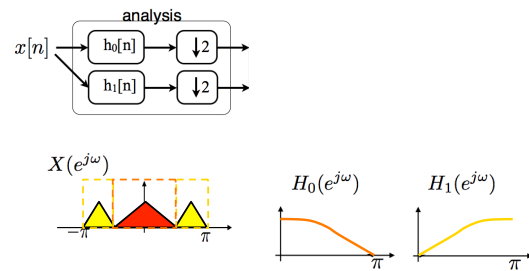


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Multi-Rate Filter Banks

- h_0, h_1 are NOT ideal low/high pass

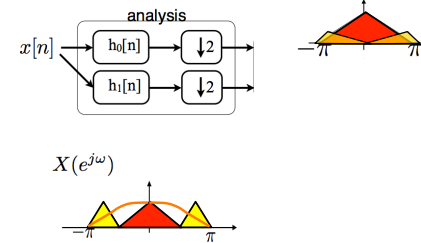


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Non Ideal Filters

- h_0, h_1 are NOT ideal low/high pass

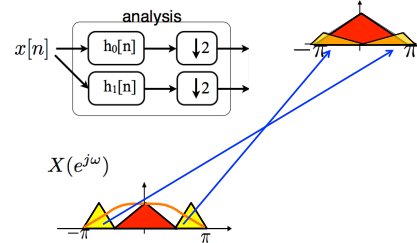


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Non Ideal Filters

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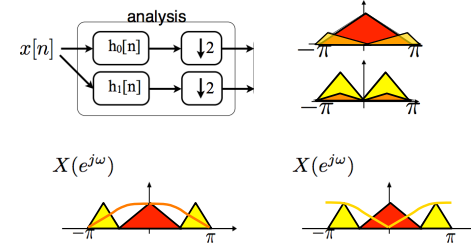


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Non Ideal Filters

- h_0, h_1 are NOT ideal low/high pass

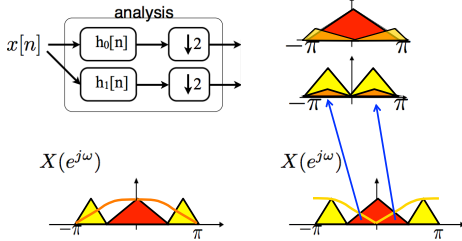


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Non Ideal Filters

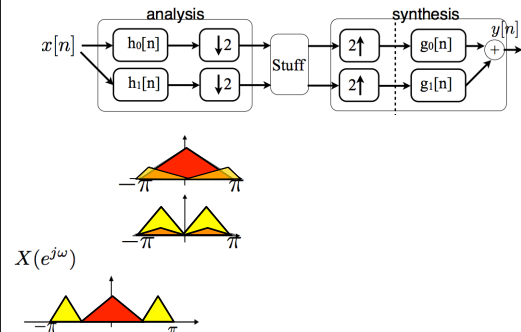
□ h_0, h_1 are NOT ideal low/high pass



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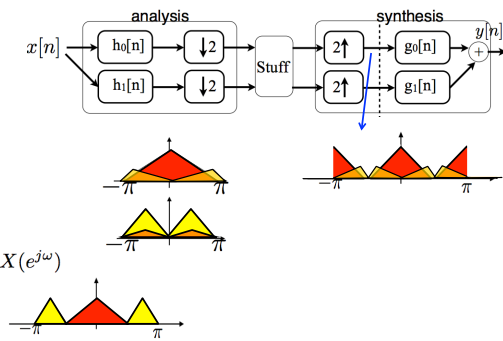
Non Ideal Filters



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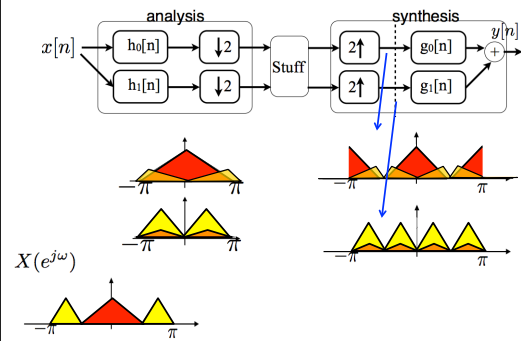
Non Ideal Filters



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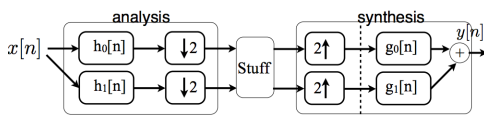
Non Ideal Filters



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Perfect Reconstruction non-Ideal Filters



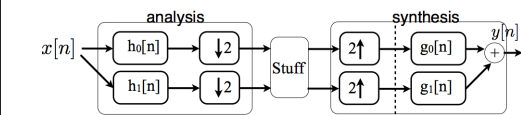
$$Y(e^{j\omega}) = \frac{1}{2} [G_0(e^{j\omega})H_0(e^{j\omega}) + G_1(e^{j\omega})H_1(e^{j\omega})] X(e^{j\omega}) + \frac{1}{2} [G_0(e^{j\omega})H_0(e^{j(\omega-\pi)}) + G_1(e^{j\omega})H_1(e^{j(\omega-\pi)})] X(e^{j(\omega-\pi)})$$

↑ need to cancel!
 ↑ aliasing

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Quadrature Mirror Filters



Quadrature mirror filters

$$\begin{aligned}
 H_1(e^{j\omega}) &= H_0(e^{j(\omega-\pi)}) \\
 G_0(e^{j\omega}) &= 2H_0(e^{j\omega}) \\
 G_1(e^{j\omega}) &= -2H_1(e^{j\omega})
 \end{aligned}$$

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Perfect Reconstruction non-Ideal Filters

$$Y(e^{j\omega}) = \frac{1}{2} [G_0(e^{j\omega})H_0(e^{j\omega}) + G_1(e^{j\omega})H_1(e^{j\omega})] X(e^{j\omega})$$

$$+ \frac{1}{2} [G_0(e^{j\omega})H_0(e^{j(\omega-\pi)}) + G_1(e^{j\omega})H_1(e^{j(\omega-\pi)})] X(e^{j(\omega-\pi)})$$

↑ need to cancel!
 ↑ aliasing

$$\begin{aligned}
 H_1(e^{j\omega}) &= H_0(e^{j(\omega-\pi)}) \\
 G_0(e^{j\omega}) &= 2H_0(e^{j\omega}) \\
 G_1(e^{j\omega}) &= -2H_1(e^{j\omega})
 \end{aligned}$$

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Haar Filter Example

$$\begin{aligned}
 H_1(e^{j\omega}) &= H_0(e^{j(\omega-\pi)}) \\
 G_0(e^{j\omega}) &= 2H_0(e^{j\omega}) \\
 G_1(e^{j\omega}) &= -2H_1(e^{j\omega})
 \end{aligned}$$

Example Haar:

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Polyphase Filter Bank

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Polyphase Decomposition

$$h_k[n] \rightarrow \downarrow M \rightarrow e_k[n]$$

$$e_k[n] = h_k[nM]$$

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Polyphase Filter Bank

$$\begin{aligned}
 e_{00} &= h_0[2n] \\
 e_{01} &= h_0[2n+1] \\
 e_{10} &= e_{00}[n] \\
 e_{11} &= -e_{01}[n]
 \end{aligned}$$

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Polyphase Filter Bank

$$\begin{aligned}
 e_{00} &= h_0[2n] \\
 e_{01} &= h_0[2n+1] \\
 e_{10} &= e_{00}[n] \\
 e_{11} &= -e_{01}[n]
 \end{aligned}$$

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ADC

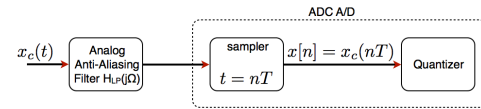
Analog to Digital Converter



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Anti-Aliasing Filter with ADC

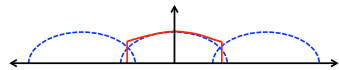


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Aliasing

- If $\Omega_N > \Omega_s/2$, $x_r(t)$ an aliased version of $x_c(t)$

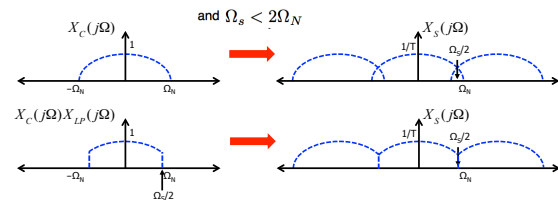
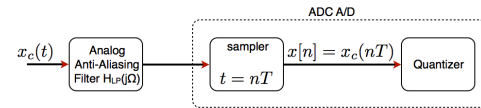


$$X_r(j\Omega) = \begin{cases} TX_s(j\Omega) & \text{if } |\Omega| \leq \Omega_s/2 \\ 0 & \text{otherwise} \end{cases}$$

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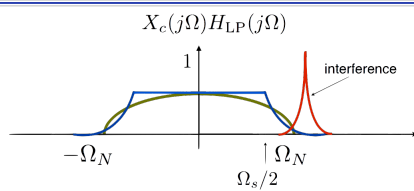
Anti-Aliasing Filter with ADC



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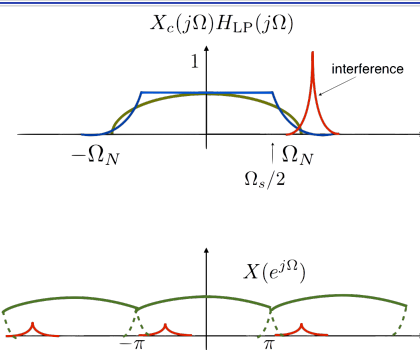
Non-Ideal Anti-Aliasing Filter



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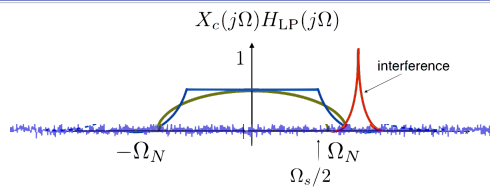
Non-Ideal Anti-Aliasing Filter



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Non-Ideal Anti-Aliasing Filter

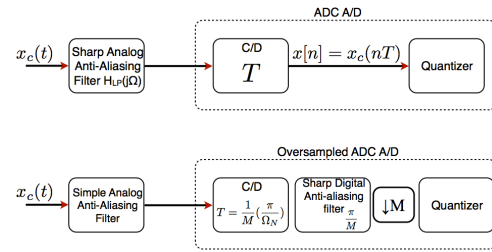


- ❑ Problem: Hard to implement sharp analog filter
- ❑ Consequence: Crop part of the signal and suffer from noise and interference

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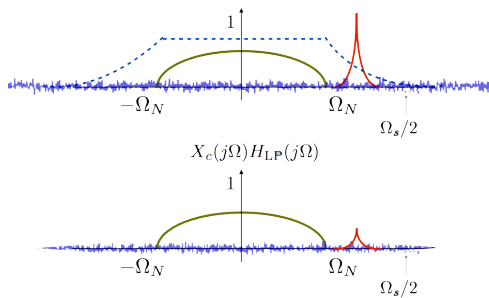
Oversampled ADC



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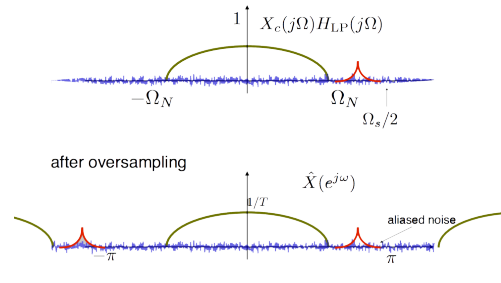
Oversampled ADC – Simple filter



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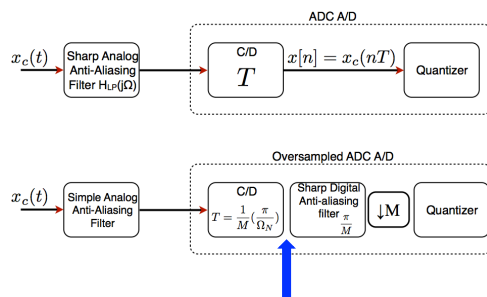
Oversampled ADC – M=2



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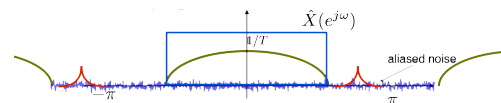
Oversampled ADC



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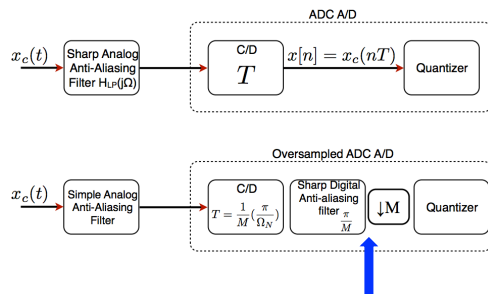
Oversampled ADC – Sharp digital filter/Downsample



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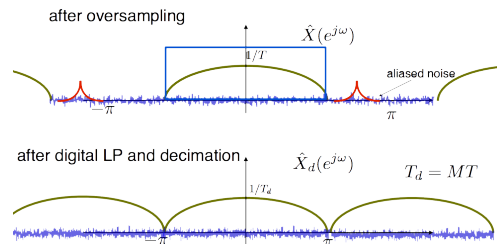
Oversampled ADC



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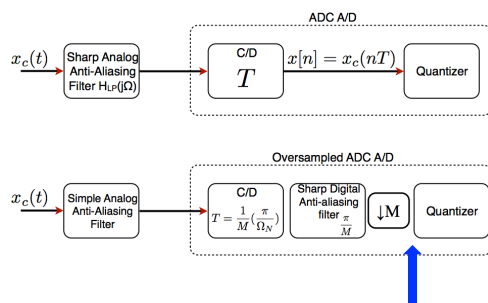
Oversampled ADC - Sharp digital filter/Downsample



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Oversampled ADC

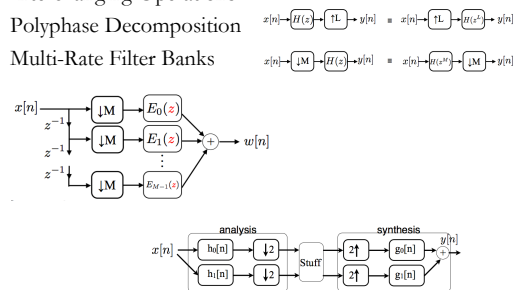


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Big Ideas

- ❑ Interchanging Operations
- ❑ Polyphase Decomposition
- ❑ Multi-Rate Filter Banks



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- ❑ HW 4 due Sunday

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