

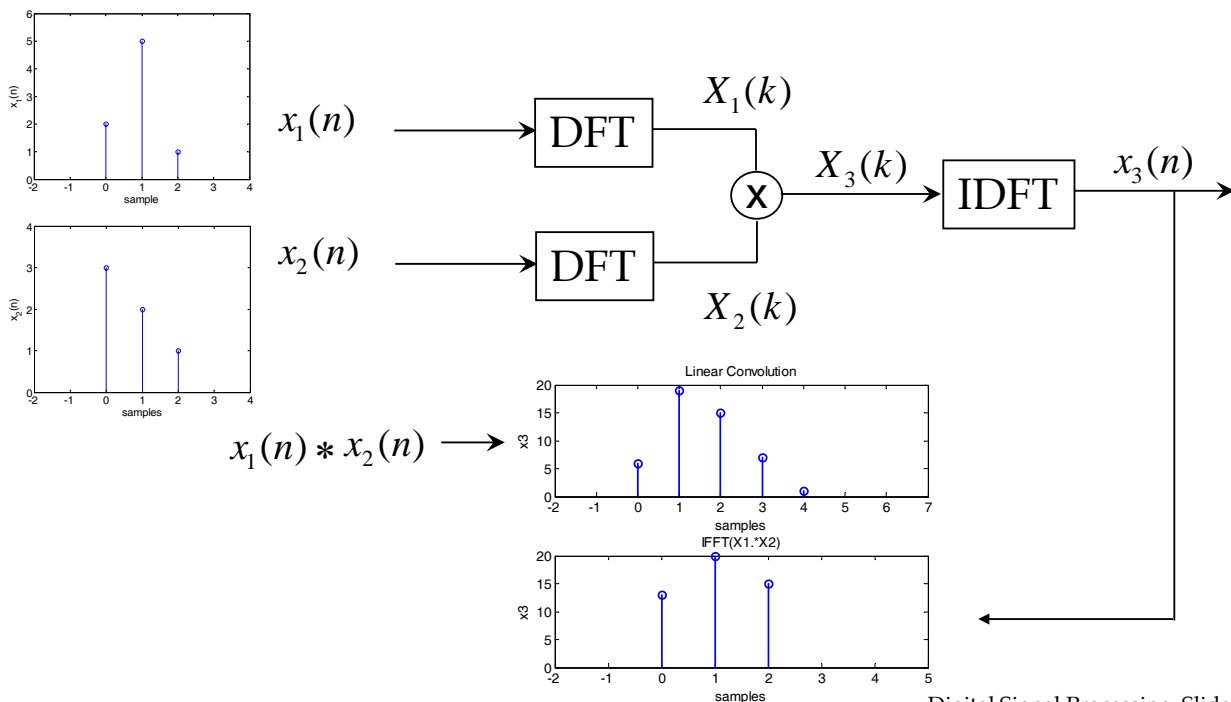
Module 3

Convolution

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Aim

- ◆ How to perform convolution in real-time systems efficiently?
- ◆ Is convolution in time domain equivalent to multiplication of the transformed sequence?



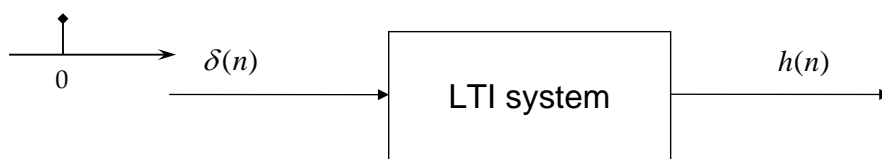
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Contents

- ◆ Review of convolution techniques
- ◆ Linear convolution and circular convolution
 - relationship to filtering
- ◆ Fast algorithms for digital filters
 - block filtering

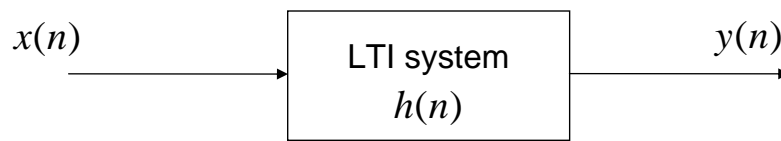
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Introduction



- ◆ Let $\delta(n)$ be the unit impulse sequence $\delta(n) = \begin{cases} 1, & n = 0 \\ 0, & \text{otherwise} \end{cases}$
- ◆ We can write $x(n) = \sum_{k=-\infty}^{\infty} x(k)\delta(n-k)$
 - represent $x(n)$ as sum of delayed and weighted impulse
- ◆ Let $h(n)$ be the output for $\delta(n)$ input
 - $h(n)$ is the impulse response
- ◆ Then $h(n-k)$ is the output for $\delta(n-k)$ input
- ◆ LTI – linear time invariance

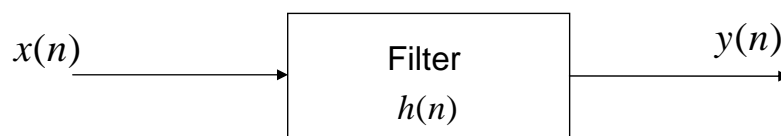
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- ◆ Then by superposition $y(n) = \sum_{k=-\infty}^{\infty} x(k)h(n-k)$
- ◆ $y(n)$ is sum of lots of delayed impulse responses
- ◆ This equation is called the CONVOLUTION SUM

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Linear Convolution



- ◆ Consider unit step input: $x(n) = u(n)$
- ◆ And example filter: $h(n) = a^n u(n)$
- ◆ Task: find $y(n)$
- ◆ Filtering is the operation of convolving a signal with the filter's impulse response.

$$\begin{aligned}
 y(n) &= x(n) * h(n) \\
 &= \sum_{m=-\infty}^{\infty} x(m)h(n-m)
 \end{aligned}$$

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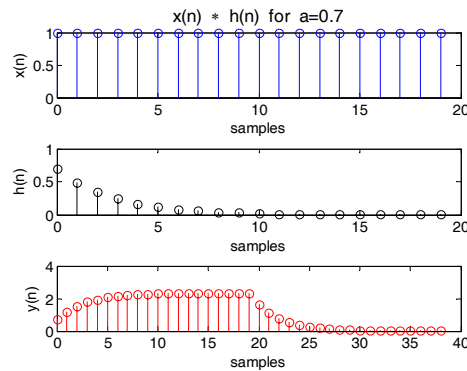
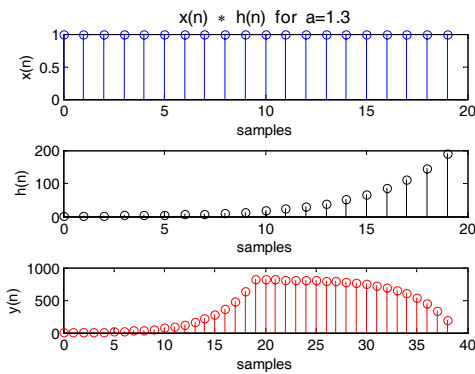
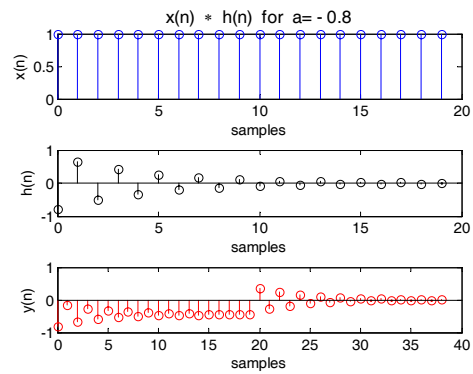
- ◆ For this example:

$$y(n) = 0, \quad n < 0$$

$$y(0) = x(0)h(0) = 1 \quad (\text{all other terms are zero})$$

$$y(n) = 1 + a + a^2 + \dots + a^3, \quad n > 0$$

$$= \frac{1 - a^{n+1}}{1 - a} u(n)$$

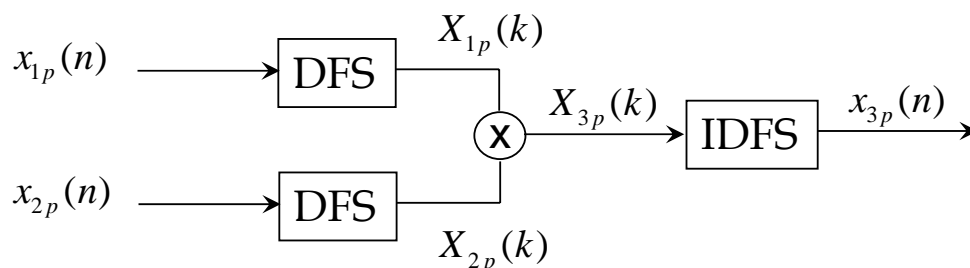


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Periodic and Circular Convolution

- ◆ Develop ideas in terms of periodic signals and DFS, then extend to aperiodic signals.
- ◆ Given 2 periodic signals $x_{1p}(n)$ and $x_{2p}(n)$ with discrete Fourier series coefficients given by $X_{1p}(k)$ and $X_{2p}(k)$ what is $x_{3p}(n)$ formed from

$$x_{3p}(n) = \text{IDFS} \{ X_{3p}(k) = X_{1p}(k) X_{2p}(k) \}$$



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Write

$$X_{3p}(k) = \sum_{l=0}^{N-1} \sum_{r=0}^{N-1} x_{1p}(l) x_{2p}(r) e^{j\frac{2\pi}{N}(-lk-rk)}$$

then

$$x_{3p}(n) = \frac{1}{N} \sum_{k=0}^{N-1} X_{3p}(k) e^{j\frac{2\pi}{N}nk}$$

and finally (proof-tutorial question)

$$x_{3p}(n) = \sum_{l=0}^{N-1} x_{1p}(l) x_{2p}(n-l).$$

Compare to linear convolution

$$x_3(n) = \sum_{m=-\infty}^{\infty} x_1(m) x_2(n-m)$$

◆ Linear convolution:

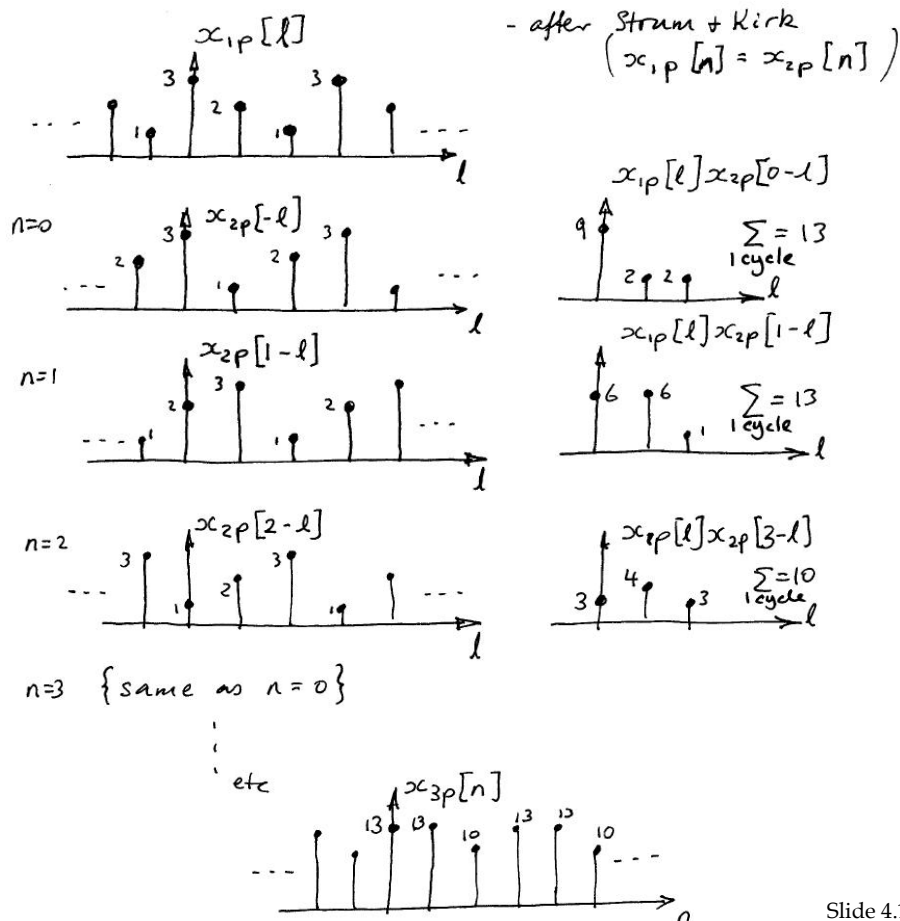
- Sum over infinite extent of signals

◆ Periodic convolution:

- Sum over one period

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Example A



Slide 4.10

Example B

- ◆ So far we have $x_{3p}(n)$ from a convolution of $x_{1p}(n)$ with $x_{2p}(n)$
- ◆ Since $X_{3p}(k) = X_{1p}(k)X_{2p}(k)$
we can also obtain $x_{3p}(n)$ from the IDFS of $X_{3p}(k)$

$$\begin{aligned}X_{1p}(k) &= \sum_{n=0}^2 x_{1p}(n) e^{-j^{2\pi/3}nk} \\ &= [6, \sqrt{3}e^{-j\pi/6}, \sqrt{3}e^{j\pi/6}]\end{aligned}$$

Similarly $X_{2p}(k) = [6, \sqrt{3}e^{-j\pi/6}, \sqrt{3}e^{j\pi/6}]$

$$\therefore X_{3p}(k) = [36, 3e^{-j\pi/3}, 3e^{j\pi/3}]$$

Hence
$$\begin{aligned}x_{3p}(n) &= \frac{1}{3} \sum_{k=0}^2 X_{3p}(k) e^{j^{2\pi/3}nk} \\ &= [13, 13, 10] \quad \text{- as before}\end{aligned}$$

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Periodic - Aperiodic

- ◆ So far we have considered periodic signals
 - Periodic convolution
 - Direct
 - Via DFS
- ◆ Now consider aperiodic signals
 - Circular convolution
 - Treat aperiodic signals as one period of periodic signals

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Circular Convolution

- ◆ Consider aperiodic signals $x_1(n)$ and $x_2(n)$

$x_{1p}(n)$ and $x_{2p}(n)$ are periodic extensions of $x_1(n)$ and $x_2(n)$.

$$x_3(n) = \text{one period of } \left\{ \sum_{l=0}^{N-1} x_{1p}(l)x_{2p}(n-l) \right\}$$

$$x_3(n) = x_1(n) \otimes x_2(n)$$

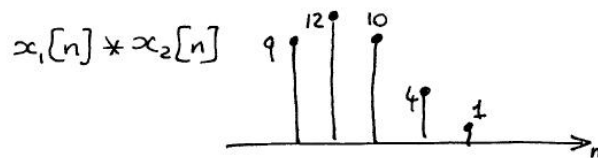
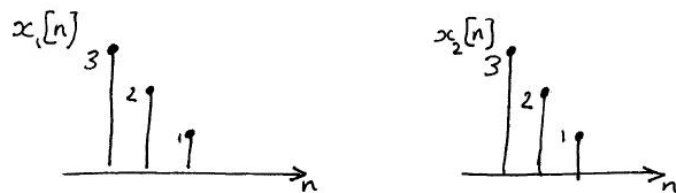
$$DFT \{x_3(n)\} = DFT \{x_1(n) \otimes x_2(n)\} = X_1(k)X_2(k)$$

- ◆ The symbol \otimes means circular convolution
 - Perform periodic extension
 - Take one period of the result of periodic convolution

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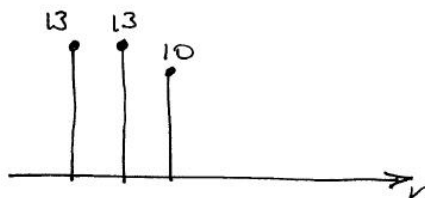
Example

- ◆ Consider Linear convolution of $x_1(n) * x_2(n)$



- ◆ Consider Circular convolution of $x_1(n) \otimes x_2(n)$

- different length
- different values



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Relationship between Linear Convolution and Circular Convolution

- ◆ Why are we interested?
 - Linear convolution is the filtering operation
 - Filters are a very important application of DSP
 - Would like to implement filters efficiently
 - FFT is a fast DFT
 - Maybe we can use FFTs to implement filters (?)

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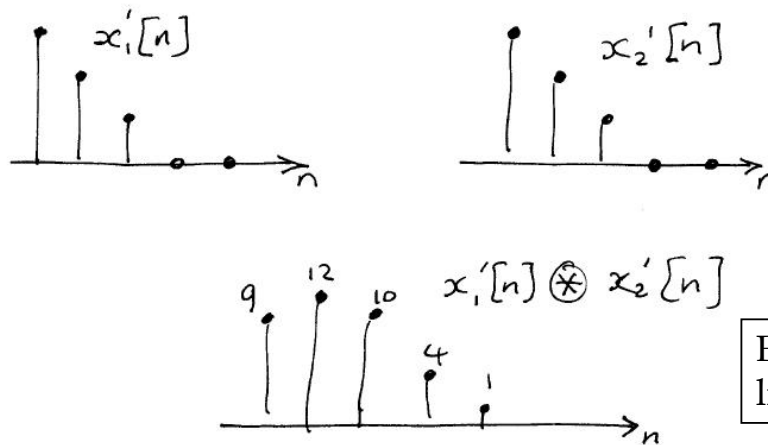
- ◆ We desire that circular and linear convolution give identical results, then we can use FFTs for fast filtering
- ◆ This can be achieved by applying zero-padding to the signals before performing circular convolution

- ◆ For a signal $x_1(n)$ of length N_1 and signal $x_2(n)$ of length N_2
- ◆ Zero-pad $x_1(n)$ with $N_2 - 1$ zeros
- ◆ Zero-pad $x_2(n)$ with $N_1 - 1$ zeros

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Example

- ◆ For a signal $x_1(n)$ of length N_1 and signal $x_2(n)$ of length N_2
- ◆ Zero-pad $x_1(n)$ with $N_2 - 1$ zeros to give $x_1'(n)$
- ◆ Zero-pad $x_2(n)$ with $N_1 - 1$ zeros to give $x_2'(n)$



Equivalent to
linear convolution

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Summary

$$x_1(n) * x_2(n) = x_1'(n) \otimes x_2'(n) = \text{IDFT} \{ X_1'(k) X_2'(k) \}$$

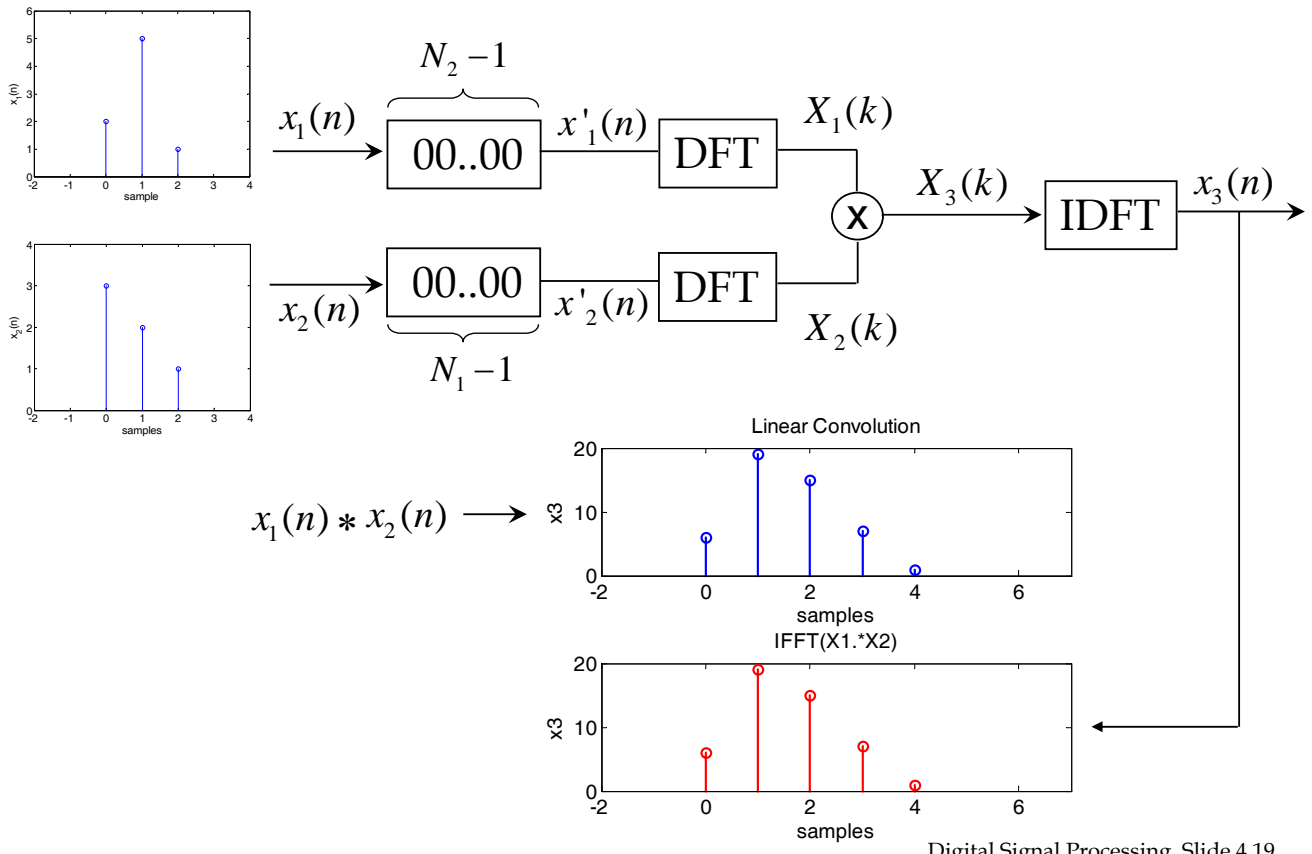
given that $X_1(k) = \text{DFT} \{ x(n) \}$

and $x_1'(n)$ is a zero-padded version of $x_1(n)$

* means Linear Convolution

⊗ means Circular Convolution

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Complexity

- ◆ Direct implementation
 - N^2 multiplies

- ◆ DFT Implementation

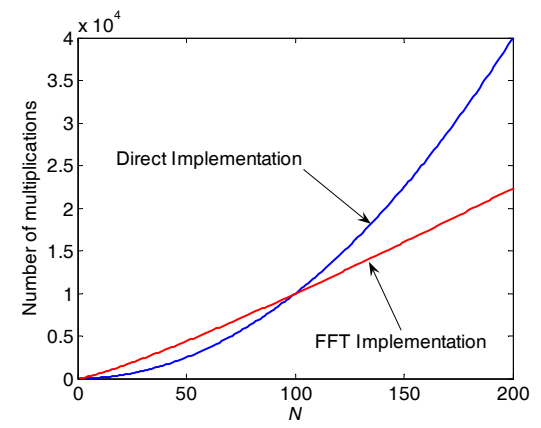
$$4 \times [2 \times (2N)^2 + 2N + (2N)^2] = 48N^2 + 8N$$

↑ for complex multiplications 2 DFTs of $2N-1$ points Product of 2 sequences of length $2N$ 1 IDFT

- ◆ FFT Implementation

$$4 \times \left[2 \times \left(\frac{2N}{2} \log_2 2N \right) + 2N + \left(\frac{2N}{2} \log_2 2N \right) \right]$$

$$= 12N \log_2 2N + 8N$$



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Block Filtering

- ◆ FFT-based convolution has advantage of lower computational complexity
 - But if data is long, must wait until all the data is captured
 - Long delay
- ◆ Solution
 - Use block filtering
 - Use FFT-based convolution on short blocks of data
 - Then join blocks together
- ◆ Sectioned convolution: two main methods
 - Overlap add
 - Overlap save

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Overlap-add Procedure

$$y(n) = \sum_{m=-\infty}^{\infty} x(m)h(n-m)$$

$x(n)$: data; divide into blocks of length L

$h(n)$: impulse response; length M

- ◆ Perform linear convolution using FFT
- ◆ Each block of $x(n)$ padded with $M-1$ zeros
- ◆ Each block of $h(n)$ padded with $L-1$ zeros

$$y_1(n) = \text{IFFT} \{ X_1'(k) H'(k) \}$$

First block

Computed once and stored

- ◆ Size of FFT: next integer power of 2 greater than or equal to $L+M-1$
 - M is fixed by the filter impulse response
 - Choose to obtain convenient size of FFT

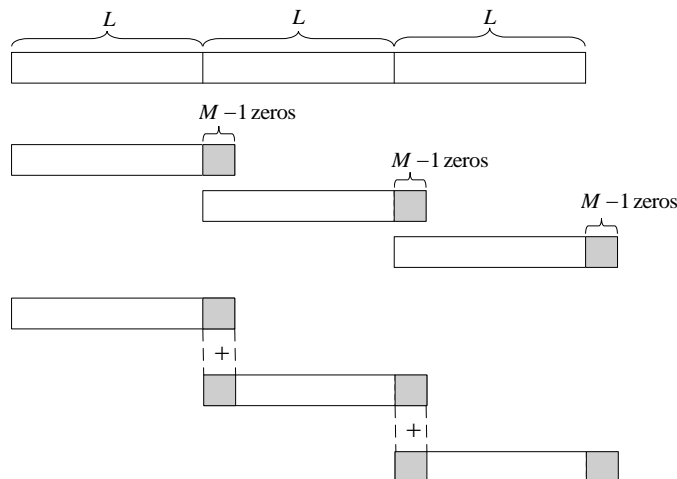
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◆ Note that the length of $y_1(n)$ is $L+M-1$

- first L samples are true values
- $M-1$ samples are in the overlap

$$y_2(n) = \text{IFFT} \{ X'_2(k) H'(k) \}$$

- $y_2(n)$ is added to $y_1(n)$ with a shift of L samples



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Overlap-save Procedure

$$y(n) = \sum_{m=-\infty}^{\infty} x(m)h(n-m)$$

$x(n)$: data; divide into blocks of length L

$h(n)$: impulse response; length M

- ◆ Perform linear convolution using FFT
- ◆ Each block of $x(n)$ consists of
 - the last $M-1$ data points from previous data block
 - follow by L new points
- ◆ Each block of $h(n)$ padded with $L-1$ zeros

$$y_1(n) = \text{IFFT} \{ X'_1(k) H'(k) \}$$

- ◆ Size of FFT: next integer power of 2 greater than or equal to $L+M-1$
 - M is fixed by the filter impulse response
 - Choose to obtain convenient size of FFT

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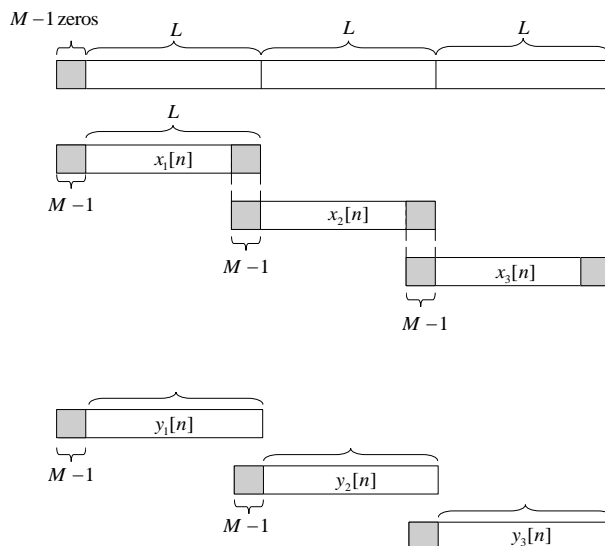
- ◆ Note that the length of $y_1(n)$ is $L+M-1$

- last L samples are true values
- $M-1$ samples are in the overlap

$$y_2(n) = \text{IFFT} \{ X'_2(k) H'(k) \}$$

second block

- Discard the first $M-1$ samples, only last L samples are saved



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Correlation

- ◆ Operation to determine some measure of similarity between two signals
- ◆ Correlation of two signals $x(n)$ and $y(n)$ is defined as

$$r_{xy}(l) = \sum_{n=-\infty}^{\infty} x(n)y(n-l), \quad l = 0, \pm 1, \pm 2, \dots$$

l is the index of the correlation function $r_{xy}(l)$ and is referred to as “lag”

- ◆ Autocorrelation is the special case when $x(n) = y(n)$

or the
lock

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◆ Relationship between correlation and convolution

■ Convolution

$$s(n) = \sum_{m=-\infty}^{\infty} x(m)y(n-m)$$

$$= x(n) * y(n)$$

Time reversed and delayed samples of $y[m]$

■ Correlation

$$r_{xy}(l) = \sum_{n=-\infty}^{\infty} x(n)y(n-l)$$

$$= \sum_{n=-\infty}^{\infty} x(n)y(-(l-n))$$

$$= x(l) * y(-l)$$

Delayed samples of $y[n]$

- ◆ Therefore, correlation can be implemented by a convolution algorithm providing one of the inputs is given time-inversed

Property of Correlation

- ◆ We can write $r_{xy}(l) = \sum_{n=-\infty}^{\infty} x(n)y(n-l)$
- $$= \sum_{n=-\infty}^{\infty} x(n+l)y(n), \quad l = 0, \pm 1, \pm 2, \dots$$

- ◆ Similarly, $r_{yx}(l) = \sum_{n=-\infty}^{\infty} y(n)x(n-l)$
- $$= \sum_{n=-\infty}^{\infty} y(n+l)x(n), \quad l = 0, \pm 1, \pm 2, \dots$$

- ◆ From which, we can deduce that

$$r_{xy}(l) = r_{yx}(-l)$$

- ◆ For the autocorrelation function, we obtain an even function

$$r_{xx}(l) = r_{xx}(-l)$$