

INTRODUCTION TO EECS II
DIGITAL COMMUNICATION SYSTEMS

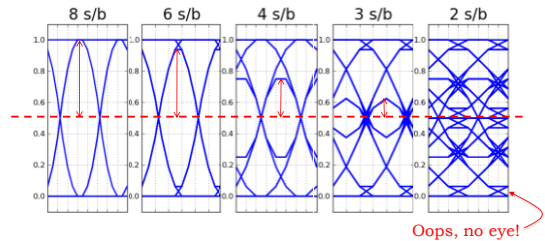
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Lecture #12

- Convolution
- LTI System Interconnections
- Deconvolution

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Lecture 12, Slide #1

Choosing Samples/Bit

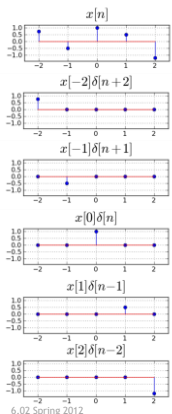


Given $h[n]$, you can use the eye diagram to pick the number of samples transmitted for each bit (N):

Reduce N until you reach the noise margin you feel is the minimum acceptable value.

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Lecture 12, Slide #2



Unit Sample Decomposition

A discrete-time signal can be decomposed into a sum of time-shifted, scaled unit sample functions.

Example: in the figure, $x[n]$ is the sum of $x[-2]\delta[n+2] + x[-1]\delta[n+1] + \dots + x[2]\delta[n-2]$.

In general:

$$x[n] = \sum_{k=-\infty}^{\infty} x[k]\delta[n-k]$$

For any particular index, only one term of this sum is non-zero

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Lecture 12, Slide #3

Convolution!

If system S is both linear and time-invariant (LTI), then we can use the **unit sample response $h[n]$** to predict the response to *any* input waveform $x[n]$:

Sum of shifted, scaled unit sample functions

$$x[n] = \sum_{k=-\infty}^{\infty} x[k]\delta[n-k] \rightarrow \boxed{\begin{matrix} S \\ h[\cdot] \end{matrix}} \rightarrow y[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k]$$

Sum of shifted, scaled unit sample responses, with the same scale factors

CONVOLUTION SUM

Indeed, the unit sample response $h[n]$ completely characterizes the LTI system S , so you often see

$$x[n] \rightarrow \boxed{h[\cdot]} \rightarrow y[n]$$

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

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To Convolve (but not to “Convolute”!)

$$y[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k]$$

A simple graphical implementation:

Plot $x[\cdot]$ and $h[\cdot]$ as a function of the dummy index (k or m above)

Flip (i.e., reverse) one signal in time, **slide** it right **by n** (slide left if n is -ve), take the **dot product** with the other.

This yields the value of the convolution at the single time n.

‘flip one, & slide by n... dot product with the other’

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Channels as LTI Systems

Many transmission channels can be effectively modeled as LTI systems. When modeling transmissions, there are few simplifications we can make:

- We'll call the time transmissions start $t=0$; the signal before the start is 0. So $x[m] = 0$ for $m < 0$.
- Real-world channels are **causal**: the output at any time depends on values of the input at only the present and past times. So $h[m] = 0$ for $m < 0$.

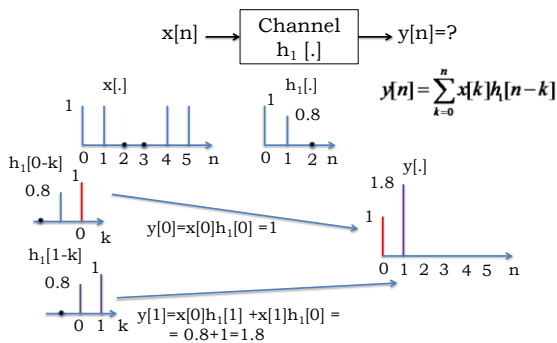
$$y[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k] = \sum_{k=0}^{\infty} x[k]h[n-k] = \sum_{k=0}^n x[k]h[n-k] = \sum_{j=0}^n x[n-j]h[j]$$

\leftarrow start at $t=0$
 \leftarrow causal
 \leftarrow $j=n-k$

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Lecture 12, Slide #6

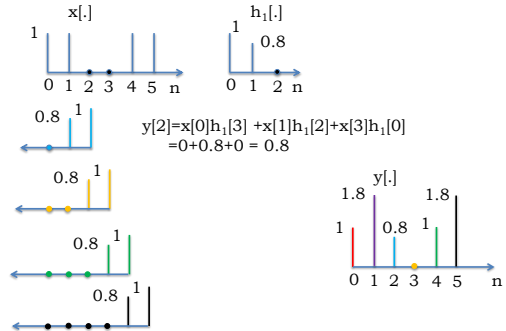
Convolution example - Echo channel



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Lecture 12, Slide #7

Convolution example - Echo channel



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Properties of Convolution

$$(x * h)[n] \equiv \sum_{k=-\infty}^{\infty} x[k]h[n-k] = \sum_{m=-\infty}^{\infty} h[m]x[n-m]$$

The second equality above, which follows from the simple change of variables $\mathbf{n-k=m}$, establishes that convolution is **commutative**:

$$x * h = h * x$$

Convolution is **associative**:

$$h_2 * (h_1 * x) = (h_2 * h_1) * x$$

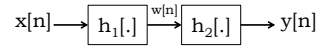
Convolution is **distributive**:

$$(h_1 + h_2) * x = (h_1 * x) + (h_2 * x)$$

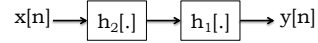
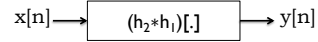
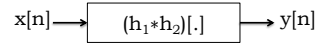
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Series Interconnection of LTI Systems



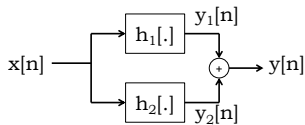
$$y = h_2 * w = h_2 * (h_1 * x) = (h_2 * h_1) * x = (h_1 * h_2) * x$$



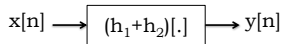
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Parallel Interconnection of LTI Systems



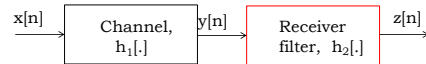
$$y = y_1 + y_2 = (h_1 * x) + (h_2 * x) = (h_1 + h_2) * x$$



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“Deconvolving” Output of Channel with Echo



Suppose channel is LTI with

$$h_1[n] = \delta[n] + 0.8\delta[n-1]$$

Find $h_2[n]$ such that $z[n] = x[n]$

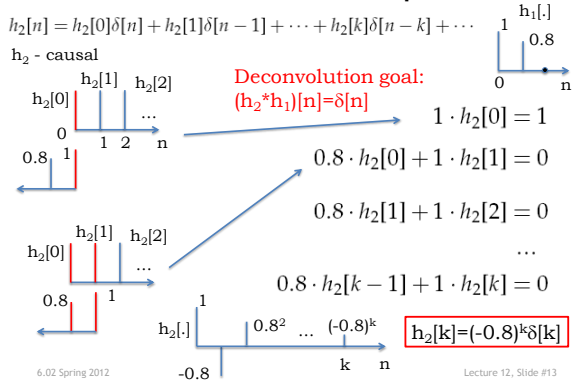
$$\Rightarrow (h_2 * h_1)[n] = \delta[n]$$

Good exercise in applying Flip/Slide/Dot.Product

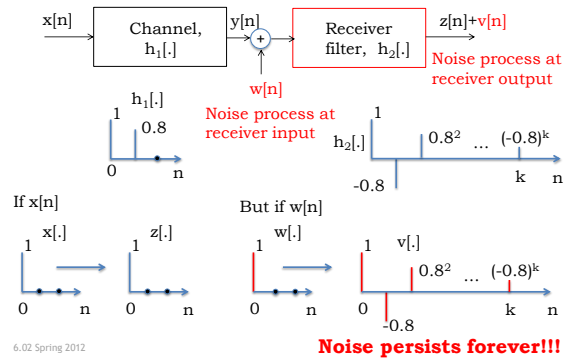
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Lecture 12, Slide #12

Deconvolution example



Noise impact on Deconvolver



Stability

What ensures that the infinite sum

$$y[n] = \sum_{m=-\infty}^{\infty} h[m]x[n-m]$$

is well-behaved?

One important case: If the unit sample response is *absolutely summable*, i.e.,

$$\sum_{m=-\infty}^{\infty} |h[m]| < \infty$$

and the input is *bounded*, i.e., $|x[k]| \leq M < \infty$

Under these conditions, the convolution sum is well-behaved, and the *output* is guaranteed to be **bounded**.

The **absolute summability** of $h[n]$ is necessary and sufficient for this **bounded-input bounded-output (BIBO) stability**.