

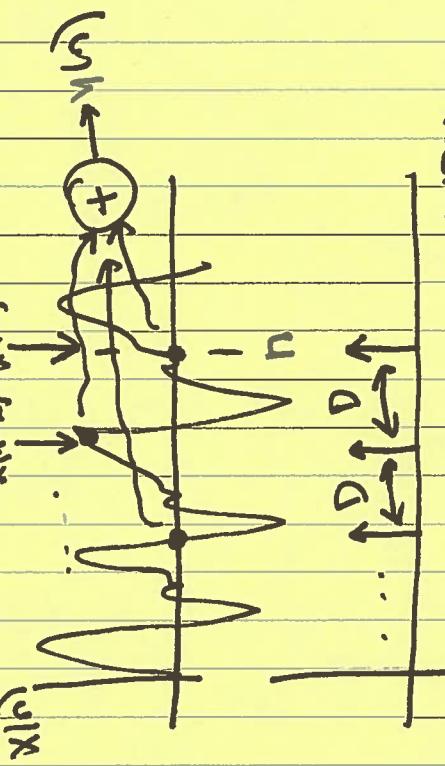
①

Signal averaging using comb filter

$$H(z) = \frac{1}{N} (1 - z^{-D} + z^{-2D} + \dots + z^{-(N-1)D})$$

$$= \frac{1}{N} \frac{1 - z^{-ND}}{1 - z^{-D}}$$

$$h(n) = \frac{1}{N} [\delta(n) + \delta(n-D) + \delta(n-2D) + \dots]$$



$$H(z) = \frac{H(z)}{z - e^{j\omega}}$$

$$\Delta \omega = \frac{2\pi}{ND}$$

$$\Delta f = \frac{1}{NT} = \frac{1}{NDT}$$

$$T_0 = DT$$

$$y(n) = \frac{1}{N} [x(n) + x(n-D) + \dots + x(n-(N-1)D)]$$

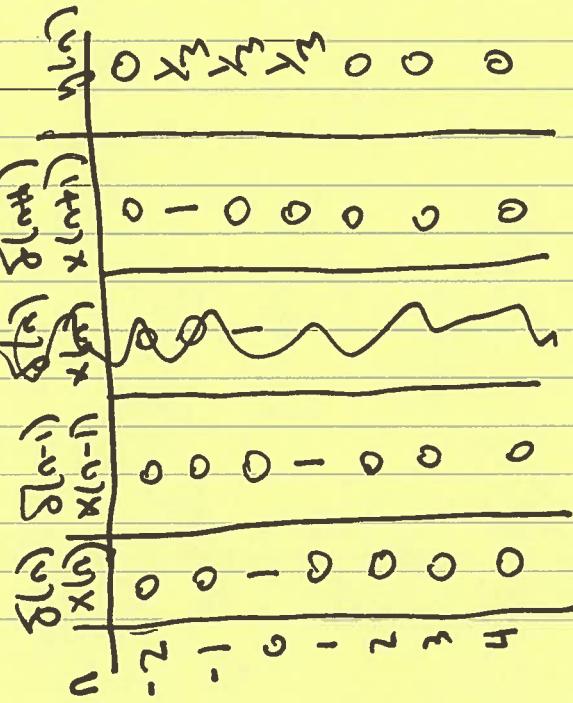
uses ND memory elements

Lecture 22: Signal Averaging

$$y(n) = \frac{1}{3} [x(n-1) + x(n) + x(n+1)]$$

Impulse response:

$$h(n) = \frac{1}{3} [\delta(n-1) + \frac{1}{3} \delta(n) + \frac{1}{3} \delta(n+1)]$$



Average = (1/3)(8 in window)

Average = 2.67

Ans 2.67

Golay Filters (Savitzky-Golay) SG

These are limits to how much smoothing.
@ on FIR filters with constant coefficients

can do.

SG filters operate using polynomial smoothing



$$x_m = c_0 \text{ constant}$$

$$x_m = c_0 + c_1 m \text{ linear}$$

$$x_m = c_0 + c_1 m + c_2 m^2 \text{ quadratic}$$

optimizes coefficients based on data

least squares error:

$$\rightarrow J = \sum_{m=-2}^2 e_m^2 = \sum_{m=-2}^2 (x_m - (c_0 + c_1 m + c_2 m^2))^2$$

minimize J with respect to c_0, c_1, c_2

$$\text{approach: } \frac{\partial J}{\partial c_0} = \dots = 0$$

Solution is well-known:

$$\hat{x} = \bar{x}$$

$$C = \bar{G}^T X$$

c: Parameter vector (c_0, c_1, c_2)

\bar{G} : is a matrix:

$$\bar{G} = \bar{S}(\bar{S}^T \bar{S})^{-1}$$

$$\bar{S} : [\bar{s}_0, \bar{s}_1, \bar{s}_2] = \begin{bmatrix} 1 & -2 & 1 \\ -1 & 0 & -1 \\ 1 & 2 & 1 \end{bmatrix}$$

relates to basis functions

$$s_0(m) = 1 \quad s_1(m) = m \quad s_2(m) = m^2$$

indications:

\bar{G} is a constant (pre-computed)

$$C = \bar{G}^T X \text{ data-dependent}$$

\Rightarrow time-varying filter

smoothed output: $\hat{x} = \bar{B}^T \bar{x}$ pre-computed

$$\hat{x} = \bar{B}^T \bar{x}$$