# Filtered Random Processes

- Consider the 2-D linear system

$$Y(m,n) = h(m,n) * X(m,n)$$

where $X(m,n)$ is a 2-D wide sense stationary random process.

- It may be easily shown that

$$R_y(m,n) = h(m,n) * h(-m,-n) * R_x(m,n)$$

$$S_y(e^{j\mu}, e^{j\nu}) = \left|H(e^{j\mu}, e^{j\nu})\right|^2 S_x(e^{j\mu}, e^{j\nu})$$

## White Noise

- Definition:
  - $X(m,n)$ - independent identically distributed (i.i.d.) Gaussian random variables with distribution $N(0,1)$.
- Then
  - $X(m,n)$ is wide sense stationary with

$$
\begin{aligned}
\mu(m,n) &= 0 \\
R_x(k,l) &= E[X(0,0)X(k,l)] \\
&= \delta(k,l) \\
S_x(e^{j\mu}, e^{j\nu}) &= DSFT\{R_x(k,l)\} \\
&= 1
\end{aligned}
$$

## Filtered White Noise

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  - $Y(m,n) = h(m,n) * X(m,n)$.
- Then
  - $Y(m,n)$ is wide sense stationary with

$$\begin{aligned} S_y(e^{j\mu}, e^{j\nu}) &= \left|H(e^{j\mu}, e^{j\nu})\right|^2 S_x(e^{j\mu}, e^{j\nu}) \\ &= \left|H(e^{j\mu}, e^{j\nu})\right|^2 \cdot 1 \\ R_y(k,l) &= h(m,n) * h(-m,-n) \\ &= \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} h(m,n) h(m+k, n+l) \end{aligned}$$

  - $R_y(k,l)$ is the autocorrelation of $h(m,n)$ with itself.

## Causal Prediction

- $Y_s$ is a 2-D wide sense stationary Gaussian random process.
- Define
  - The past values are $Y_{<s} = \{Y_r : r < s\}$.
  - The minimum mean squared error (MMSE) predictor of $Y_s$ given the past is

$$\hat{Y}_s = E[Y_s | Y_{<s}]$$

  - The prediction error is $X_s = Y_s - \hat{Y}_s$.

## Properties of Causal Predictors

- Fact 1: (WLOG, assume $r < s$.)

$$
\begin{aligned}
E[X_s X_r] &= E[E[X_s X_r | Y_{<s}]] \\
&= E[E[(Y_s - \hat{Y}_s)(Y_r - \hat{Y}_r) | Y_{<s}]] \\
&= E[E[(Y_s - \hat{Y}_s) | Y_{<s}](Y_r - \hat{Y}_r)] \\
&= E[(E[Y_s | Y_{<s}] - \hat{Y}_s)(Y_r - \hat{Y}_r)] \\
&= E[(\hat{Y}_s - \hat{Y}_s)(Y_r - \hat{Y}_r)] \\
&= E[0(Y_r - \hat{Y}_r)] = 0
\end{aligned}
$$

- Fact 2: $\sigma^2 \triangleq E[X_s^2]$ is the prediction variance.
- Fact 3: The predictor must be space invariant and linear.

$$
\hat{Y}_s = \sum_{r > (0,0)} h_r Y_{s-r}
$$

## Autoregressive (AR) Processes

- Definitions:
  - $Y_s$ - 2-D wide sense stationary Gaussian random process.
  - $h_s$ - MMSE linear predictor for $Y_s$.
  - $X_s = Y_s - h_s * Y_s$ - predictor error.

- If $h_s$ is FIR, then $Y_s$ is known as an autoregressive (AR) process.

## Properites of AR Processes

- Remember that

$$X_s = Y_s - h_s * Y_s$$

- Then
  - We know that

$$Y(e^{j\mu}, e^{j\nu}) = \frac{1}{1 - H(e^{j\mu}, e^{j\nu})} X(e^{j\mu}, e^{j\nu})$$

  - Since $X_s$ is white noise,

$$\begin{aligned} R_x(s) &= \sigma^2 \delta(s) \\ S_x(e^{j\mu}, e^{j\nu}) &= \sigma^2 \end{aligned}$$

  - So the power spectrum of $Y_s$ is given by

$$S_y(e^{j\mu}, e^{j\nu}) = \frac{\sigma^2}{\left|1 - H(e^{j\mu}, e^{j\nu})\right|^2}$$

## Spectral Estimate Using AR Processes

- Compute MMSE linear predictor $\hat{h}_s$ for $Y_s$.
- Compute the prediction variance

$$\hat{\sigma}^2 = \frac{1}{|S|} \sum_{s \in S} |Y_s - h_s * Y_s|^2$$

  where $S$ is a finite set of points in plain, and $|S|$ is the number of points in $S$.

- Estimate the power spectrum

$$S_y(e^{j\mu}, e^{j\nu}) = \frac{\hat{\sigma}^2}{\left|1 - \hat{H}(e^{j\mu}, e^{j\nu})\right|^2}$$

- Can produce a more accurate estimate of the power spectrum.

## Generating AR Processes

- Select a causal prediction filter $h_s$.
- Apply IIR filter to white noise random process $X_s$

$$Y(e^{j\mu}, e^{j\nu}) = \frac{1}{1 - H(e^{j\mu}, e^{j\nu})} X(e^{j\mu}, e^{j\nu})$$

- $Y_s$ is sometimes referred to as a white noise driven process.
- Do linear FIR prediction filters $\hat{h}_s$ always form a stable IIR filter?
  - In 1-D, yes.
  - In 2-D, not always!
- Other problems:
  - Causal ordering of points may cause asymmetric artifacts in results.
  - Complexity increases rapidly with IIR filter order $P$.