



## Overview of vector random (stochastic) processes

- A stochastic or random process is a family of random vectors indexed by a parameter set ("time" in our case)
- For example, we might refer to a random process  $X_k$  for generic  $k$ 
  - Value of random process at any specific time  $k = m$  is a random variable  $X_m$
- Usually assume stationarity
  - The statistics (*i.e.*, pdf) of the RV are time-shift invariant
  - Therefore,  $\mathbb{E}[X_k] = \bar{x}$  for all  $k$  and  $\mathbb{E}[X_{k_1} X_{k_2}^T] = R_X(k_1 - k_2)$



## Properties and important points

1. Autocorrelation:  $R_X(k_1, k_2) = \mathbb{E}[X_{k_1} X_{k_2}^T]$ . If stationary,

$$R_X(\tau) = \mathbb{E}[X_k X_{k+\tau}^T]$$

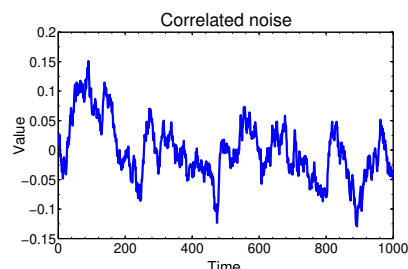
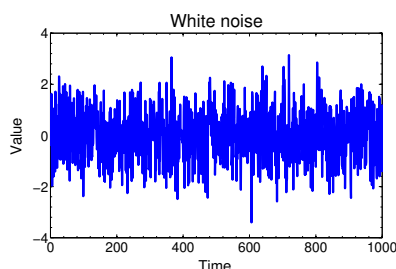
- Provides a measure of correlation between elements of the process having time displacement  $\tau$
  - $R_X(0) = \sigma_X^2$  for zero-mean  $X$
  - $R_X(0)$  is always the maximum value of  $R_X(\tau)$
2. Autocovariance:  $C_X(k_1, k_2) = \mathbb{E}[(X_{k_1} - \mathbb{E}[X_{k_1}])(X_{k_2} - \mathbb{E}[X_{k_2}])^T]$ . If stationary,

$$C_X(\tau) = \mathbb{E}[(X_k - \bar{x})(X_{k+\tau} - \bar{x})^T]$$



## White noise

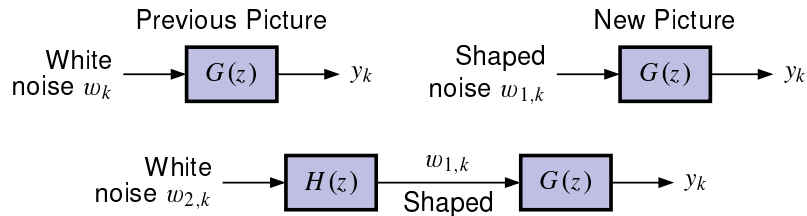
- White noise: Some processes have a unique autocorrelation:
  1. Zero mean
  2.  $R_X(\tau) = \mathbb{E}[X_k X_{k+\tau}^T] = S_X \delta(\tau)$  where  $\delta(\tau)$  is the Dirac delta.  $\delta(\tau) = 0 \forall \tau \neq 0$
- Therefore, the process is uncorrelated in time
- Clearly an abstraction, but proves to be a very useful one





## Shaping filters: Idea

- Will assume noise inputs to dynamic systems are white
  - Limiting assumption, but one that can be easily fixed
    - ➡ Can use second linear system to “shape” the noise as desired.



- Can drive our linear system with noise that has desired characteristics by introducing shaping filter  $H(z)$  that itself is driven by white noise



## Shaping filters: Model

- Combined system  $GH(z)$  looks exactly the same as before, *but*  $G(z)$  is not driven by pure white noise any more
  - Analysis *augments* original system model with filter states. Original system has
  - Shaping filter with white input and desired output statistics has

$$\begin{aligned} x_{k+1} &= Ax_k + B_w w_{1,k} \\ y_k &= Cx_k \end{aligned}$$

$$\begin{aligned} x_{s,k+1} &= A_s x_{s,k} + B_s w_{2,k} \\ w_{1,k} &= C_s x_{s,k} \end{aligned}$$

- Combine into larger-order augmented system driven by white noise:

$$\begin{bmatrix} x_{k+1} \\ x_{s,k+1} \end{bmatrix} = \begin{bmatrix} A & B_w C_s \\ 0 & A_s \end{bmatrix} \begin{bmatrix} x_k \\ x_{s,k} \end{bmatrix} + \begin{bmatrix} 0 \\ B_s \end{bmatrix} w_{2,k}$$

$$y_k = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x_k \\ x_{s,k} \end{bmatrix}$$



## Gaussian processes

- We will work with Gaussian noises to a large extent
  - Uniquely defined by the first- and second central moments of the statistics ➡ Gaussian assumption not essential
  - Our filters will always track only the first two moments.

**NOTATION:** Until now, we have always used capital letters for random variables

- State of system driven by random process is an RV, so we could call it  $X_k$
- More common to retain standard notation  $x_k$  and understand from context that we are discussing an RV



## Summary

- Random process is a family of RVs indexed by time
- Will assume our random processes are stationary
- Autocorrelation and autocovariance measure self-predictability of a signal at different time offsets
- White noise is zero mean signal, completely uncorrelated with self (“completely random”)
  - An abstraction, but a very useful one
- If noises in a system of interest are not white, can filter white noise to create same general characteristics
- From now on, unless stated otherwise, all noise signals will be white and Gaussian