ECE 417 Identification & Adaptive Control Fall 2001

Handout: Spectral Densities and Linear Systems

Wide sense stationary processes Let $u = \{u_k : k \ge 0\}$ be a (wide sense) stationary process, so that the following limits hold.

$$\mu := \lim_{N \to \infty} \frac{1}{N} \sum_{k=1}^{N} u(k) = \mathsf{E}[u(0)]; \quad R(n) := \lim_{N \to \infty} \frac{1}{N} \sum_{k=1}^{N} (u(k) - \mu)(u(k+n) - \mu) = \mathsf{E}[u(0)u(n)].$$

Any signal \boldsymbol{u} of the form $u(k) = \sum_{i=1}^{m} \alpha_i \sin(\omega_i k + \phi_i)$ is WSS, but this family of signals is far larger than merely sums of sinusoids.

We call R the *autocorrelation sequence* of u. The *spectral density* is defined as

$$f(\omega) = \lim_{N \to \infty} \sum_{k=-N}^{N} R(k) e^{-jk\omega}$$

= the discrete time Fourier transform of R(n)

The spectral density satisfies numerous special properties:

- (i) *periodic*, with period 2π ;
- (ii) even, $f(\omega) = f(-\omega)$ for all ω ;
- (iii) positive valued, $f(\omega) \ge 0$ for all ω .

(iv)
$$R(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{jn\omega} f(\omega) \, d\omega$$
 (from the inversion formula for Fourier transforms)

Hence R(n) is represented by its spectral density. The process u can also be represented through a random spectral process ξ :



Interpretation: The process u is approximated by a random sum of sinusoids:

$$u(n) \approx \sum_{k=-N+1}^{N} \gamma_k e^{jn\omega_k}$$
, where $\gamma_k = \xi(\omega_k) - \xi(\omega_{k-1})$, and $\omega_k = k\pi/N$.

Properties of the spectral process ξ : For $\omega_1 < \omega_2 < \omega_3$,

Orthoganl increments $\mathsf{E}[(\xi(\omega_3) - \xi(\omega_2))(\xi(\omega_2) - \xi(\omega_1))] = 0.$

Bounded power
$$\mathsf{E}[|\xi(\omega_2) - \xi(\omega_1)|^2] = \frac{1}{2\pi} \int_{\omega_1}^{\omega_2} f(\tau) d\tau.$$



Simple examples of autocorrelation and spectral density functions Note: In these examples, the mean is $\mu = 10 \neq 0$. Hence, the spectral density possesses mass at the origin, corresponding to a non-zero DC component in the signal \boldsymbol{z} . This will be subtracted, so that the mean of \boldsymbol{z} is zero.

Consider the two processes,

$$z(t) = 10 + u(t) - u(t-1),$$
 $z(t) = 10 + u(t) - u(t-1),$

where u is a sequence of uncorrelated, random Normal variables with mean zero and variance one. Below are sample paths from the two models



Model 1: z(k) = 10 + u(k) + u(k-1)

Model 2: z(k) = 10 + u(k) - u(k-1)

Using the definition, $R(k) = \mathsf{E}[(z(t) - \mu)(z(t + k) - \mu)]$, where $\mu = \mathsf{E}[z(t)] = 10$, we can compute the respective autocovariances:

$$R(k) = \begin{cases} 2.0 & \text{if } k = 0; \\ 1.0 & \text{if } |k| = 1; \\ 0 & \text{if } |k| \ge 2. \end{cases} \qquad R(k) = \begin{cases} 2.0 & \text{if } k = 0; \\ -1.0 & \text{if } |k| = 1; \\ 0 & \text{if } |k| \ge 2. \end{cases}$$

Using this information we may compute the spectral densities,



The first model possesses a zero at the frequency $\omega = \pm \pi$, while the second model possesses a zero at the DC value $\omega = 0$. The relatively smooth behavior of the sample path for the first model is reflected in the spectral densities.

Linear stochastic systems Consider the SISO system



The transfer function H is the Fourier transform of the impluse response:

$$H(e^{j\omega}) = \sum_{n=0}^{\infty} h_n e^{-j\omega n}$$

The output y is then

$$y(t) = \sum_{n=0}^{\infty} h_n u(t-n)$$

=
$$\sum_{n=0}^{\infty} h_n \int_{-\pi}^{\pi} e^{j\omega(t-n)} d\xi_u(\omega)$$

=
$$\int_{-\pi}^{\pi} e^{j\omega t} H(e^{j\omega}) d\xi_u(\omega)$$

We thus have the formula $d\xi_y(\omega) = H(e^{j\omega})d\xi_u(\omega)$. This actually means that

$$\xi_y(\omega) = \int_{-\pi}^{\omega} H(e^{j\omega}) \, d\xi_u(\omega).$$

Given this formula, we can also compute the spectral density f_y :

$$f_y(\omega) = |H(e^{j\omega})|^2 f_u(\omega)$$

So, the linear system transforms signals as one would expect: frequencies are amplified or attenuated, depending on the magnitude of the frequency response. Note however that all phase information is lost in the spectral density.