

## BUSSGANG PROCESSES

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### *Definition of Bussgang Process*

In the early 1950's, Bussgang [see Barrett and Lampard (1955)], demonstrated an interesting and useful result concerning noise and non-linear devices. He showed that for Gaussian processes, the cross-correlation (C/C) between the input and output, obtained by passing a time series through a zero-memory non-linear (ZNL) device, was proportional to the autocorrelation (A/C) of the input. A practical application of this result is computing the A/C by correlating a time series with the sgn of itself. No multiplications are involved; the variance of the time series, however, must be independently computed. With a view of extending this result to processes other than Gaussian, Barrett and Lampard defined a new class of distributions called the  $\Lambda$  class, which also had the "Bussgang" property. The general telegraph matrix  $P_t$  ("Modeling Seismic Impedance by Markov Chains - Model Properties," this report) is in fact a member of the  $\Lambda$ -class, and although Bussgang, the autocorrelation function is strictly exponential. For Gaussian processes the A/C function is arbitrary. Are there any other useful distributions or probability transition matrices that are not Gaussian, do not have an exponential A/C, and are still Bussgang?

### *The class of Bussgang Processes*

To answer the question posed above, we follow Barrett and Lampard and expand a general second order stationary probability density function (pdf) into a double Fourier series involving one set of normalized orthogonal polynomials:

$$f_{x_1, x_2}(x_1, x_2; t) = f_x(x_1) f_x(x_2) \sum_{m, n=0}^{\infty} a_{mn}(t) o_m(x_1) o_n(x_2) \quad (1a)$$

$f_{x_1, x_2}(x_1, x_2; t)$  = second order pdf whose random variables (RV)  $X_1$  and  $X_2$  are members of the process  $\{X_t\}$  separated by  $t$  units.

$f_x(x)$  = first-order pdf. All RV's in  $\{X_t\}$  have identical first-order pdf.

$o_j$  = orthogonal [with respect to  $f_x(x)$ ] polynomials:

$$\int f_x(x_1) o_m(x_1) o_n(x_1) dx_1 = \delta_{mn} \quad (1b)$$

$a_{mn}(t)$  = Fourier coefficients

$$= \iint f_{x_1, x_2}(x_1, x_2; t) o_m(x_1) o_n(x_2) dx_1 dx_2$$

*Theorem:* A second-order stationary stochastic process is Bussgang if and only if:

$$E[X_1 | X_2 = x_2; t] = p(t) h(x_2) \quad (2)$$

$p(t)$  = autocorrelation of  $\{X_t\}$

$h(\cdot)$  = arbitrary function

*Corollary:* The process is Bussgang if and only if the Fourier coefficients have the minimal restriction:

$$a_{1j}(t) = a_{j1}(t) = 0 \text{ or } a_{11}(t), j \neq 1 \quad (3)$$

*Proof*

Assume that  $\{X_t\}$  is zero-mean, unit variance.

(1) For  $\{X_t\}$  to be Bussgang, the C/C must be symmetric:

$$E[X_1 g(X_2); t] = E[X_2 g(X_1); t]$$

$g$  = ZNL

$$\text{But } E[X_1 g(X_2); t] = \iint x_1 g(x_2) f_{x_1, x_2}(x_1, x_2; t) dx_1 dx_2 \quad (4)$$

Making use of the expansion (1a), Equation (4) becomes

$$E[X_1 g(X_2); t] = \sum_{mn} a_{mn}(t) \int g(x_2) f_{x_2}(x_2) o_n(x_2) \left[ \int x_1 f_{x_1}(x_1) o_m(x_1) dx_1 \right] dx_2 \quad (5)$$

Before proceeding, we define the first two polynomials:

$$o_0(x) = 1 \quad (6a)$$

$$o_1(x) = x \quad (6b)$$

Both (6a) and (6b) are consistent with Equation (1b). Since the  $o_j$  are mutually orthogonal, the inner integral in Equation (5) exists only when  $m = 1$ , and we obtain

$$E[X_1 g(X_2); t] = \sum_n a_{1n}(t) \int g(x_2) f_{x_2}(x_2) o_n(x_2) dx_2 \quad (7a)$$

Similarly,

$$E[X_2 g(X_1); t] = \sum_m a_{m1}(t) \int g(x_1) f_{x_1}(x_1) o_m(x_1) dx_1 \quad (7b)$$

Equation (7a) and (7b) are equal if and only if:

$$a_{1q} = a_{q1}, \quad q \geq 0 \quad (8)$$

(2) Next, determine the functional form of  $R_{xx}(t)$

$$\begin{aligned} R_{xx}(t) &= E[X_1 X_2; t] \\ &= \iint x_1 x_2 f_{x_1, x_2}(x_1, x_2; t) dx_1 dx_2 \end{aligned}$$

If the expansion in Equation (1a) is substituted into the above equation, we eventually find that

$$R_{xx}(t) = a_{11}(t) \triangleq p(t) \quad (9)$$

- (3) Third, determine the crosscorrelation,  $R_{xg(x)}(t)$  where  $g$  is a ZNL:

$$\begin{aligned} R_{xg(x)}(t) &= E[X_1 g(X_2); t] \\ &= \iint x_1 g(x_2) f_{x_1, x_2}(x_1, x_2; t) dx_1 dx_2 \\ &= \int g(x_2) \left[ \int x_1 f_{x_1 | x_2}(x_1 | x_2; t) dx_1 \right] f_x(x_2) dx_2 \end{aligned}$$

The term in brackets is the conditional expectation:

$$R_{xg(x)}(t) = \int g(x_2) E[X_1 | X_2 = x_2; t] f_x(x_2) dx_2 \quad (10)$$

- (4) Bussgang property holds if and only if the ratio of Equations (9) and (10) is constant:

$$\begin{aligned} \frac{R_{xg(x)}(t)}{R_{xx}(t)} &= \text{constant if and only if:} \\ E[X_1 | X_2 = x_2; t] &= a_{11}(t) h(x_2) \quad (11) \end{aligned}$$

where  $h(\cdot)$  is an arbitrary function.

- (5) Equation (11) can be simplified if the conditional expectation is expanded:

$$\begin{aligned} E[X_1 | X_2 = x_2; t] &= \frac{\int x_1 f_{x_1, x_2}(x_1, x_2; t) dx_1}{f_x(x_2)} \\ &= \sum_n a_{1n} o_n(x_2) \quad (12) \end{aligned}$$

Equating Equations (11) and (12), we have

$$a_{1j} = 0 \quad \text{or} \quad a_{11}, \quad j \neq 1 \quad (13)$$

We note the following relation (see *Examples*):

$$a_{1j} = 0, \quad j \neq 1 \iff E[X_1 | X_2 = x_2; t] = a_{11}(t) x_2$$

The corollary is obtained by using Equations (13) and (8).

Although the theorem is quite tedious to prove, it can be used to readily determine whether a process is Bussgang.

### Examples

- (1) A process having a second order Gaussian pdf of arbitrary correlation  $p(t)$  is Bussgang. The theorem can be used to give a one-line proof. Write down the well-known formula for conditional density:

$$f_{X_1|X_2}(x_1|x_2;t) = \frac{1}{\sqrt{2\pi\sigma^2[1-p(t)^2]}} \exp\left[\frac{-[x_1 - p(t)x_2]^2}{2\sigma^2[1-p(t)^2]}\right]$$

from which  $E[X_1|X_2=x_2;t] = p(t)x_2$  is readily obtained. QED.

- (2) This example is from "Modeling Seismic Impedance...", where it was shown that processes synthesized using the general telegraph matrix  $P_T$  are Bussgang. An alternative proof of this result makes use of the above theorem. First, expand  $P_T$  in terms of its eigenvectors:

$$P_T^k = \sum_{i=1}^M \lambda_i^k \mu_i \beta_i^T \quad (14)$$

$\mu_i$  = column eigenvector

$\beta_i^T$  = row eigenvector

Since  $\lambda_1 = 1$  and  $\lambda_i = \lambda$ ,  $i \geq 2$ , Equation (14) becomes

$$P_T^k = \Gamma \alpha^T + \lambda^k \sum_{i=2}^M \mu_i \beta_i^T \quad (15)$$

$\Gamma$  = column vector of ones

$\alpha$  = probability mass function

$$\text{But } I = \sum_{i=1}^M \mu_i \beta_i^T = \Gamma \alpha^T + \sum_{i=2}^M \mu_i \beta_i^T \quad (16)$$

Using (16), Equation (15) becomes

$$\begin{aligned} P_T^k &= \Gamma \alpha^T + \lambda^k (I - \Gamma \alpha^T) \\ &= \lambda^k I + (1 - \lambda^k) \Gamma \alpha^T \end{aligned}$$

$$\text{or } \{P_T^k\}_{ij} = \lambda^k \delta_{ij} + (1 - \lambda^k) \Gamma_i \alpha_j \quad (17)$$

Next, calculate the conditional expectation:

$$\begin{aligned} E[X_1 | X_2 = x_i; k] &= \sum_j x_j P_r [Q_{N+k} = x_j | Q_N = x_i] \\ &= \sum_j x_j \{P_T^k\}_{ij} \end{aligned} \quad (18)$$

Substituting Equation (17) into (18) and noting that  $\alpha^T x = 0$ , gives

$$\begin{aligned} E[X_1 | X_2 = x_i; k] &= \sum_j x_j \lambda^k \delta_{ij} + (1 - \lambda^k) \sum_j \Gamma_i x_j \alpha_j \\ &= \lambda^k x_i \quad \dots \quad \text{Bussgang} \end{aligned}$$

#### REFERENCE

BARRETT, B.F. and D.G. LAMPARD, "An expansion for some second-order probability distributions and its applications to noise problems," *IRE Transactions - Information Theory*, March 1955.