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16 April 03

Regression in the complex case.

$$Y_j = \beta x_j + \epsilon_j, \quad j=1, \dots, n$$

x 's fixed

$$\epsilon_j: \mathcal{I}N^c(0, \sigma^2)$$

$$EY_j = \beta x_j \quad \text{var } Y_j = \sigma_j^2$$

$$\begin{aligned} \text{LSE } \hat{\beta} &= \frac{\sum_j Y_j \bar{x}_j}{\sum_j |x_j|^2} \\ &= \beta + \frac{\sum_j \epsilon_j \bar{x}_j}{\sum_j |x_j|^2} \end{aligned}$$

$$\hat{\beta} \sim N^c(\beta, \sigma^2 / \sum_j |x_j|^2)$$

$$\begin{aligned} \hat{\sigma}^2 &= \frac{\sum_j |Y_j - \hat{\beta} x_j|^2}{n-1} \\ &\sim \sigma^2 \chi_{2(n-1)}^2 / 2(n-1) \end{aligned}$$

$$\hat{\beta} \perp \hat{\sigma}^2$$

$$1 - |\hat{R}|^2 = \frac{\sum_j |Y_j - \hat{\beta} x_j|^2}{\sum_j |Y_j|^2}$$

$$0 \leq |\hat{R}|^2 \leq 1$$

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Cross-spectral analysis

Separate regression at each frequency

Model

$$Y(t) = \mu + \sum_a a(u)X(t-u) + \epsilon(t) \quad (*)$$

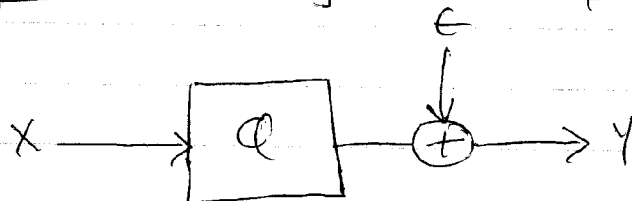
$\{\epsilon(\cdot)\}$ 0-mean, stationary

$$EY(t) = \mu + \sum_a a(u)X(t-u)$$

nonstationary

 $\{a(\cdot)\}$ impulse response

$$A(\lambda) = \sum_a e^{-i\lambda u} a(u) \quad \underline{\text{transfer function}}$$

 $|A(\lambda)|$: gain $\arg A(\lambda)$: phase
System identification

Estimate $\{a(\cdot)\}$, $\{A(\cdot)\}$, $f_{\epsilon\epsilon}(\lambda)$ from
 data $(X(t), Y(t))$, $t=0, \dots, T-1$

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Pick n distinct $\frac{2\pi j}{T}$ near λ

FT \otimes

$$d_y^T(\lambda) \approx A(\lambda)d_x^T(\lambda) + d_\epsilon^T(\lambda)$$

$$d_y^T\left(\frac{2\pi j}{T}\right) \approx A(\lambda)d_x^T\left(\frac{2\pi j}{T}\right) + d_\epsilon^T\left(\frac{2\pi j}{T}\right)$$

ex. $y_j = \beta x_j + \epsilon_j$

CLT for $d_\epsilon^T\left(\frac{2\pi j}{T}\right)$: $IN^c(0, 2\pi T f_{\epsilon\epsilon}(\lambda))$

$$y_j \sim d_y^T\left(\frac{2\pi j}{T}\right); x_j \sim d_x^T\left(\frac{2\pi j}{T}\right); \epsilon_j \sim d_\epsilon^T\left(\frac{2\pi j}{T}\right)$$

$$\beta \sim A(\lambda); \sigma^2 \sim 2\pi T f_{\epsilon\epsilon}(\lambda)$$

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$$A^T(\lambda) = \sum_j d_y^T\left(\frac{2\pi j}{T}\right) \overline{d_x^T\left(\frac{2\pi j}{T}\right)} / \sum_j |d_x^T\left(\frac{2\pi j}{T}\right)|^2$$

$$\sim N^c\left(A(\lambda), 2\pi T f_{ee}(\lambda) / \sum_j |d_x^T\left(\frac{2\pi j}{T}\right)|^2\right)$$

||

$$f_{ee}^T(\lambda) = \sum_j |d_y^T\left(\frac{2\pi j}{T}\right) - A^T(\lambda) d_x^T\left(\frac{2\pi j}{T}\right)|^2 / 2\pi T (n-1)$$

$$\sim f_{ee}(\lambda) \chi_{2(n-1)}^2 / 2(n-1)$$

$$\sum_j |d_x^T\left(\frac{2\pi j}{T}\right)|^2 \sim 2\pi T n f_{xx}^T(\lambda)$$

$$|R_{yx}^T(\lambda)|^2 = 1 - f_{ee}^T(\lambda) / f_{yy}^T(\lambda)$$

$$= |f_{yx}^T(\lambda)|^2 / f_{xx}^T(\lambda) f_{yy}^T(\lambda)$$

$$E |R_{yx}^T(\lambda)|^2 \sim 1/(n-1)$$

$$100 \alpha \% \text{ pt. } 1 - (1-\alpha)^{1/(n-1)}$$

$$f_{ee}^T(\lambda) = [1 - |R_{yx}^T(\lambda)|^2] f_{yy}^T(\lambda)$$

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$$f_{YX}^T(\omega) = \frac{1}{2\pi T} \frac{1}{m} \sum_j d_Y^T\left(\frac{2\pi j}{T}\right) \overline{d_X^T\left(\frac{2\pi j}{T}\right)}$$

Plot

$$|R_{YX}^T(\omega)|^2$$

$$\log |A^T(\omega)|$$

$$\arg A^T(\omega)$$

$$AV(\log |A^T(\omega)|) \sim \frac{1}{2m} [|R_{YX}^T(\omega)|^{-2} - 1]$$

See DRB book Chapter 6

m can be $m_T \rightarrow \infty$, $\frac{m_T}{T} \rightarrow 0$

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Splitting approach

Suppose $T = LV$ having in mind
 $V \rightarrow \infty$, L fixed

Let $j = 1, \dots, L$

Compute

$$g_j = d_y^V(\lambda, j) = \sum_{n=0}^{V-1} e^{-i\lambda n} \gamma(n + j - 1 - V)$$

$$x_j = d_x^V(\lambda, j) =$$

Better for higher-order spectra

L can be L_T

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Importance of pre filtering

$$Y(t) = \alpha X(t-\nu) + e(t)$$

$$E f_{YX}^T(\omega) \approx \frac{1}{2\pi T} \frac{1}{n} \sum_j A\left(\frac{2\pi j}{T}\right) |d_X^T\left(\frac{2\pi j}{T}\right)|^2$$

$$\approx \frac{1}{2\pi T} \frac{1}{n} \sum_j e^{i\frac{2\pi j\nu}{T}} |d_X^T\left(\frac{2\pi j}{T}\right)|^2$$

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Estimating impulse response

$$a(u) = \frac{1}{2\pi} \int_0^{2\pi} A(\lambda) e^{i u \lambda} d\lambda$$

$$\approx \frac{1}{P} \sum_{p=0}^{P-1} A\left(\frac{2\pi p}{P}\right) e^{i 2\pi p u / P}$$

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System identification

Linear time invariant case

Forget noise for the moment

$$Y(t) = \sum_u a(t-u)X(u)$$

After $\{a(\cdot)\}$, $\{A(\cdot)\}$
I. Deterministic input

1. Pulse probe

$$X(t) = \delta(t) \Rightarrow Y(t) = a(t)$$

2. Periodic pulses

Suppose $a(u) = 0$, $u < 0$ or $u > U$

$$X(t) = \sum_{j=1}^J \delta\{t - j\Delta\} \quad \text{with } \Delta > U$$

Stack and average curves

Evoked response experiments

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3. Sinusoid

$$X(t) = e^{i\lambda t}$$

$$Y(t) = \sum_u a(u) e^{i\lambda(t-u)}$$

$$= e^{i\lambda t} A(\lambda)$$

4. m-sequence (pseudorandom binary)

$$X(t) = \pm 1, \quad \text{period } N = 2^m - 1$$

mean $1/N$ \sim whiteautcor $-1/N - 1/N^2$

$$Y(t) = \sum_u a(u) X(t-u)$$

$$\sum_v Y(t) X(t-v) = \sum_u a(u) \sum_v X(t-u) X(t-v)$$

$\sim \sum_v a(v)$

e.g. $X_t = X_{t-1} X_{t-4} X_{t-6} X_{t-12}$ period 4095

$X_t = -1 \quad t=1, \dots, 12$

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5. General $\{X(t)\}$

$$c_{yx}^T(\nu) \sim \sum_u a(u) c_{xx}^T(\nu - u)$$

deconvolve
FT

$$f_{yx}^T(\lambda) \sim A(\lambda) f_{xx}^T(\lambda)$$

6. Chirps

$$A(\lambda) = 0 \quad 0 \leq \lambda < \lambda_0 \text{ and } \lambda_1 < \lambda$$

$$X(t) = \cos(\lambda_t t) \quad 0 \leq t \leq T$$

$$\lambda_t = \lambda_0 + (\lambda_1 - \lambda_0) \frac{t}{T}$$

$$f_{xx}^T(\lambda) \sim \begin{cases} 0 & 0 \leq \lambda < \lambda_0 \text{ and } \lambda_1 < \lambda \\ C & \lambda_0 \leq \lambda \leq \lambda_1 \end{cases}$$

Repeat, stack, average

sonar, radar, bats, VIBROSEIS

II. Stochastic input (stationary)

1. Binary white noise

$$X(t) = \begin{matrix} +1 & \pi \\ -1 & 1-\pi \end{matrix}$$

$$c_{xx}(u) = \pi(1-\pi) \quad u=0 \quad \text{and} = 0 \quad u \neq 0$$

$$c_{yx}(v) = \sum_u a(u) c_{xx}(v-u)$$

$$c_{yx}(v) = \sigma_x^2 a(v)$$

2. Gaussian white noise

Good for nonlinear systems

3. Mixture of white noises

still white

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4. Band-limited white noise

$$A(\lambda) = 0 \quad 0 < \lambda < \lambda \quad \text{and} \quad \lambda < \lambda$$

Spread spectrum

$\{w(t)\}$

white

$$X(t) = w(t) \cos \lambda_0 t$$

Average Evoked Responses - Several M's, Several Intensities

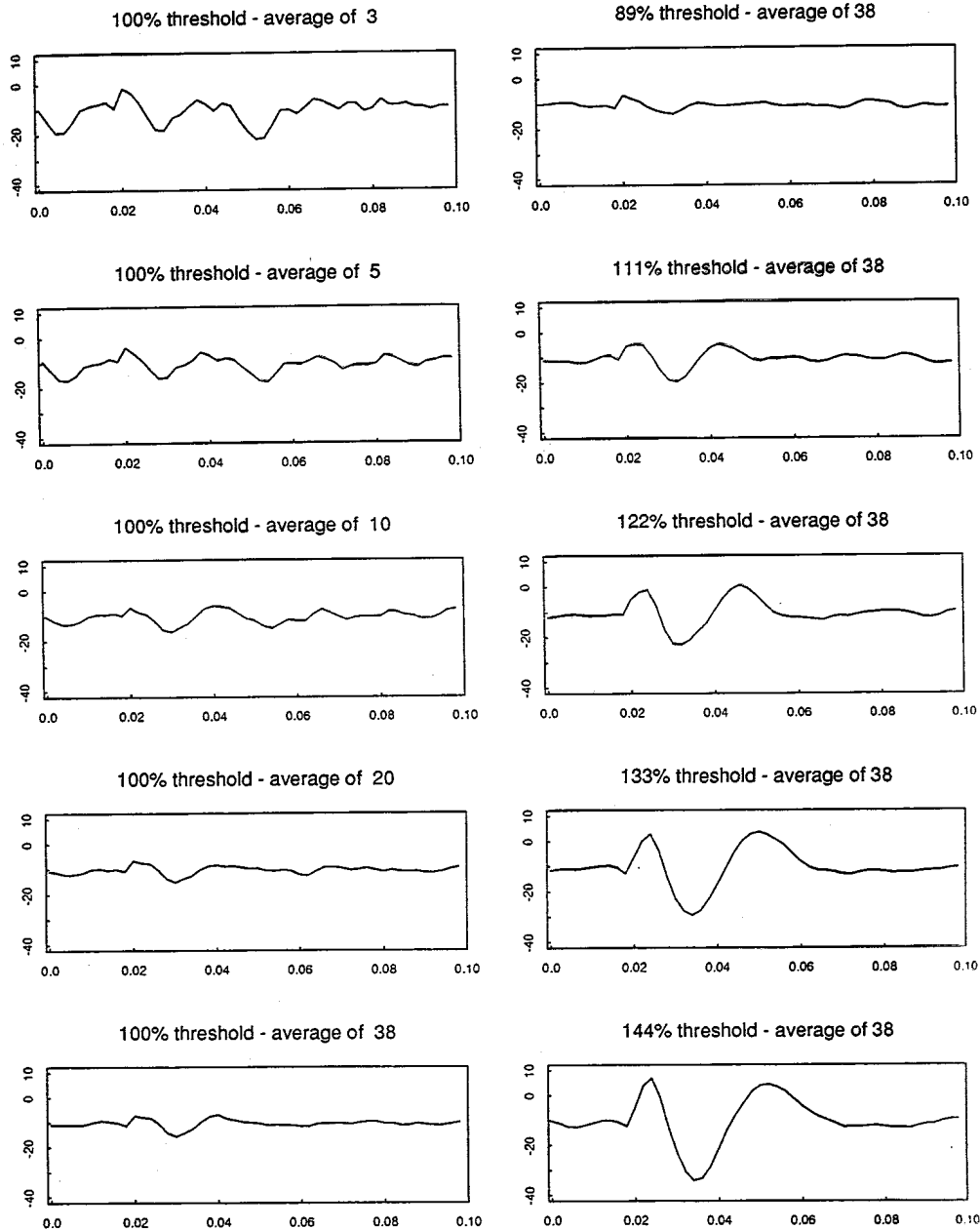


FIG. 22. The various graphs here are meant to show the effects of changing the number of responses averaged (left column) and the strength of stimulus applied (right column) for data such as that of Figure 21.

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