

Nom: Prénom:

Exercice 1 (5.5)

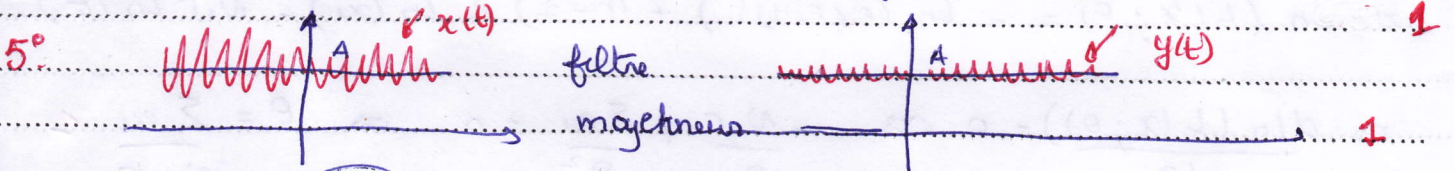
1°/ $X(t) = A + b(t)$ $R_b(\tau) = \sigma^2 \delta(\tau) \Rightarrow S_b(f) = \sigma^2$, $E\{b(t)\} = 0$ 0.5
 $R_x(t, \tau) = E\{X(t)X^*(t-\tau)\} = E\{A^2\} + E\{Ab(t)\} + E\{Ab^*(t-\tau)\} + R_b(\tau)$
 $= A^2 + R_b(\tau) + A \cdot E\{b(t)\} + A \cdot E\{b^*(t-\tau)\} = A^2 + R_b(\tau)$ 1

2°/ $\mu_x(t) = E\{A\} + E\{b(t)\} = A = \text{cste}$, $R_x(t, \tau) = R_x(\tau) \Rightarrow \text{SSL}$ 0.5

3°/ $\mu_y(t)$ puisque $x(t)$ SSL $\Rightarrow y(t)$ SSL $\Rightarrow \mu_y = \mu_x H(0)$
 $H(f) = \text{TF}\left\{\frac{1}{T} \Pi\left(\frac{f}{T}\right)\right\} = \text{sinc}(fT) e^{-j\pi fT} \Rightarrow H(0) = 1 \Rightarrow \mu_y = A$ 1

4°/ $R_{yy}(\tau) = \text{TF}^{-1}\{S_y(f)\} = \text{TF}^{-1}\{|H(f)|^2 S_x(f)\} = \text{TF}^{-1}\{\text{sinc}^2(fT) S_x(f)\}$ 0.5
 $\Rightarrow R_{yy}(\tau) = \text{TF}^{-1}\{\text{sinc}^2(fT) [A^2 \delta(f) + \sigma^2]\}$
 $= \text{TF}^{-1}\{A^2 \delta(f) + \sigma^2 \text{sinc}^2(fT)\} = A^2 + \sigma^2 \frac{1}{T} \Lambda\left(\frac{\tau}{T}\right)$ 1

Sachant que $R_{yy}(0) = \mu_y^2 + \sigma_y^2$ $R_y(0) = \mu_y^2 \Rightarrow \mu_y = A$ et $\sigma_y^2 = \sigma^2/T$ 1



Exercice 2 (4.5)

1°/ $R_y(k) = \alpha^{|k|} = R_y(k)$ $k \rightarrow \infty$ $R_y(k) \rightarrow 0 \Rightarrow$ Processus AR1

2°/ $x(n) \xrightarrow{\text{bb. deconvolue}} h(n) \xrightarrow{\text{bb. deconvolue}} y(n)$ signal à modéliser avec $H(z) = \frac{1}{1 + \sum_{i=1}^N a_i z^{-i}}$ 0.5
 paramètres du modèle 0.5

$R_x(k) = \sigma_x^2 \delta(k)$

3°/ bb. Ergodicité 0.5

4°/ $\begin{bmatrix} R_{yy}(0) & R_{yy}(1) \\ R_{yy}(1) & R_{yy}(0) \end{bmatrix} \begin{bmatrix} 1 \\ a_1 \end{bmatrix} = \begin{bmatrix} \sigma_x^2 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & \alpha \\ \alpha & 1 \end{bmatrix} \begin{bmatrix} 1 \\ a_1 \end{bmatrix} = \begin{bmatrix} \sigma_x^2 \\ 0 \end{bmatrix} \Rightarrow \begin{cases} a_1 = -\alpha \\ \sigma_x^2 = 1 - \alpha^2 \end{cases}$ 1

Exercice 3 (4.5)

$y(n) = z(n) + b(n)$ 0.5 $R_{zz}(0) = 0 \Rightarrow \mu_z = 0$ $R_{bb}(0) = 0 \Rightarrow \mu_b = 0$ 1

1°/ Adapté et moyenné pour filtre signal déterministe 0.5

2°/ $R_y(k) = E\{y(n)y(n-k)\} = R_z(k) + E\{z(n)b(n-k)\} + E\{z(n-k)b(n)\} + R_b(k)$ 0.5

0.5 $R_{zy}(k) = E\{z(n)y(n-k)\} = R_z(k) + E\{z(n)b(n-k)\} = R_z(k)$

Nom: Prénom:

$$\begin{bmatrix} R_{33}(0) + R_{bb}(0) & R_{33}(1) + R_{bb}(1) \\ R_{33}(1) + R_{bb}(1) & R_{33}(0) + R_{bb}(1) \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} = \begin{bmatrix} R_{33}(0) \\ R_{33}(1) \end{bmatrix} \quad 0.5$$

$$\Rightarrow \begin{bmatrix} 2 & 0.75 \\ 0.75 & 2 \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} = \begin{bmatrix} 1.5 \\ 1 \end{bmatrix} \Rightarrow b_0 = \quad \text{et } b_1 = \quad 1$$

$$3\% \quad H(z) = \quad + \quad z^{-1} \quad 0.5$$

Exercice 4 (4.5)

1% Pour déterminer une variable déterministe à partir d'observations aléatoires indépendantes et identiquement distribuées.

$$2\% \quad L(x; \theta) = \prod_{i=1}^n p(x_i; \theta) = \frac{1}{n! (r-1)!} \frac{\pi x_i^{r-1}}{\theta^{n \cdot r}} e^{-\frac{\sum x_i}{\theta}}$$

$$\Rightarrow \ln(L(x; \theta)) = -\ln(n! (r-1)!) + (r-1) \sum \ln(x_i) - n \cdot r \ln(\theta) - \frac{\sum x_i}{\theta}$$

$$\Rightarrow \frac{d \ln(L(x; \theta))}{d\theta} = 0 \Rightarrow -\frac{n \cdot r}{\theta} + \frac{\sum x_i}{\theta^2} = 0 \Rightarrow \theta = \frac{\sum x_i}{n \cdot r} \quad 1$$

$$3\% \quad b_0 = E\{\hat{\theta}\} - \theta = E\left\{\frac{\sum x_i}{n \cdot r}\right\} - \theta = \frac{1}{n \cdot r} \sum E\{x_i\} - \theta = \frac{1}{n \cdot r} \sum \theta \cdot r - \theta = \theta - \theta = 0 \quad 0.5$$

$$4\% \quad \sigma_{\hat{\theta}}^2 = E\{(\hat{\theta} - E\{\hat{\theta}\})^2\} = E\left\{\left(\frac{\sum x_i}{n \cdot r} - \theta\right)^2\right\} = E\left\{\left(\frac{\sum x_i}{n \cdot r} - \frac{\sum \theta \cdot r}{n \cdot r}\right)^2\right\} \\ = \frac{1}{n^2 \cdot r^2} E\left\{\left(\sum (x_i - \theta \cdot r)\right)^2\right\}$$

Sachant que les x_i sont indépendantes et que $E\{x_i - \theta \cdot r\} = 0$ puisque $E\{x_i - \theta \cdot r\} = E\{x_i\} - \theta \cdot r = 0$.

$$\Rightarrow \sigma_{\hat{\theta}}^2 = \frac{1}{n^2 \cdot r^2} E\left\{\sum (x_i - \theta \cdot r)^2\right\} = \frac{1}{n^2 \cdot r^2} \sum E\{x_i - \theta \cdot r\}^2$$

$$\Rightarrow \sigma_{\hat{\theta}}^2 = \frac{1}{n^2 \cdot r^2} \sum r \theta^2 = \frac{1}{n^2 \cdot r^2} \cdot n \cdot r \theta^2 = \theta^2 / n \cdot r \quad 1.5$$

$$5\% \quad b = 0 \quad \sigma_{\hat{\theta}} \rightarrow 0 \text{ pour } n \rightarrow \infty \Rightarrow \text{constant} \quad 0.5$$