

NPTEL MOOC Estimation: Assignment #4

1. Consider the fading channel estimation problem where the output symbol $y(k)$ is $y(k) = hx(k) + v(k)$, with h , $x(k)$, $v(k)$ denoting the *complex* channel coefficient, pilot symbol and noise sample respectively. Let $\mathbf{x} = [2 + j \quad -1 - j \quad 1 - 2j \quad -1 + j]^T$ denote the pilot vector of transmitted pilot symbols and $\mathbf{y} = [2 + 2j \quad -j \quad -2 + j \quad 1 - j]^T$ denote the corresponding received symbol vector. Let $v(k)$ be IID Gaussian noise with zero-mean and dB variance $\sigma^2 = 3$ dB. Let $\mu_h = 1 + j$, $\sigma_h^2 = 1/2$ denote the prior mean, variance of the complex symmetric Gaussian parameter h . The MSE of the MMSE estimate of \hat{h} is,

- a. 1/9
- b. 1/8
- c. 1/10
- d. 1/7

Ans a

2. Consider the fading channel estimation problem where the output symbol $y(k)$ is $y(k) = hx(k) + v(k)$, with h , $x(k)$, $v(k)$ denoting the *complex* channel coefficient, pilot symbol and noise sample respectively. Let $\mathbf{x} = [2 + j \quad -1 - j \quad 1 - 2j \quad -1 + j]^T$ denote the pilot vector of transmitted pilot symbols and $\mathbf{y} = [2 + 2j \quad -j \quad -2 + j \quad 1 - j]^T$ denote the corresponding received symbol vector. Let $v(k)$ be IID Gaussian noise with zero-mean and dB variance $\sigma^2 = 3$ dB. Let $\mu_h = 1 + j$, $\sigma_h^2 = 1/2$ denote the prior mean, variance of the complex symmetric Gaussian parameter h . The MSEs of the real, imaginary parts of \hat{h} are,

- a. 1/2
- b. 1/9
- c. 1/18
- d. 1/4

Ans c

3. Consider the fading channel estimation problem where the output symbol $y(k)$ is $y(k) = hx(k) + v(k)$, with h , $x(k)$, $v(k)$ denoting the *real* channel coefficient, pilot symbol and noise sample respectively. Let $\mathbf{x} = [2 + j \quad -1 - j \quad 1 - 2j \quad -1 + j]^T$ denote the pilot vector of transmitted pilot symbols and $\mathbf{y} = [2 + 2j \quad -j \quad -2 + j \quad 1 - j]^T$ denote the corresponding received symbol vector. Let $v(k)$ be IID Gaussian noise with zero-mean and dB variance $\sigma^2 = 3$ dB. Let $\mu_h = 1 + j$, $\sigma_h^2 = 1/2$ denote the prior mean, variance of the parameter h . What is the probability that both the real and imaginary parts

of the MMSE estimate \hat{h} lie within a radius of $\frac{1}{2}$ from the real and imaginary parts of the unknown complex symmetric Gaussian parameter h respectively

- a. $\left(1 - 2Q\left(\frac{9}{2}\right)\right)^2$
- b. $\left(1 - 2Q\left(\sqrt{\frac{9}{2}}\right)\right)^2$
- c. $\left(1 - 2Q\left(\sqrt{\frac{9}{2}}\right)\right)$
- d. $\left(1 - 2Q\left(\frac{9}{2}\right)\right)$

Ans b

4. Consider MMSE estimation for the wireless sensor network (WSN) scenario as described in lectures with each observation $y(k) = h + v(k)$, for $1 \leq k \leq N$, i.e. number of observations N and independent **non-identical** Gaussian noise samples $v(k)$ of variance σ_k^2 . What is the expression for the MMSE estimate \hat{h} of the unknown Gaussian parameter h

- a. $\hat{h} = \frac{\frac{(1^T y)/N + \frac{\mu_h}{\sigma_h^2}}{\frac{1}{\sigma^2/N} + \frac{1}{\sigma_h^2}}}$
- b. $\hat{h} = \frac{\sum_{k=1}^N \frac{y(k) + \frac{\mu_h}{\sigma_k^2}}{2\sigma_k^2 + \sigma_h^2}}{\sum_{k=1}^N \frac{1}{\sigma_k^2} + \frac{1}{\sigma_h^2}}$
- c. $\hat{h} = \frac{\sum_{k=1}^N \frac{y(k) + \frac{\mu_h}{\sigma_k^2}}{2\sigma_k^2 + \sigma_h^2}}{\sum_{k=1}^N \frac{1}{2\sigma_k^2} + \frac{1}{\sigma_h^2}}$
- d. $\hat{h} = \frac{\sum_{k=1}^N \frac{y(k) + \frac{\mu_h}{\sigma_k^2}}{\sigma_k^2 + \sigma_h^2}}{\sum_{k=1}^N \frac{1}{\sigma_k^2} + \frac{1}{\sigma_h^2}}$

Ans d

5. Consider MMSE estimation for the wireless sensor network (WSN) scenario as described in lectures with each observation $y(k) = h + v(k)$, for $1 \leq k \leq N$, i.e. number of observations N and independent **non-identical** Gaussian noise samples $v(k)$ of variance σ_k^2 . What is the expression for the MSE of the MMSE estimate \hat{h} of the unknown Gaussian parameter h

- a. $\left(\sum_{k=1}^N \frac{1}{\sigma_k^2} + \frac{1}{\sigma_h^2}\right)^{-1}$

- b. $\left(\sum_{k=1}^N \frac{1}{\sigma_k^2} + \frac{2}{\sigma_h^2}\right)^{-1}$
 c. $\sum_{k=1}^N \frac{2}{\sigma_k^2} + \frac{1}{\sigma_h^2}$
 d. $\sum_{k=1}^N \frac{1}{\sigma_k^2} + \frac{1}{\sigma_h^2}$

Ans a

6. Which of the following statements is true about the LMMSE estimate
- LMMSE estimate is always the MMSE estimate
 - MMSE estimate is always the LMMSE estimate
 - The LMMSE estimate is identical to the MMSE estimate for a Gaussian parameter
 - The MMSE and LMMSE estimates are always different

Ans c

7. Consider LMMSE estimation for the wireless sensor network (WSN) scenario as described in lectures with each observation $y(k) = h + v(k)$, for $1 \leq k \leq N$, i.e. number of observations N and IID Gaussian noise samples of variance σ^2 . What is the expression for the LMMSE estimate \hat{h} of the unknown parameter h , which is not necessarily Gaussian

- a. $\hat{h} = \frac{\frac{(\mathbf{x}^T \mathbf{y}) / \|\mathbf{x}\|^2 + \frac{\mu_h}{\sigma^2}}{\frac{1}{\sigma^2} + \frac{1}{\sigma_h^2}}}{\frac{1}{\sigma^2} + \frac{1}{\sigma_h^2}}$
 b. $\hat{h} = \frac{\frac{(1^T \mathbf{y}) / N + \frac{\mu_h}{\sigma^2}}{\frac{1}{2\sigma^2} + \frac{1}{\sigma_h^2}}}{\frac{1}{2\sigma^2/N} + \frac{1}{\sigma_h^2}}$
 c. $\hat{h} = \frac{\frac{(1^T \mathbf{y}) / N + \frac{\mu_h}{\sigma^2}}{\frac{1}{\sigma^2} + \frac{1}{\sigma_h^2}}}{\frac{1}{\sigma^2/N} + \frac{1}{\sigma_h^2}}$
 d. $\hat{h} = \mathbf{r}_{hy} \mathbf{R}_{yy}^{-1} \mathbf{y}$

Ans d

8. Consider a multi-antenna channel estimation scenario with $N = 4$ pilot vectors $\mathbf{x}(1) = [1, 1]^T$, $\mathbf{x}(2) = [1, -2]^T$, $\mathbf{x}(3) = [2, 1]^T$, $\mathbf{x}(4) = [1, -1]^T$. Let the corresponding received vector be $\mathbf{y} = [2, 1, 1, 3]^T$. Let the channel coefficients be IID Gaussian with dB variance $\sigma_h^2 = -3$ dB and dB noise variance $\sigma^2 = 3$ dB. The number of antennas M in this scenario is,

- 1
- 2
- 3
- 4

Ans b

9. Consider a multi-antenna channel estimation scenario with $N = 4$ pilot vectors $\mathbf{x}(1) = [1, 1]^T$, $\mathbf{x}(2) = [1, -2]^T$, $\mathbf{x}(3) = [2, 1]^T$, $\mathbf{x}(4) = [1, -1]^T$. Let the corresponding received vector be $\mathbf{y} = [2, 1, 1, 3]^T$. Let the channel coefficients be IID Gaussian with dB variance $\sigma_h^2 = -3$ dB and dB noise variance $\sigma^2 = 3$ dB. The corresponding pilot matrix \mathbf{X} is

a.
$$\begin{bmatrix} 1 & 1 & 2 & 1 \\ 1 & -2 & 1 & -1 \end{bmatrix}$$

b.
$$\begin{bmatrix} 1 \\ 1 \\ 2 \\ 1 \\ 1 \\ -2 \\ 1 \\ -1 \end{bmatrix}$$

c.
$$[1 \ 1 \ 2 \ 1 \ 1 \ -2 \ 1 \ -1]$$

d.
$$\begin{bmatrix} 1 & 1 \\ 1 & -2 \\ 2 & 1 \\ 1 & -1 \end{bmatrix}$$

Ans d

10. Consider a multi-antenna channel estimation scenario with $N = 4$ pilot vectors $\mathbf{x}(1) = [1, 1]^T$, $\mathbf{x}(2) = [1, -2]^T$, $\mathbf{x}(3) = [2, 1]^T$, $\mathbf{x}(4) = [1, -1]^T$. Let the corresponding received vector be $\mathbf{y} = [2, 1, 1, 3]^T$. Let the channel coefficients be IID Gaussian with dB variance $\sigma_h^2 = -3$ dB and dB noise variance $\sigma^2 = 3$ dB. The pilot matrix \mathbf{X} for this scenario satisfies the property that

- It is invertible
- It has identical columns
- It has orthogonal columns
- None of the above

Ans c