

TSKS04 Digital Communication

Continuation Course

Lecture 5

Phase and Delay Estimation, Hypothesis testing

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Recall: Proper Complex Gaussian

Definition: The $N \times 1$ complex random vector $\mathbf{x} = \mathbf{x}_c + j\mathbf{x}_s$ is *proper complex Gaussian* if the real vectors $\mathbf{x}_c, \mathbf{x}_s$ are jointly Gaussian and

$$E\{(\mathbf{x} - E\{\mathbf{x}\})(\mathbf{x} - E\{\mathbf{x}\})^T\} = \mathbf{0}$$

Notation:

- Mean value: $\mathbf{m}_x = E\{\mathbf{x}\}$
- Covariance matrix: $\mathbf{C}_x = E\{(\mathbf{x} - E\{\mathbf{x}\})(\mathbf{x} - E\{\mathbf{x}\})^H\}$
- PDF:

$$p(\mathbf{x}) = \frac{1}{\pi^N \det(\mathbf{C}_x)} e^{-(\mathbf{x} - \mathbf{m}_x)^H \mathbf{C}_x^{-1} (\mathbf{x} - \mathbf{m}_x)}$$

Notation: $\mathbf{x} \sim CN(\mathbf{m}_x, \mathbf{C}_x)$

Complex White Gaussian Noise (WGN)

Definition: A stochastic process $n(t)$ is complex white Gaussian noise (WGN) if $n(t) = n_c(t) + jn_s(t)$, where $n_c(t), n_s(t)$ are independent and identically distributed (i.i.d.) real WGN.

Property: A Complex WGN is a zero mean, proper complex Gaussian process with ACF

$$C_n(t_1, t_2) = 2\sigma^2 \delta(t_1 - t_2)$$

PSD of real and imaginary part ($N_0 = 2\sigma^2$)

Property: Let $s(t)$ be a complex-valued signal and $n(t)$ is complex WGN, then

$$Z = \langle n, s \rangle \sim CN(0, 2\|s\|^2\sigma^2)$$

Proofs: Section 4.5.1

Receiver Synchronization (2/2)

- Acquire channel gain A ← Called “gain” but is really an attenuation
 - Channel estimation:
- Timing synchronization
 - Estimate delay τ : ← At order of symbol times
- Carrier synchronization
 - Estimate carrier offset Δf
 - Estimate phase $\theta = -j2\pi f_c \tau$ ← Large f_c : Essentially uniform distribution $[0, 2\pi)$

Principle: Estimate using training symbols

Signals in Known Subspace (1/2)

Recall: K observations of a signal in noise:

$$\mathbf{y} = \theta \mathbf{1} + \mathbf{w}$$

- Signal “lives” in the subspace $\mathbf{1}$
- Noise is spread in all K dimensions
- MVU estimator: $\hat{\theta}(\mathbf{y}) = \mathbf{1}^T \mathbf{y} / \|\mathbf{1}\| = \sum_{k=1}^K \frac{y[k]}{K}$

Principle: Project \mathbf{y} onto signal subspace!

This is a general principle that we have seen before:

Signals along different orthogonal basis functions can be treated separately!

Signals in Known Subspace (2/2)

Consider a noisy signal modeled in complex baseband as

$$y(t) = s(t)f(\theta) + n(t)$$

- θ : Unknown parameter
- $f(\cdot)$: A known function
- $s(t)$: Known complex-valued signal
- $n(t)$: Complex white Gaussian noise with PDF $N_0/2$ per real dim

To estimate θ it is sufficient to consider $z = \langle y, s \rangle$ ← Called: sufficient statistic

The log-likelihood function is

$$p(z|\theta) = \frac{1}{\pi \|s\|^2 N_0} e^{-\frac{1}{\|s\|^2 N_0} |z - \|s\|^2 f(\theta)|^2}$$

Parameter Estimation with Hypotheses

Hypothesis Testing

- Goal: Guess properties of a signal
- M hypothesis H_0, \dots, H_{M-1}
- Bayesian modeling: $\Pr\{H_i\}$ for $i = 0, \dots, M - 1$
- Select the “best” hypothesis based on an observation

Applications in Digital Communication

- Detect which constellation point was sent
- Further application: Estimate delay, phase, and carrier offset

Example: Two Signals in Noise

Additive noise channel:

$$Y = S + W$$

- S is 0 or 1, equal probability
- $W \sim N(0, \sigma_W^2)$ is independent Gaussian noise

H_0 : $S = 0$, thus $Y|S \sim N(0, \sigma_W^2)$ and likelihood

$$p(y|0) = \frac{1}{\sqrt{2\pi}\sigma_W} e^{-\frac{y^2}{2\sigma_W^2}}$$

H_1 : $S = 1$, thus $Y|S \sim N(1, \sigma_W^2)$ and likelihood

$$p(y|1) = \frac{1}{\sqrt{2\pi}\sigma_W} e^{-\frac{(y-1)^2}{2\sigma_W^2}}$$

Likelihood ratio test:

$$L(y) = \frac{p(y|1)}{p(y|0)}$$

$L(y) > 1$: H_1 most likely

$L(y) < 1$: H_0 most likely

Likelihood function of signal in complex AWGN

Consider a received signal $y(t)$ with complex AWGN $n(t)$

- Check if it contains the signal $s(t)$

H_0 (dummy): Received signal is $y(t) = n(t)$

H_1 : Received signal is $y(t) = s(t) + n(t)$

Theorem: The likelihood ratio with respect to the dummy hypothesis is

$$L(y|s) = e^{\frac{1}{\sigma^2} \left(\text{Re}\{\langle y, s \rangle\} - \frac{\|s\|^2}{2} \right)}.$$

It is called the *likelihood function*.

Most Likely Hypothesis (1/2)

Finite number: M hypotheses

- H_i : The signal is $s_i(t)$
- Likelihood function $L(y|i)$
- Maximum likelihood (ML):

$$\hat{s}_{ML}(y) = s_k(t) \quad \text{where} \quad k = \operatorname{argmax}_{1 \leq i \leq M} L(y|i)$$

Infinite number of hypotheses

- Consider a signal $s(t, \Gamma)$
- Likelihood function $L(y|\Gamma)$
- Maximum likelihood (ML):

$$\hat{s}_{ML}(y) = s(t, \Gamma_*) \quad \text{where} \quad \Gamma_* = \operatorname{argmax}_{\Gamma} L(y|\Gamma)$$

This might be a vector
(for Γ from any set)

Most Likely Hypothesis (2/2)

Hypothesis testing with prior information


- H_i : The signal is $s_i(t)$
- H_i : Occurs with probability $\pi(i)$
- Likelihood function $L(y|i)$
- Bayes' rule:

Finite hypotheses: Probability mass function
Infinite hypotheses: Probability density function

$$p(i|y) = \frac{L(y|i)\pi(i)}{p(y)}$$

Maximum a posteriori (MAP):

$$\hat{s}_{MAP}(y) = s(t, \Gamma_*) \quad \text{where} \quad \Gamma_* = \operatorname{argmax}_{\Gamma} L(y|\Gamma)\pi(\Gamma)$$



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