

Optimal Receiver using Complex Baseband Representation

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Passband Signals in Passband Noise

Consider M -ary passband signaling over a channel with passband Gaussian noise

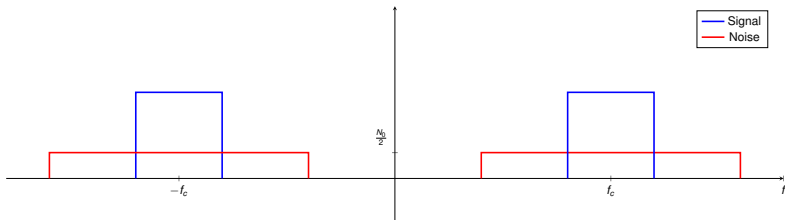
$$H_i : y_p(t) = s_{i,p}(t) + n_p(t), \quad i = 1, \dots, M$$

where

$y_p(t)$ Real passband received signal

$s_{i,p}(t)$ Real passband signals

$n_p(t)$ Real passband GN with PSD $\frac{N_0}{2}$



Note: A WSS random process is passband if its autocorrelation function is a passband signal

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where

$y_p(t)$ Real passband received signal

$s_{i,p}(t)$ Real passband signals

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The equivalent problem in complex baseband is

$$H_i : y(t) = s_i(t) + n(t), \quad i = 1, \dots, M$$

where

$y(t)$ Complex envelope of $y_p(t)$

$s_i(t)$ Complex envelope of $s_{i,p}(t)$

$n(t)$ Complex envelope of $n_p(t)$

What is the optimal receiver in terms of the complex baseband signals?

Complex Envelope of Passband Gaussian Noise

- The complex baseband representation of $n_p(t)$ is given by

$$n(t) = n_c(t) + jn_s(t) = \frac{1}{\sqrt{2}} [n_p(t) + j\hat{n}_p(t)] e^{-j2\pi f_c t}$$

where $\hat{n}_p(t)$ is the Hilbert transform of $n_p(t)$

- The inphase and quadrature components of $n(t)$ are given by

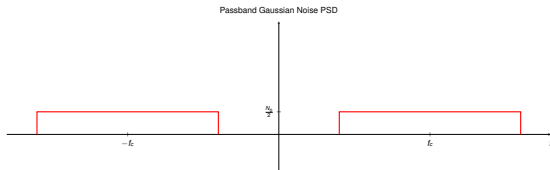
$$n_c(t) = \frac{1}{\sqrt{2}} [n_p(t) \cos 2\pi f_c t + \hat{n}_p(t) \sin 2\pi f_c t]$$

$$n_s(t) = \frac{1}{\sqrt{2}} [\hat{n}_p(t) \cos 2\pi f_c t - n_p(t) \sin 2\pi f_c t]$$

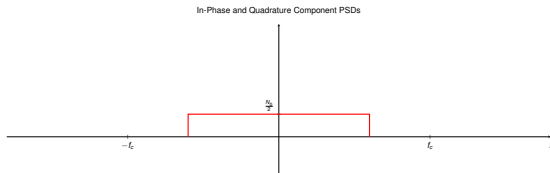
- $n_c(t)$ and $n_s(t)$ are jointly Gaussian and independent random processes (Proof in Proakis Section 2.9)

In-Phase and Quadrature Component PSDs

$$S_{n_p}(f) = \begin{cases} \frac{N_0}{2} & |f - f_c| < W \\ 0 & \text{otherwise} \end{cases}$$



$$S_{n_c}(f) = S_{n_s}(f) = \begin{cases} \frac{N_0}{2} & |f| < W \\ 0 & \text{otherwise} \end{cases}$$

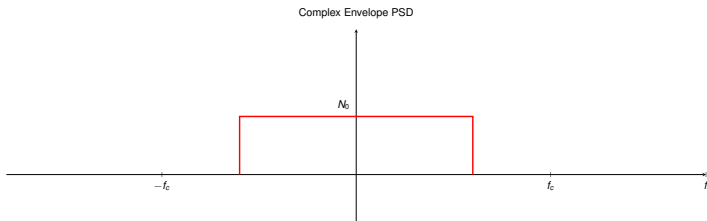


Complex Envelope PSD

- By the independence of $n_c(t)$ and $n_s(t)$, we have

$$R_n(\tau) = E[n(t + \tau)n^*(t)] = R_{n_c}(\tau) + R_{n_s}(\tau)$$

- $S_n(f) = S_{n_c}(f) + S_{n_s}(f)$



- If $n_c(t)$ and $n_s(t)$ are approximated by white Gaussian noise, $n(t)$ is said to be complex white Gaussian noise

Complex White Gaussian Noise

Definition (Complex Gaussian Random Process)

A complex random process $Z(t) = X(t) + jY(t)$ is a Gaussian random process if $X(t)$ and $Y(t)$ are jointly Gaussian random processes.

Definition (Complex White Gaussian Noise)

A complex Gaussian random process $Z(t) = X(t) + jY(t)$ is complex white Gaussian noise with PSD N_0 if $X(t)$ and $Y(t)$ are independent white Gaussian noise processes with PSD $\frac{N_0}{2}$.

Optimal Detection in Complex Baseband

- The continuous time hypothesis testing problem in complex baseband

$$H_i : y(t) = s_i(t) + n(t), \quad i = 1, \dots, M$$

where

$y(t)$ Complex envelope of $y_p(t)$

$s_i(t)$ Complex envelope of $s_{i,p}(t)$

$n(t)$ Complex white Gaussian noise with PSD $N_0 = 2\sigma^2$

- The equivalent problem in terms of complex random vectors

$$H_i : \mathbf{Y} = \mathbf{s}_i + \mathbf{N}, \quad i = 1, \dots, M$$

where \mathbf{Y} , \mathbf{s}_i and \mathbf{N} are the projections of $y(t)$, $s_i(t)$ and $n(t)$ respectively onto the signal space spanned by $\{s_i(t)\}$.

- $\mathbf{m} = E[\mathbf{N}] = \mathbf{0}$, $\mathbf{C}_N = 2\sigma^2\mathbf{I}$

Complex White Gaussian Noise through Correlators

$$\begin{aligned}\text{cov}(\langle n, \psi_1 \rangle, \langle n, \psi_2 \rangle) &= E[\langle n, \psi_1 \rangle (\langle n, \psi_2 \rangle)^*] \\ &= E\left[\int n(t)\psi_1^*(t) dt \int n^*(s)\psi_2(s) ds\right] \\ &= \int \int \psi_2(t)\psi_2^*(s)E[n(t)n^*(s)] dt ds \\ &= \int \int \psi_2(t)\psi_1^*(s)2\sigma^2\delta(t-s) dt ds \\ &= 2\sigma^2 \int \psi_2(t)\psi_1^*(t) dt \\ &= 2\sigma^2 \langle \psi_2, \psi_1 \rangle\end{aligned}$$

MPE and ML Rules in Complex Baseband

- \mathbf{N} is a circularly symmetric Gaussian vector and the pdf of \mathbf{Y} under H_i is

$$\begin{aligned} p_i(\mathbf{y}) &= \frac{1}{\pi^K \det(\mathbf{C}_N)} \exp\left(-(\mathbf{y} - \mathbf{s}_i)^H \mathbf{C}_N^{-1} (\mathbf{y} - \mathbf{s}_i)\right) \\ &= \frac{1}{(2\pi\sigma^2)^K} \exp\left(-\frac{\|\mathbf{y} - \mathbf{s}_i\|^2}{2\sigma^2}\right) \end{aligned}$$

- The MPE rule is given by

$$\begin{aligned} \delta_{MPE}(\mathbf{y}) &= \operatorname{argmax}_{1 \leq i \leq M} \operatorname{Re}(\langle \mathbf{y}, \mathbf{s}_i \rangle) - \frac{\|\mathbf{s}_i\|^2}{2} + \sigma^2 \log \pi_i \\ &= \operatorname{argmax}_{1 \leq i \leq M} \operatorname{Re}(\langle \mathbf{y}, \mathbf{s}_i \rangle) - \frac{\|\mathbf{s}_i\|^2}{2} + \sigma^2 \log \pi_i \end{aligned}$$

- The ML rule is given by

$$\begin{aligned} \delta_{ML}(\mathbf{y}) &= \operatorname{argmin}_{1 \leq i \leq M} \|\mathbf{y} - \mathbf{s}_i\|^2 = \operatorname{argmax}_{1 \leq i \leq M} \operatorname{Re}(\langle \mathbf{y}, \mathbf{s}_i \rangle) - \frac{\|\mathbf{s}_i\|^2}{2} \\ &= \operatorname{argmin}_{1 \leq i \leq M} \|\mathbf{y} - \mathbf{s}_i\|^2 = \operatorname{argmax}_{1 \leq i \leq M} \operatorname{Re}(\langle \mathbf{y}, \mathbf{s}_i \rangle) - \frac{\|\mathbf{s}_i\|^2}{2} \end{aligned}$$

ML Receiver for QPSK

QPSK signals where $p(t)$ is a real baseband pulse, A is a real number and $1 \leq m \leq 4$

$$\begin{aligned} s_m^p(t) &= \sqrt{2}Ap(t) \cos \left(2\pi f_c t + \frac{\pi(2m-1)}{4} \right) \\ &= \operatorname{Re} \left[\sqrt{2}Ap(t) e^{j \left(2\pi f_c t + \frac{\pi(2m-1)}{4} \right)} \right] \end{aligned}$$

Complex Envelope of QPSK Signals

$$s_m(t) = Ap(t) e^{j \frac{\pi(2m-1)}{4}}, \quad 1 \leq m \leq 4$$

Orthonormal basis for the complex envelope consists of only

$$\phi(t) = \frac{p(t)}{\sqrt{E_p}}$$

ML Receiver for QPSK

Let $\sqrt{E_b} = \frac{A\sqrt{E_p}}{\sqrt{2}}$. The vector representation of the QPSK signals is

$$s_1 = \sqrt{E_b} + j\sqrt{E_b}$$

$$s_2 = -\sqrt{E_b} + j\sqrt{E_b}$$

$$s_3 = -\sqrt{E_b} - j\sqrt{E_b}$$

$$s_4 = \sqrt{E_b} - j\sqrt{E_b}$$

The hypothesis testing problem in terms of vectors is

$$H_i : Y = s_i + N, \quad i = 1, \dots, 4$$

where $N \sim \mathcal{CN}(0, 2\sigma^2)$

The ML rule is given by

$$\delta_{ML}(y) = \underset{1 \leq i \leq 4}{\operatorname{argmin}} \|y - s_i\|^2$$

Thanks for your attention