EE140 Introduction to Communication Systems

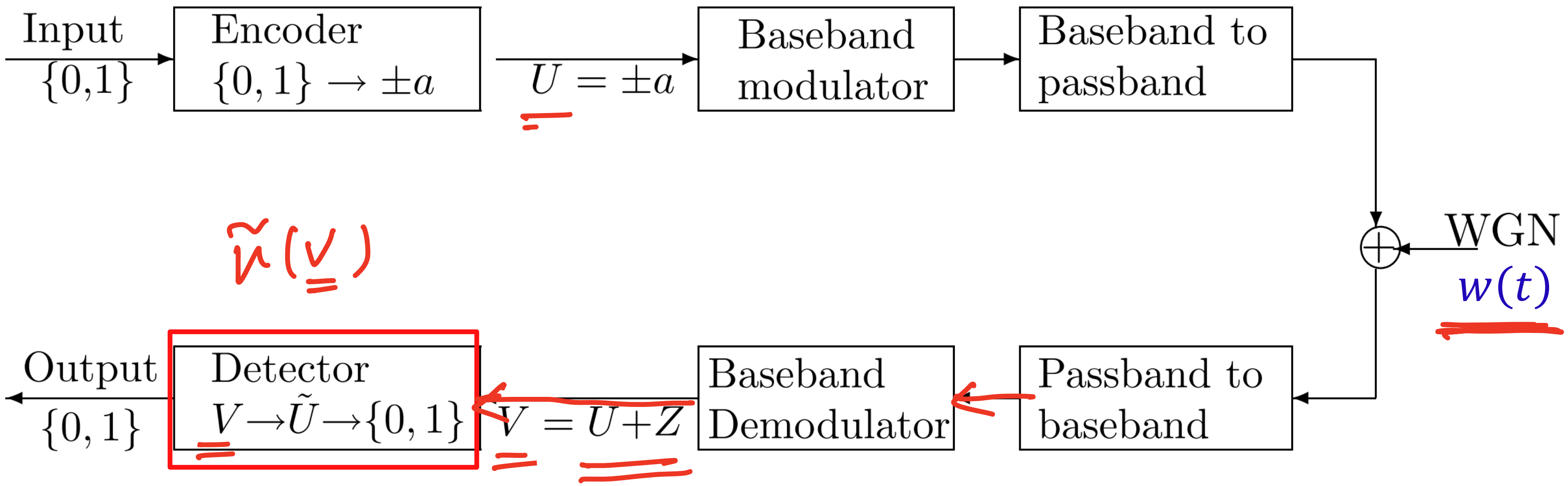
Lecture 15

Instructor: Prof. Lixiang Lian
ShanghaiTech University, Fall 2025

1 0 >PAM

-a 0 a

Detection



PAM antipodal modulation (*i.e.*, 2-PAM)

V=U+Z

- A detector observes a sample value v of a rv (vector, process or symbol) V, called observation, and on the basis of that observation, make a decision about the value of another rv U, with values in $\mathcal{A} = \{a_1, \ldots, a_M\}$, called M hypothesis.
- Synonyms: Decision making, hypothesis testing, decoding.

Detection

- Assume $U = a_m \in \mathcal{A}$ is sent, receiver observes $V = v$
  - Prior probability: $p_U(a_m) \triangleq p_m$
    - (the probability of the hypothesis before the observation of V)
  - Posteriori probability: $p_{U|V}(a_m|v)$
    - (the probability that a_m is the correct hypothesis conditional on the observation v)
  - Likelihood probability: $p_{V|U}(v|a_m)$
  - Criteria: maximize the correct probability, i.e., minimize the error probability
    - Maximum a posteriori probability (MAP) rule:

$$\boxed{\tilde{u}(v) = \arg\max_m [p_{U|V}(a_m \mid v)]}$$

$\tilde{u}(v) = a_{m^*}$

$$\max \begin{cases} p_{U|V}(a_1|v) \\ p_{U|V}(a_2|v) \\ p_{U|V}(a_m|v) \end{cases}$$

Detection

- Assume $U = a_m \in \mathcal{A}$ is sent, receiver observes $V = v$
  - Criteria: maximize the correct probability, i.e., minimize the error probability

$P_{V|U}(v|a_m) P_U(a_m)$

$\Updownarrow$

    - Maximum a posteriori probability (MAP) rule:

$$\boxed{\tilde{u}(v) = \arg\max_m [p_{U|V}(a_m \mid v)]}$$

$\max_m P_{U|V}(a_m|v) = \dfrac{P_{U,V}(a_m, v)}{P_V(v)}$

Theorem: The MAP rule maximizes the probability of correct decision, both for each observed sample value v and as an average over V. The MAP rule is determined solely by the joint distribution of U and V.

    - Maximum likelihood (ML) rule:

$$\boxed{\tilde{u}(v) = \arg\max_m \left[p_{V|U}(v|a_m)\right]}$$

$\left.\begin{array}{l} P_{V|U}(v|a_1) \\ P_{V|U}(v|a_2) \\ \vdots \end{array}\right\} \max$

    - When prior probability is equal, MAP→ ML.

$P_U(a_m) = \frac{1}{M}$, MAP $\Leftrightarrow$ ML

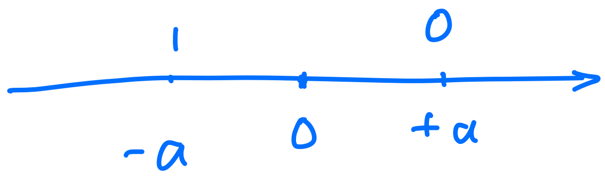
① How to MAP / ML Detection

② How to calculate Detection error probability (P_e)

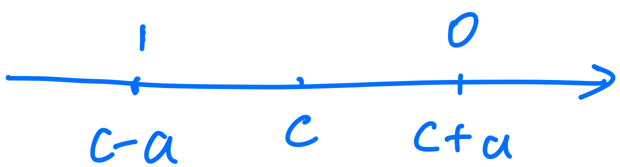
① Binary Detection in WGN

one bit $\{0, 1\}$ $M=2$

Standard 2PAM (Antipodal signal)

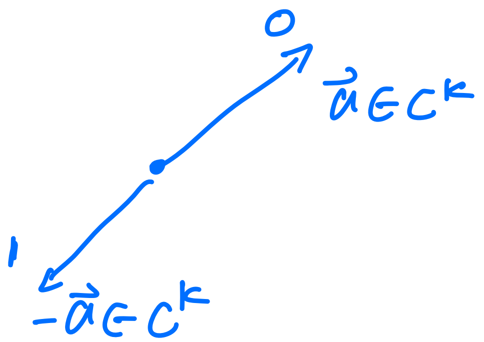


2PAM with offset (Non Antipodal signal)



Binary real vector Detection

Binary complex vector Detection



② M-ary Detection and sequence Detection

b-bit $\rightarrow \{\vec{a}_1, \vec{a}_2, \cdots \vec{a}_m\}$ $\quad \vec{a}_m \in R^n / C^n$

M-ary QAM: $\vec{a}_m \in R^2 / C^1$

M-ary Detection with arbitrary Modulation

$\Rightarrow$ Sequence Detection

Binary Detection

- Assume only one binary digit is being sent, rather than a sequence.
- Priori probability: $U = \begin{cases} 0, & p_0 \\ 1, & p_1 \end{cases}$

- constellation: $0 \to a_0, 1 \to a_1$.
- Likelihood: $f_{V|U}(v|a_0)$, $f_{V|U}(v|a_1)$
- Marginal density of V: $f_V(v) = p_0 f_{V|U}(v|a_0) + p_1 f_{V|U}(v|a_1)$
- Posteriori probability of U:

$$\boxed{p_{U|V}(a_m \,|\, v) = \frac{p_m f_{V|U}(v \,|\, a_m)}{f_V(v)}}$$

- MAP Rule:

$P(a_0|v)$ $P(a_1|v)$

$$\boxed{\frac{p_0 f_{V|U}(v \,|\, a_0)}{f_V(v)} \mathop{\gtrless}^{\tilde{U}=a_0}_{\tilde{U}=a_1} \frac{p_1 f_{V|U}(v \,|\, a_1)}{f_V(v)}}$$

Binary Detection: MAP

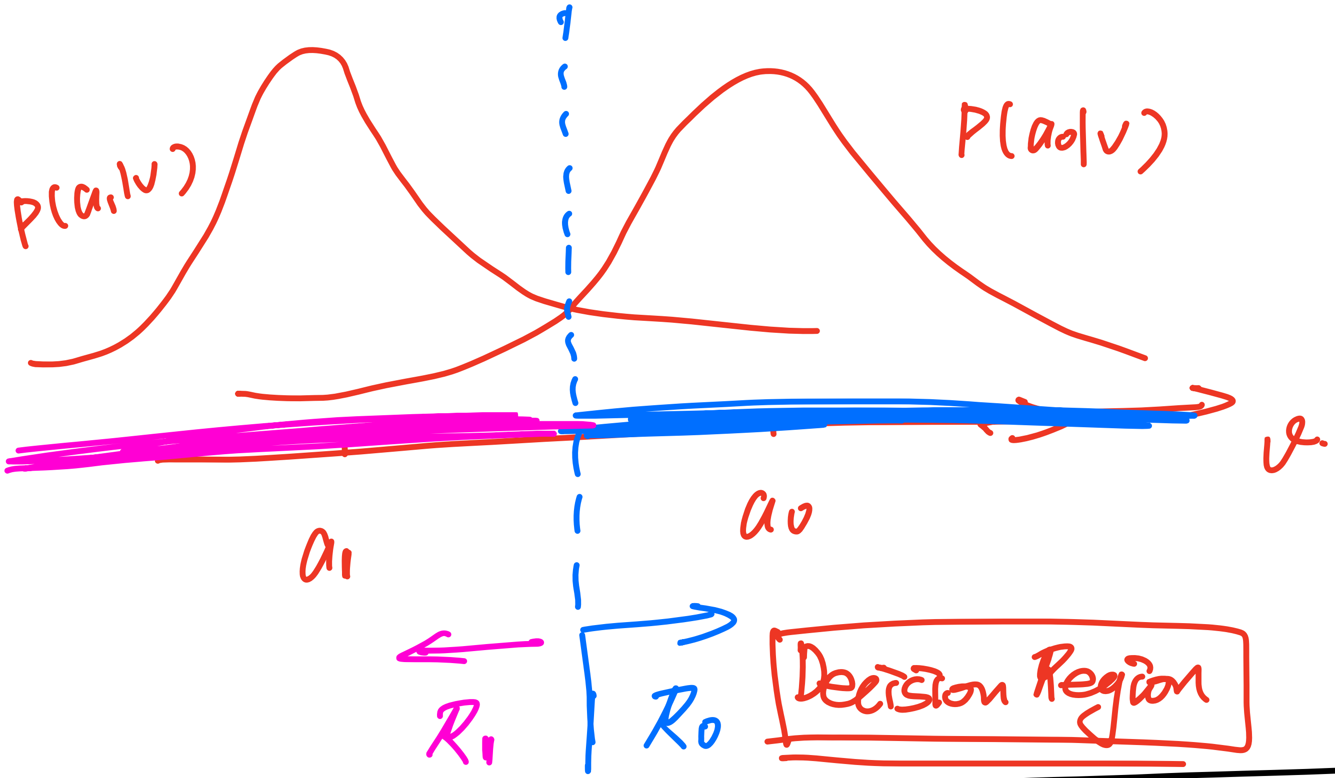
- MAP Rule:

$$\boxed{\frac{p_0 f_{V|U}(v \mid a_0)}{f_V(v)} \begin{array}{c} \geq^{\tilde{U}=a_0} \\ <_{\tilde{U}=a_1} \end{array} \frac{p_1 f_{V|U}(v \mid a_1)}{f_V(v)}}$$

- Likelihood ratio: $\Lambda(v) = f_{V|U}(v|a_0)/f_{V|U}(v|a_1)$, then MAP becomes

$$\boxed{\underline{\Lambda(v)} = \frac{f_{V|U}(v \mid a_0)}{f_{V|U}(v \mid a_1)} \begin{array}{c} \geq^{\tilde{U}=a_0} \\ <_{\tilde{U}=a_1} \end{array} \frac{p_1}{p_0} = \eta}$$

- $\eta = p_1/p_0$: threshold, depends on priori probability



$P(\hat{x}(v)=a_0)$

$\Leftrightarrow P(v \in R_0)$

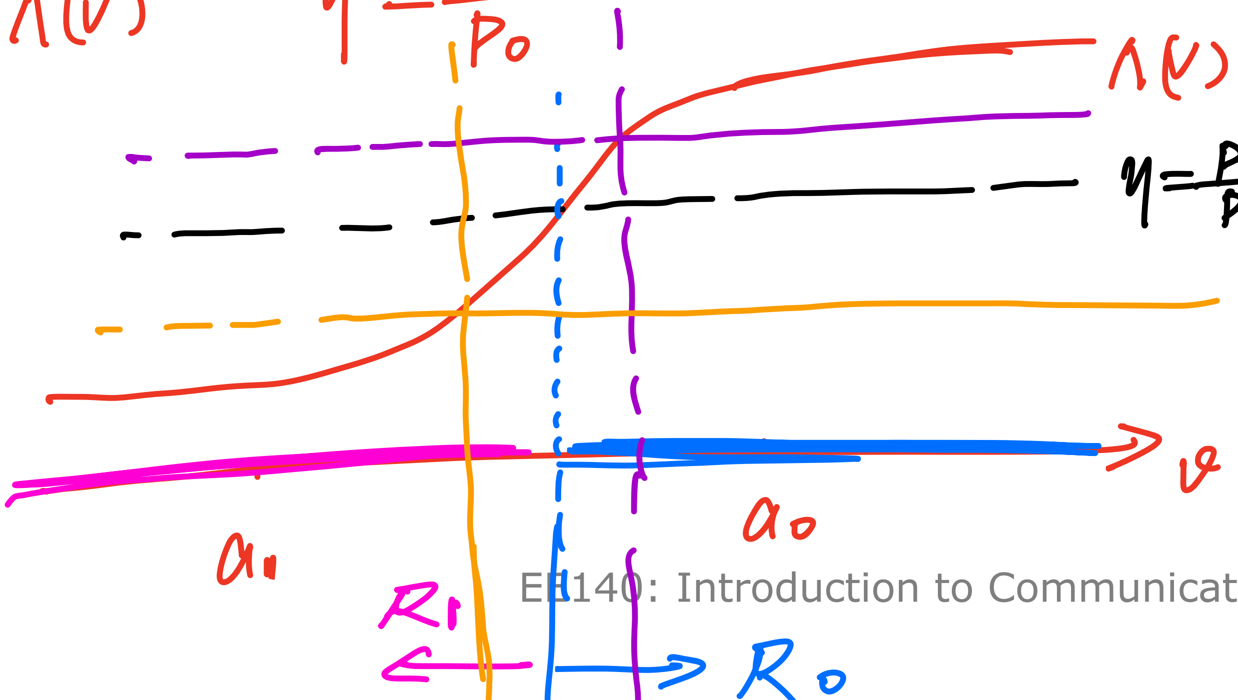
$\Leftrightarrow P(P(a_0|v) > P(a_1|v))$

$P(\hat{x}(v)=a_1)$

$\Leftrightarrow P(v \in R_1)$

$\Leftrightarrow P(P(a_1|v) > P(a_0|v))$

$\Lambda(v)$ $\quad \eta = \frac{P_1}{P_0}$



$\eta = \frac{P_1}{P_0} = 1$

$\eta = 1$ $\quad P_1 = P_0$ (MAP $\Leftrightarrow$ ML)

$\eta > 1$ $\quad P_1 > P_0$

$\eta < 1$ $\quad P_1 < P_0$

Binary Detection: ML

$\mathcal{R}_1$ $\mathcal{R}_0$ $\mathcal{R}_1$ $\mathcal{R}_0$

- When $p_0 = p_1$, the MAP decision rule becomes ML Rule:

$$\frac{f_{V|U}(v|a_0)}{f_{V|U}(v|a_1)} \underset{\tilde{U}=a_1}{\overset{\tilde{U}=a_0}{\gtreqless}} 1$$

- Error probability:

$$\Pr\{e\} = p_0 \Pr\{e \mid U{=}a_0\} + p_1 \Pr\{e \mid U{=}a_1\}$$

In radar (image detection) field

- $\Pr[e|U=0]$: probability of false alarm (no signal, but detect signal)
- $\Pr[e|U=1]$: probability of a miss (there is signal, but detect nothing)

In statistics field

- $\Pr[e|U=0]$ probability of error of the first kind
- $\Pr[e|U=1]$ probability of error of the second kind

Binary Detection: Error Probability

- Calculation of Error probability:

The MAP decision rule

$$\wedge(v) = \frac{f_{V|U}(v|0)}{f_{V|U}(v|1)} \underset{\hat{U}=1}{\overset{\hat{U}=0}{\gtrless}} \frac{p_1}{p_0} = \eta$$

Partition the space of observed sample values into 2 regions:

$$R_0 = \{v : \wedge(v) \geq \eta\}, \quad R_1 = \{v : \wedge(v) < \eta\}$$

$P(e|u=a_0)$

$$\Pr[e|U=0] = \int_{R_1} f_{V|U}(v|0)dv, \quad \Pr[e|U=1] = \int_{R_0} f_{V|U}(v|1)dv$$

Or calculate by: $= P(\hat{u}=a_1|u=a_0) = P(v \in R_1 | u=a_0)$

$$\Pr[e|U=0] = \Pr[\wedge(V) < \eta | U=0], \quad \Pr[e|U=1] = \Pr[\wedge(V) \geq \eta | U=1]$$

Binary Detection: Sufficient Statistic

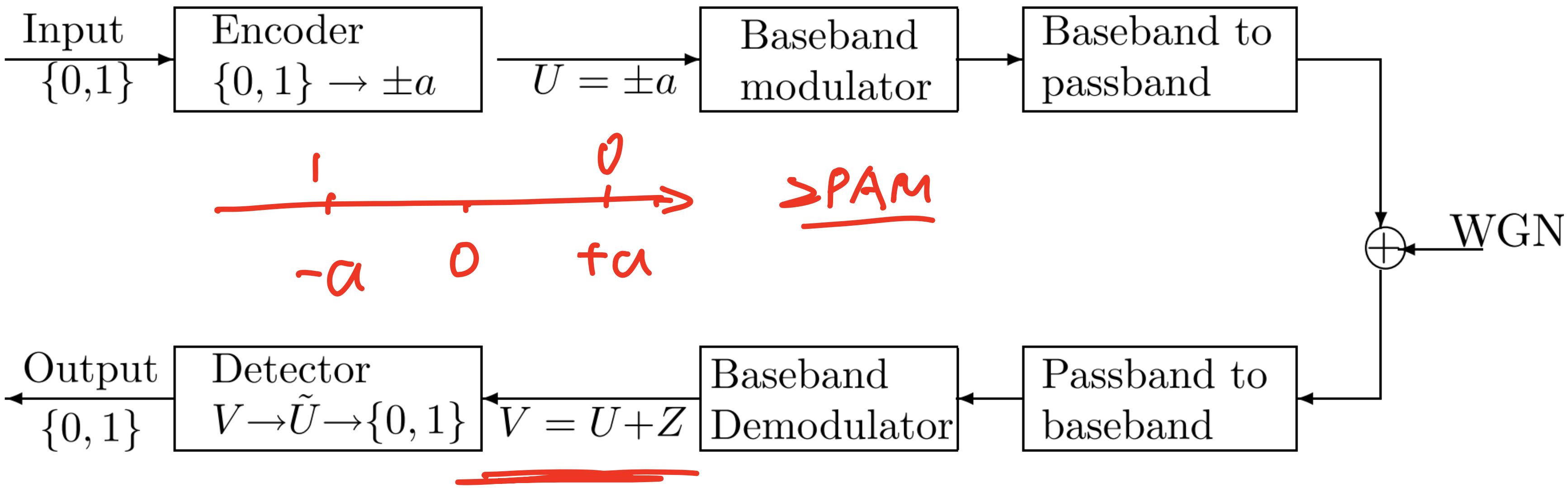
Sufficient Statistic: Given a set $\mathbf{X}$ of independent identically distributed data conditioned on an unknown parameter θ , a sufficient statistic is a function $T(\mathbf{X})$ whose value contains all the information needed to compute any estimate of the parameter.

Example: $\wedge(V)$ is sufficient statistic when doing ML estimate:

- Any function of the observation v from which the likelihood ratio can be calculated.
- $\wedge(V)$ and $\boxed{LLR(V) = \ln[\wedge(V)]}$ are sufficient statistic
- Usefulness: When calculating $\Pr[e]$, it is often simpler to work with $\wedge(V)$ than v.

Binary Detection in WGN: Antipodal Sig

- Detection for 2PAM antipodal signals (send only a single binary symbol rather than a sequence)



- Modulator input: $U = \pm a$ $(0 \rightarrow +a, 1 \rightarrow -a)$,
  - $p(U = +a) = p_0$, $p(U = -a) = p_1$
- Demodulator output: $V = a + Z$ *if* $U = a$ *or* $V = -a + Z$ *if* $U = -a$.
- Noise $Z \sim N(0, \frac{N_0}{2})$, independent of U.

Binary Detection in WGN: Antipodal Sig

$V = a + Z$

$V = -a + Z \quad Z \sim N(0, \frac{N_0}{2})$

- Likelihood function:

$$f_{V|U}(v\,|\,a) = \frac{1}{\sqrt{\pi N_0}} \exp\left[\frac{-(v-a)^2}{N_0}\right] \qquad f_{V|U}(v\,|\,-a) = \frac{1}{\sqrt{\pi N_0}} \exp\left[\frac{-(v+a)^2}{N_0}\right]$$

- Likelihood ratio:

$$\Lambda(v) = \exp\left[\frac{-(v-a)^2 + (v+a)^2}{N_0}\right] = \exp\left[\frac{4av}{N_0}\right]$$

- MAP rule:

$$\boxed{\exp\left[\frac{4av}{N_0}\right] \begin{array}{c} \geq^{\tilde{U}=a} \\ <_{\tilde{U}=-a} \end{array} \frac{p_1}{p_0} = \eta}$$

- Logarithm likelihood ratio (LLR):

$$\boxed{\mathrm{LLR}(v) = \left[\frac{4av}{N_0}\right] \begin{array}{c} \geq^{\tilde{U}=a} \\ <_{\tilde{U}=-a} \end{array} \ln(\eta)} \Rightarrow \boxed{v \begin{array}{c} \geq^{\tilde{U}=a} \\ <_{\tilde{U}=-a} \end{array} \frac{N_0 \ln(\eta)}{4a}}$$

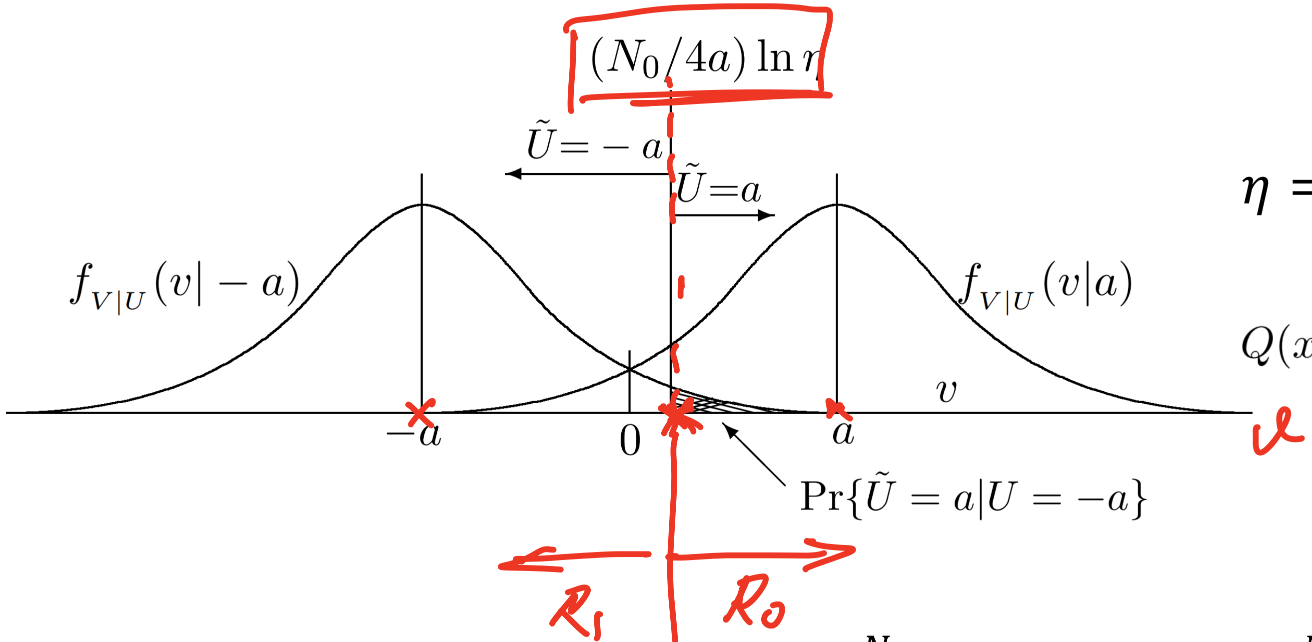
Binary Detection in WGN: Antipodal Sig

$$V = \frac{N_0 \ln(\eta)}{4a}$$

$$\eta = \frac{p_1}{p_0} \qquad \underline{p_1 = p_0}$$

- MAP rule:

$$\boxed{v \; \underset{<_{\tilde{U}=-a}}{\geq^{\tilde{U}=a}} \; \frac{N_0 \ln(\eta)}{4a}}$$



$$\eta = \frac{p_1}{p_0} = \frac{p_U(-a)}{p_U(a)}$$

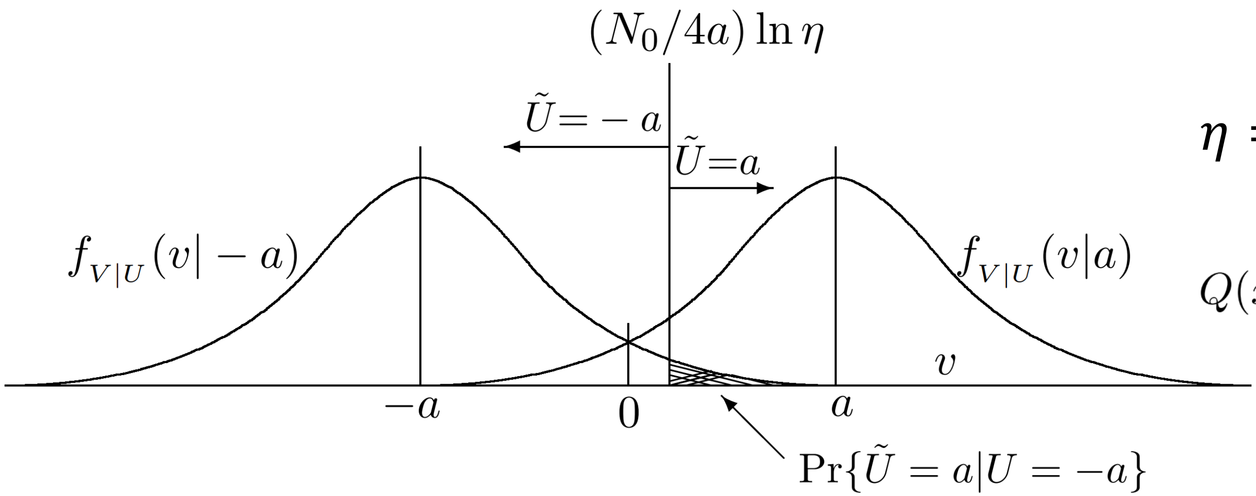
$$Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$

Given $U = -a$, error occurs if $v \geq \frac{N_0}{4a} \ln \eta \Leftrightarrow z \geq a + \frac{N_0}{4a} \ln \eta \Leftrightarrow$ $\frac{z}{\sqrt{N_0/2}} \geq \frac{a}{\sqrt{N_0/2}} + \frac{\sqrt{N_0/2}}{2a} \ln \eta$, thus $\Pr\{e \,|\, U = -a\} = Q\left(\frac{a}{\sqrt{N_0/2}} + \frac{\sqrt{N_0/2} \ln \eta}{2a}\right)$

Binary Detection in WGN: Antipodal Sig

- MAP rule:

$$\boxed{v \;\; \underset{<_{\tilde{U}=-a}}{\geq^{\tilde{U}=a}} \;\; \frac{N_0 \ln(\eta)}{4a}}$$



$$\eta = \frac{p_1}{p_0} = \frac{p_U(-a)}{p_U(a)}$$

$$Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}\,dx$$

Given $U = a$, error occurs if $v \leq \frac{N_0}{4a}\ln\eta \Leftrightarrow -z \geq a - \frac{N_0}{4a}\ln\eta \Leftrightarrow$
$\frac{-z}{\sqrt{N_0/2}} \geq \frac{a}{\sqrt{\frac{N_0}{2}}} - \frac{\sqrt{N_0/2}}{2a}\ln\eta$, thus $\Pr\{e\,|\,U=a\} = Q\left(\frac{a}{\sqrt{N_0/2}} - \frac{\sqrt{N_0/2}\ln\eta}{2a}\right)$

Binary Detection in WGN: Antipodal Sig

- The energy per bit is $E_b = a^2$
- For communication, usually assume $p_0 = p_1$, so $\eta = 1$
- ML=MAP, we have

$$\boxed{\Pr\{e\} = \Pr\{e \,|\, U{=}-a\} = \Pr\{e \,|\, U{=}a\} = Q\left(\sqrt{\frac{2E_b}{N_0}}\right)}$$

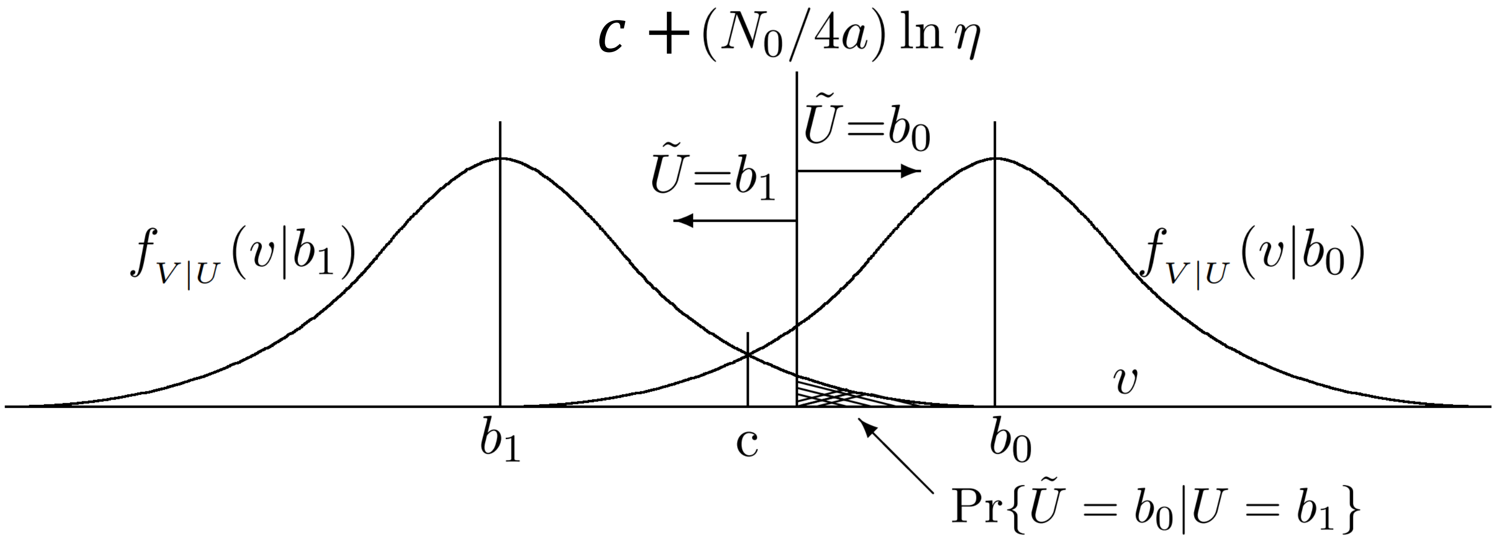
- Only ratio E_b/N_0 can be relevant, since both can be scaled together.

Binary Detection in WGN: Non-Antipodal

- Detection for 2PAM non-antipodal signals (send only a single binary symbol rather than a sequence)
- Modulator input: $U = \{b_0, b_1\}\,(0 \to b_0, 1 \to b_1)$,
  - $p(U = b_0) = p_0,\; p(U = b_1) = p_1$
  - Center point $c = \frac{b_0 + b_1}{2}$
  - $a = b_0 - c = c - b_1 (b_1 < b_0)$
- Demodulator output: $V = c + a + Z\; if\; U = b_0\;\; or\; V = c - a + Z\; if\; U = b_1$.
- Noise $Z \sim N(0, \frac{N_0}{2})$, independent of U.
- Define $\tilde{V} = V - c = \pm a + Z$. Estimate $\tilde{U} = a\; or - a$ based on $\tilde{V}$. Map $a \to b_0, -a \to b_1$.
- Compared to antipodal case, shift the result by constant c.

Binary Detection in WGN: Non-Antipodal

- The error probability



$$\Pr\{e\,|\,U{=}-a\} = Q\left(\frac{a}{\sqrt{N_0/2}} + \frac{\sqrt{N_0/2}\ln\eta}{2a}\right)$$

$$\Pr\{e\,|\,U{=}a\} = Q\left(\frac{a}{\sqrt{N_0/2}} - \frac{\sqrt{N_0/2}\ln\eta}{2a}\right)$$

Binary Detection in WGN: Non-Antipodal

- The energy per bit: $E_b = \frac{b_0^2 + b_1^2}{2} = a^2 + c^2$. Let $\gamma = \frac{a^2}{a^2+c^2}$. We have

$$\Pr\{e \,|\, U{=}b_1\} = Q\left(\sqrt{\frac{2\gamma E_b}{N_0}} + \frac{\ln \eta}{2\sqrt{2\gamma E_b/N_0}}\right)$$

$$\Pr\{e \,|\, U{=}b_0\} = Q\left(\sqrt{\frac{2\gamma E_b}{N_0}} - \frac{\ln \eta}{2\sqrt{2\gamma E_b/N_0}}\right)$$

- For ML, we have

$$\Pr[e|U=1] = \Pr[e|U=0] = Q\left(\sqrt{\frac{2\gamma E_b}{N_0}}\right)$$

- γ is the fraction of energy E_b used for signal

- Q: $\Pr[e]$ for on-off keying scheme: $0 \to 2a, 1 \to 0$.
- Ans: In this case, $\gamma = ½$. For ML, the probability of error then becomes $Q\left(\sqrt{E_b/N_0}\right)$.

Binary Vector Detection in WGN

- $U = 0 \to \boldsymbol{a} = (a_1, \ldots, a_K)$ and $U = 1 \to -\boldsymbol{a} = (-a_1, \ldots, -a_K)$

$$\boldsymbol{V} = \pm\boldsymbol{a} + \boldsymbol{Z}$$

where $\boldsymbol{Z} = (Z_1, \ldots, Z_K)$, i.i.d, $Z_i \sim \mathcal{N}(0, N_0/2)$.

$$f_{V|U}(\boldsymbol{v}|\boldsymbol{a}) = \frac{1}{\pi N_0^{k/2}} e^{\frac{-\|\boldsymbol{v}-\boldsymbol{a}\|^2}{N_0}}, \quad f_{V|U}(\boldsymbol{v}|-\boldsymbol{a}) = \frac{1}{\pi N_0^{k/2}} e^{\frac{-\|\boldsymbol{v}+\boldsymbol{a}\|^2}{N_0}}$$

$$\text{LLR}(\boldsymbol{v}) = \frac{-\|\boldsymbol{v}-\boldsymbol{a}\|^2 + \|\boldsymbol{v}+\boldsymbol{a}\|^2}{N_0} = \frac{4\langle \boldsymbol{v}, \boldsymbol{a}\rangle}{N_0}$$

- MAP test:

$$\text{LLR}(\boldsymbol{v}) = \frac{4\langle \boldsymbol{v}, \boldsymbol{a}\rangle}{N_0} \underset{\hat{U}=1}{\overset{\hat{U}=0}{\gtrless}} \ln\frac{p_1}{p_0} = \ln\eta$$

- In other words, $\langle \boldsymbol{v}, \boldsymbol{a}\rangle$ is a sufficient statistic.

Binary Vector Detection in WGN

MAP test:

$$\mathsf{LLR}(\boldsymbol{v}) = \frac{4\langle \boldsymbol{v}, \boldsymbol{a}\rangle}{N_0} \underset{\hat{U}=1}{\overset{\hat{U}=0}{\gtrless}} \ln \frac{p_1}{p_0} = \ln \eta$$

Equivalent to:

$$\frac{\langle \boldsymbol{v}, \boldsymbol{a}\rangle}{\|\boldsymbol{a}\|} \underset{\hat{U}=1}{\overset{\hat{U}=0}{\gtrless}} \frac{N_0 \ln(\eta)}{4\|\boldsymbol{a}\|}$$

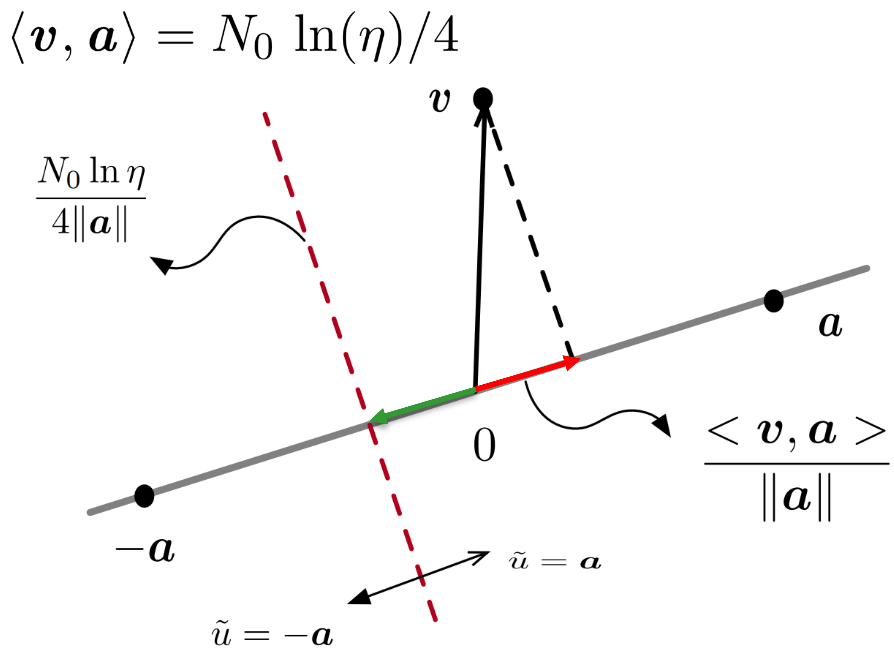
ML test:

$$\langle \boldsymbol{v}, \boldsymbol{a}\rangle \underset{\hat{U}=1}{\overset{\hat{U}=0}{\gtrless}} 0$$

- The projection of $\boldsymbol{v}$ onto $\boldsymbol{a}$ is $\frac{\langle \boldsymbol{v}, \boldsymbol{a}\rangle}{\|\boldsymbol{a}\|} \frac{\boldsymbol{a}}{\|\boldsymbol{a}\|}$
- Decision only depends on the component of $\boldsymbol{v}$ in the direction of $\boldsymbol{a}$
- $\langle \boldsymbol{v}, \boldsymbol{a}\rangle = ||\boldsymbol{a}||^2 + \langle \boldsymbol{z}, \boldsymbol{a}\rangle$
- Only the noise in the direction of the signal should be relevant in detecting the signal.

Binary Vector Detection in WGN

- MAP test

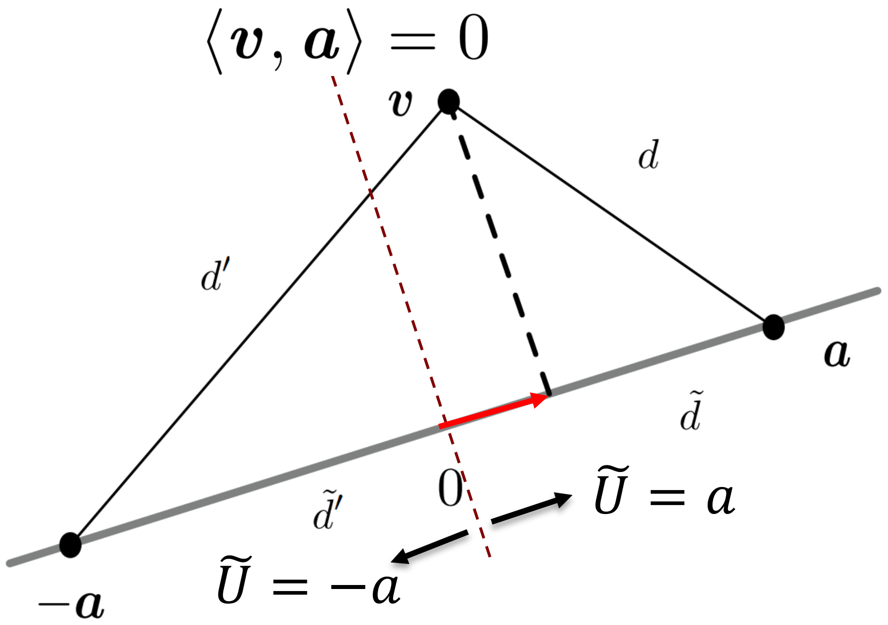


$$\frac{\langle \boldsymbol{v}, \boldsymbol{a} \rangle}{\|\boldsymbol{a}\|} \underset{\hat{U}=1}{\overset{\hat{U}=0}{\gtrless}} \frac{N_0 \ln(\eta)}{4\|\boldsymbol{a}\|}$$

  – The noise is spherically symmetric around the origin

Binary Vector Detection in WGN

- ML test

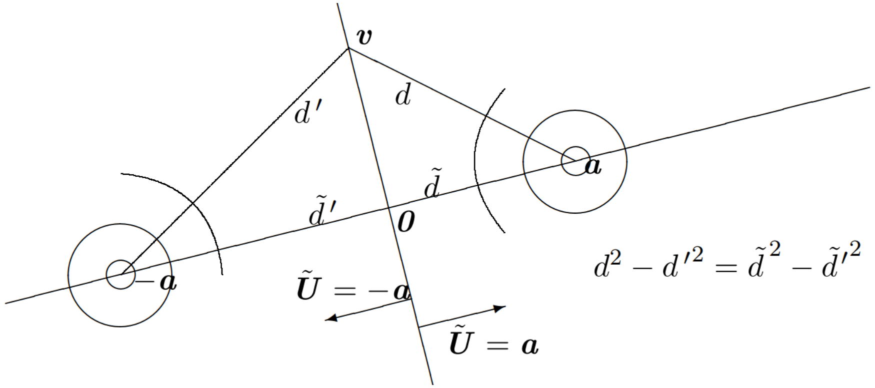


$$\langle \boldsymbol{v}, \boldsymbol{a} \rangle \underset{\hat{U}=1}{\overset{\hat{U}=0}{\gtrless}} 0$$

$$\mathrm{LLR}(\boldsymbol{v}) = \frac{-\|\boldsymbol{v}-\boldsymbol{a}\|^2 + \|\boldsymbol{v}+\boldsymbol{a}\|^2}{N_0} \underset{\hat{U}=1}{\overset{\hat{U}=0}{\gtrless}} 0$$

  - The likelihoods depend only on the distance from the origin.
  - $d = \big||\boldsymbol{v} - \boldsymbol{a}|\big|, d' = \big||\boldsymbol{v} + \boldsymbol{a}|\big|$
  - If d>d', then $\widetilde{U} = -a$, vice versa. Choose estimate which is closer to $\boldsymbol{v}$. (minimum distance rule)

Binary Vector Detection in WGN



- Error Probability

$$\frac{\langle \boldsymbol{v}, \boldsymbol{a} \rangle}{\|\boldsymbol{a}\|} \mathop{\gtrless}_{\tilde{U}=-\boldsymbol{a}}^{\tilde{U}=\boldsymbol{a}} \frac{N_0 \ln(\eta)}{4\|\boldsymbol{a}\|}$$

  - Given $\boldsymbol{U} = -\boldsymbol{a}$, $\boldsymbol{V} = -\boldsymbol{a} + \boldsymbol{Z}$. Thus

$$\frac{<\boldsymbol{V},\boldsymbol{a}>}{\|\boldsymbol{a}\|} = -\|\boldsymbol{a}\| + < \boldsymbol{Z}, \frac{\boldsymbol{a}}{\|\boldsymbol{a}\|} >$$

  - Z_k is $\mathcal{N}(0, N_0/2)$. $\frac{<\boldsymbol{V},\boldsymbol{a}>}{\|\boldsymbol{a}\|}$ is $\mathcal{N}(-\|\boldsymbol{a}\|, N_0/2)$.
  - $\Pr\{e|\boldsymbol{U} = -\boldsymbol{a}\} \Leftrightarrow \Pr\left\{\frac{<\boldsymbol{V},\boldsymbol{a}>}{\|\boldsymbol{a}\|} \geq \frac{\mathrm{N}_0 \ln(\eta)}{4\|\boldsymbol{a}\|}\right\} \Leftrightarrow \Pr\left\{Z \geq \|\boldsymbol{a}\| + \frac{\mathrm{N}_0 \ln(\eta)}{4\|\boldsymbol{a}\|}\right\}$

$$\Pr\{e \mid \boldsymbol{U} = -\boldsymbol{a}\} = Q\left(\sqrt{\frac{2\|\boldsymbol{a}\|^2}{N_0}} + \frac{\ln \eta}{2\sqrt{2\|\boldsymbol{a}\|^2/N_0}}\right)$$

$$\Pr\{e \mid \boldsymbol{U} = \boldsymbol{a}\} = Q\left(\sqrt{\frac{2\|\boldsymbol{a}\|^2}{N_0}} - \frac{\ln \eta}{2\sqrt{2\|\boldsymbol{a}\|^2/N_0}}\right)$$

Binary Vector Detection in WGN

- Error Probability
  - The energy per bit: $\mathrm{E_b} = \|\boldsymbol{a}\|^{\mathbf{2}}$
  - If $\eta = 1$, we have

$$\Pr\{e\} = Q\left(\sqrt{\frac{2E_b}{N_0}}\right)$$

  - The error probability only depends on the distance $2\|\boldsymbol{a}\|$ between the signals.
  - The component of $\boldsymbol{v}$ in directions orthogonal to the signal do not affect the LLR (theorem of irrelevance)

Binary Complex Vector Detection in WGN

- Input $\boldsymbol{U} = \boldsymbol{a}$ with p_0, $\boldsymbol{U} = -\boldsymbol{a}$ with p_1, $\boldsymbol{a}$ is a complex random n-vector.
- Observation is a complex random n-vector: $\boldsymbol{V} = \boldsymbol{U} + \boldsymbol{Z}$
- $\boldsymbol{Z}$ is complex random vectors with $\mathcal{R}(Z_k) \sim \mathcal{N}\left(0, \frac{N_0}{2}\right)$, $\mathcal{I}(Z_k) \sim \mathcal{N}\left(0, \frac{N_0}{2}\right)$, thus $Z_k \sim \mathcal{CN}(0, N_0)$.
- Likelihood:

$$f_{\boldsymbol{V}|\boldsymbol{U}}(\boldsymbol{v}|\boldsymbol{a}) = f_{\boldsymbol{V}'|\boldsymbol{U}'}(\boldsymbol{v}'|\boldsymbol{a}') = \frac{1}{(\pi N_0)^n} \exp \sum_{k=1}^{n} \frac{-\Re(v_k - a_k)^2 - \Im(v_k - a_k)^2}{N_0}$$

$$f_{\boldsymbol{V}|\boldsymbol{U}}(\boldsymbol{v}|-\boldsymbol{a}) = f_{\boldsymbol{V}'|\boldsymbol{U}'}(\boldsymbol{v}'|-\boldsymbol{a}') = \frac{1}{(\pi N_0)^n} \exp \sum_{k=1}^{n} \frac{-\Re(v_k + a_k)^2 - \Im(v_k + a_k)^2}{N_0}.$$

$$\mathrm{LLR}(\boldsymbol{v}) = \frac{-\|\boldsymbol{v} - \boldsymbol{a}\|^2 + \|\boldsymbol{v} + \boldsymbol{a}\|^2}{N_0}$$

- MAP test: $$\frac{\Re[\langle \boldsymbol{v}, \boldsymbol{a} \rangle]}{\|\boldsymbol{a}\|} \;\substack{\geq^{\tilde{U}=\boldsymbol{a}} \\ <_{\tilde{U}=-\boldsymbol{a}}}\; \frac{N_0 \ln(\eta)}{4\|\boldsymbol{a}\|}$$
  - Error probabilities are the same.

M-ary Detection in WGN

- Input: n-vector $\boldsymbol{U} \in (\boldsymbol{a}_1, \ldots, \boldsymbol{a}_M)$ with a priori proba. $p_1, \ldots, p_M$
- Observation: n-vector $\boldsymbol{V}$
- Posteriori probability: $p_{\boldsymbol{U}|\boldsymbol{V}}(\boldsymbol{a}_m|\boldsymbol{v})$
- Likehood: $f_{\boldsymbol{V}|\boldsymbol{U}}(\boldsymbol{v}|\boldsymbol{a}_m)$

MAP rule:

$$\begin{aligned}\hat{\boldsymbol{U}}(v) &= \arg\max_{\boldsymbol{a}_m}\; p_{\boldsymbol{U}|\boldsymbol{V}}\{\boldsymbol{a}_m|\boldsymbol{v}\} \\ &= \arg\max_{\boldsymbol{a}_m}\; p_m f_{\boldsymbol{V}|\boldsymbol{U}}(\boldsymbol{v}|\boldsymbol{a}_m)\end{aligned}$$

M-ary rule is multiple binary hypothesis testing problems: $\hat{\boldsymbol{U}}(v) = \boldsymbol{a}_m$ if for all m'

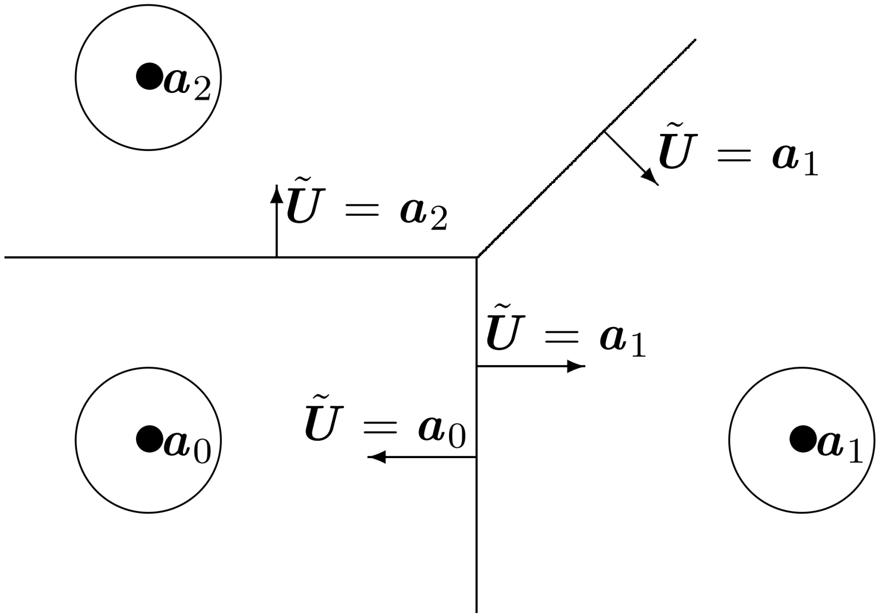
$$\wedge_{m,m'}(\boldsymbol{v}) = \frac{f_{\boldsymbol{V}|\boldsymbol{U}}(\boldsymbol{v}|\boldsymbol{a}_m)}{f_{\boldsymbol{V}|\boldsymbol{U}}(\boldsymbol{v}|\boldsymbol{a}_{m'})} \geq \frac{p_{m'}}{p_m}$$

M-ary Complex Vector Detection in WGN

$$\boldsymbol{V} = \boldsymbol{U} + \boldsymbol{Z}$$

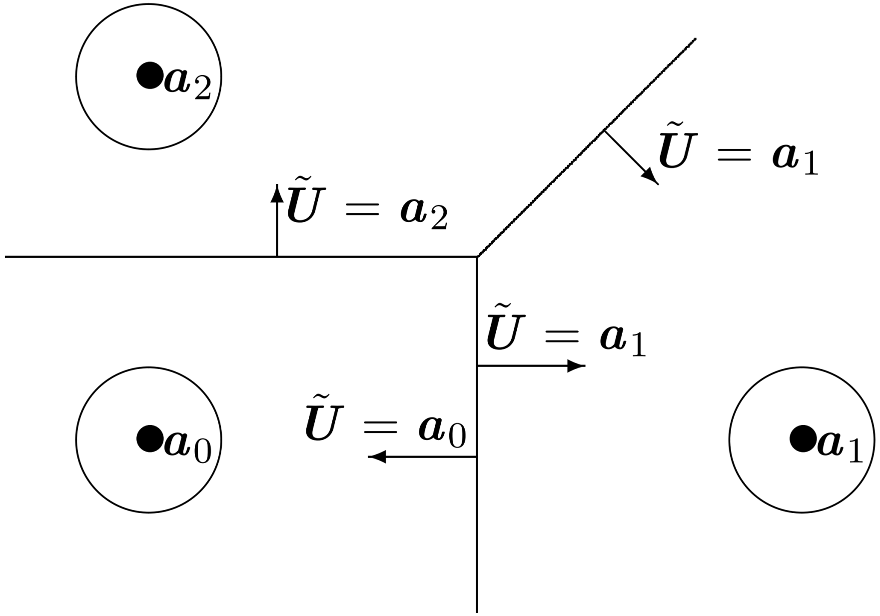
where $\boldsymbol{Z} = (Z_1, \ldots, Z_K)$, i.i.d, $\text{Re}[Z_i], \text{Im}[Z_i] \sim \mathcal{N}(0, N_0/2)$.

$$\text{LLR}_{m,m'}(\boldsymbol{v}) = \frac{-\|\boldsymbol{v} - \boldsymbol{a}_m\|^2 + \|\boldsymbol{v} - \boldsymbol{a}_{m'}\|^2}{N_0}$$



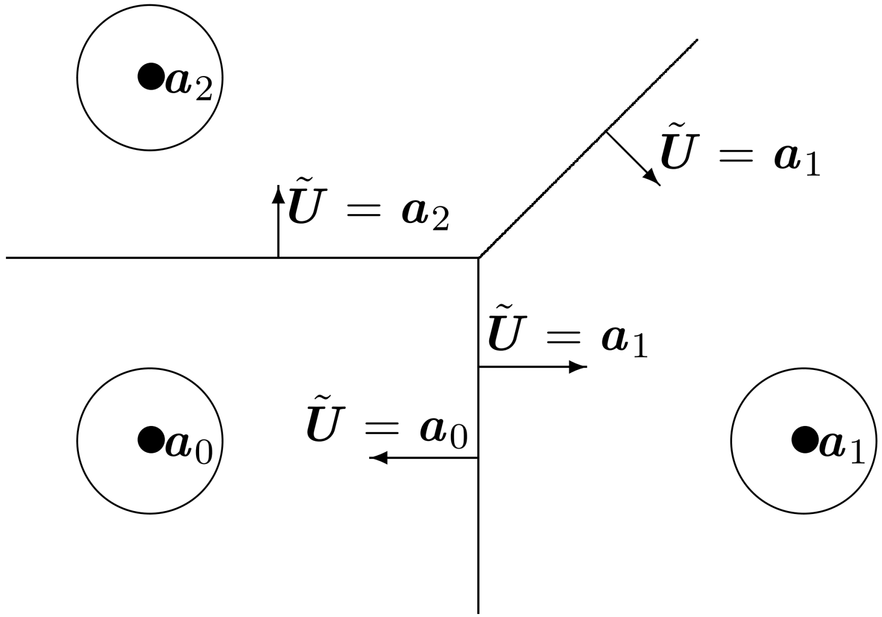
ML: decision regions are Voronoi regions

M-ary Complex Vector Detection in WGN



- For ML, each binary test separates the observation space into two regions separated by the perpendicular bisector between the two points.
- If $\{p_1, \ldots, p_M\}$ are unequal, perpendicular bisectors are shifted.

M-ary Complex Vector Detection in WGN



Union bound:

$$\mathbb{P}\left(\bigcup_{i=1}^{\infty} A_i\right) \le \sum_{i=1}^{\infty} \mathbb{P}(A_i)$$

- Error probability:

Given $\boldsymbol{U} = \boldsymbol{a}_m$,

$$\Pr[e|\boldsymbol{U} = \boldsymbol{a}_m] = \Pr\left[\cup_{m' \neq m} \left(\widetilde{\boldsymbol{U}}(\boldsymbol{v}) = \boldsymbol{a}_{m'} \middle| \boldsymbol{U} = \boldsymbol{a}_m\right)\right]$$

Thus,

$$\Pr[e] = \sum_m p_m \Pr[e|\boldsymbol{U} = \boldsymbol{a}_m]$$

M-ary QAM Detection in WGN

- Consider a QAM modulation using pulse $p(t)$
  - $\{p(t-kT)\}$ are orthonormal functions.
  - $\mathcal{A} = \{a_1, \dots, a_M\}$
  - Baseband waveform: $u(t) = \sum_{k=1}^{n} u_k p(t-kT)$.
  - Let $\{\phi_k(t); k \geq 1\}$ be an orthonormal basis of complex $\mathcal{L}_2$ waveforms such that the first n basis are given by $\phi_k(t) = p(t-kT), 1 \leq k \leq n$.
  - Baseband noise: $z(t) = \sum_k Z_k \phi_k(t)$
  - The received baseband signal:

$$V(t) = \sum_{k=1}^{\infty} V_k \phi_k(t) = \sum_{k=1}^{n} (u_k + Z_k) p(t-kT) + \sum_{k>n} Z_k \phi_k(t)$$

- Detection:
  - M^n hypotheses for $\{U_1, \dots, U_n\}$
  - $\boldsymbol{u} = (u_1, \dots, u_n)^T, \boldsymbol{v} = (v_1, \dots, v_n, \dots, v_l)^T, l > n,$

M-ary QAM Detection in WGN

$$V(t) = \sum_{k=1}^{\infty} V_k \phi_k(t) = \sum_{k=1}^{n} (u_k + Z_k) p(t - kT) + \sum_{k>n} Z_k \phi_k(t)$$

- Likelihood of $\boldsymbol{v}$ conditioned on $\boldsymbol{u}$ is

$$f_{\boldsymbol{V}|\boldsymbol{U}}(\boldsymbol{v}|\boldsymbol{u}) = \prod_{k=1}^{n} f_Z(v_k - u_k) \prod_{k=n+1}^{\ell} f_Z(v_k)$$

- Likelihood ratio:

$$\Lambda_{\boldsymbol{u},\boldsymbol{u}'}(\boldsymbol{v}) = \prod_{k=1}^{n} \frac{f_Z(v_k - u_k)}{f_Z(v_k - u'_k)}$$

$$\mathrm{LLR}_{\boldsymbol{u},\boldsymbol{u}'}(\boldsymbol{v}) = \frac{-\|\boldsymbol{v} - \boldsymbol{u}\|^2 + \|\boldsymbol{v} - \boldsymbol{u}'\|^2}{N_0}$$

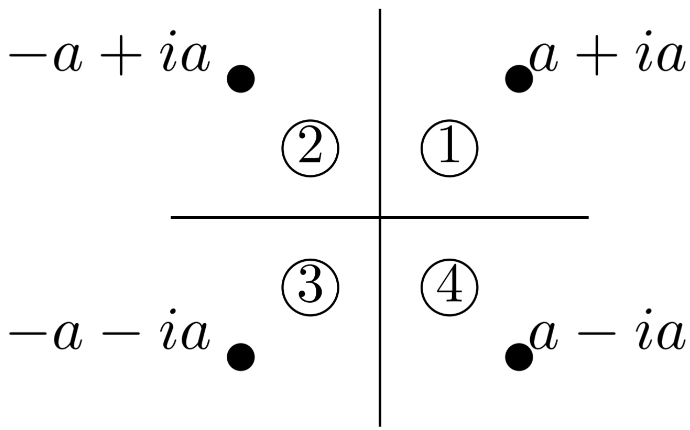
  - The only relevant terms in the decision are $\boldsymbol{v} = (v_1, \dots, v_n)^T$
- ML detection:
  - $\tilde{u}(\boldsymbol{v}) = \arg\min_{i \in M^n} \|\boldsymbol{v} - \boldsymbol{u_i}\|$ (minimum distance detection)

M-ary QAM Detection in WGN

- ML detection:
  - $\tilde{u}(\boldsymbol{v}) = \arg\min_{\boldsymbol{u_i} \in \mathcal{A}^n} \|\boldsymbol{v} - \boldsymbol{u_i}\|$ (minimum distance detection)
  - $\tilde{u}(v_k) = \arg\min_{u_k \in \mathcal{A}} \|v_k - u_k\|$
  - ML sequence detector with M^n hypothesis detects each U_k by minimizing $(v_k - u_k)^2$ over M hypothesis for that U_k.
  - Theorem: Let $U(t) = \sum_{k=1}^{n} U_k p(t - kT)$ be a QAM or PAM baseband input to a WGN channel, assume $\{p(t - kT)\}$ are orthonormal functions. Then the M^n-ary ML decision on $\boldsymbol{U} = (U_1, \dots, U_n)^T$ is equivalent to making separate M-ary ML decision on each U_k.
  - Detection Error Probability:
    - $\mathrm{Pr}(e) = 1 - (1 - \mathrm{P})^{\mathrm{n}}$, P is the error probability for single symbol.

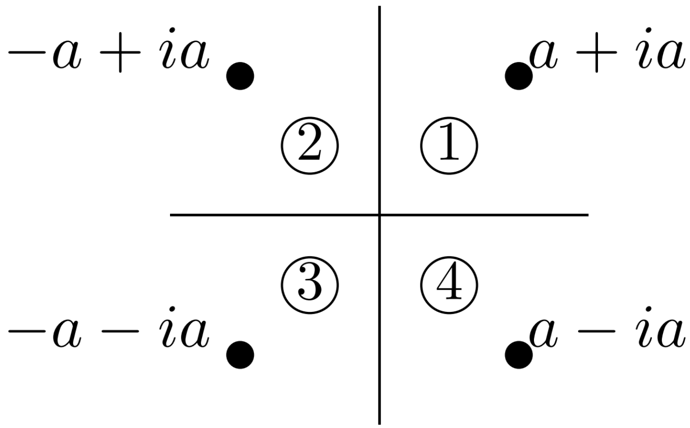
M-ary QAM Detection in WGN

- Example:
- Consider 4-QAM with four signal points $u = \pm a \pm ia$. Assume Gaussian noise with $\mathcal{N}\left(0, \frac{N_0}{2}\right)$ per dimension. Sketch the signal set and ML decision regions. Find the exact probability of error (in terms of Q function) for this signal set using ML detection.
- Sol:



M-ary QAM Detection in WGN

- Example:
- Sol:



- $$P(e|U=a+ia) = P(a+ia+\mathcal{R}(Z)+i\mathcal{I}(Z) \in \{R_2 \cup R_3 \cup R_4\})$$
$$= P(\{a+\mathcal{R}(Z)<0\} \cup \{a+\mathcal{I}(Z)<0\})$$
$$= P(\{a+\mathcal{R}(Z)<0\}) + P(\{a+\mathcal{I}(Z)<0\}) - P(\{a+\mathcal{R}(Z)<0\} \cap \{a+\mathcal{I}(Z)<0\})$$
$$= 2Q\left(\sqrt{\frac{2a^2}{N_0}}\right) - Q\left(\sqrt{\frac{2a^2}{N_0}}\right)^2$$

* We focus on signal (symbol) error probability (constellation)
Not bit error probability (mapping from bits to symbol)

M-ary QAM Detection in WGN

- Example:
- For QPSK, $E_b = \frac{2a^2}{2} = a^2$, $P(e) = 2Q\left(\sqrt{\frac{2a^2}{N_0}}\right) - Q\left(\sqrt{\frac{2a^2}{N_0}}\right)^2$
- For 4PAM, $E_b = \frac{5a^2}{2}$, $\mathcal{A} = \{-3a, -a, a, 3a\}$

$$\begin{aligned} P(e|U = a) &= P(a + Z < 0) + P(a + Z > 2a) \\ &= P(-Z > a) + P(Z > a) \\ &= 2Q\left(\sqrt{\frac{2a^2}{N_0}}\right) \end{aligned}$$

$$P(e) = \frac{1}{2} * 2Q\left(\sqrt{\frac{2a^2}{N_0}}\right) + \frac{1}{2} * Q\left(\sqrt{\frac{2a^2}{N_0}}\right) = \frac{3}{2} Q\left(\sqrt{\frac{2a^2}{N_0}}\right)$$

- Comparing 4PAM and QPSK, for the same error probability, approximately 2.5 times more transmit energy is needed. This loss is even more significant for larger constellations.
- It is much more energy-efficient to use both I and Q channels.

M-ary Detection with Arbitrary Modulation in WGN

- PAM
  - Real hypotheses $\mathcal{A} = \{a_0, \ldots, a_{M-1}\}$
  - $\{u_k; k \in \mathbb{Z}\} \to u(t) = \sum_k u_k p(t - kT) \to x(t) = 2\cos 2\pi f_c t \left(\sum_k u_k p(t - kT)\right)$
- QAM
  - Complex hypotheses $\mathcal{A} = \{a_0, \ldots, a_{M-1}\}$
  - $\{u_k; k \in \mathbb{Z}\} \to u(t) = \sum_k u_k p(t - kT) \to x(t) = 2\cos 2\pi f_c t \sum_k u'_k p(t - kT) - 2\sin 2\pi f_c t \sum_k u''_k p(t - kT)$
- Arbitrary modulation scheme
  - Signal set $\mathcal{A} = \{\boldsymbol{a_0}, \ldots, \boldsymbol{a_{M-1}}\}$, $\boldsymbol{a_m} = \left(a_{m,1}, \ldots, a_{m,n}\right)^T \in \mathbb{R}^n$
  - Choose orthonormal functions $\{\phi_k(t); k \geq 1\}$, span the space of real $\mathcal{L}_2$ waveforms
  - $\boldsymbol{a_m} \to \boldsymbol{b_m}(\boldsymbol{t}) = \sum_{k=1}^{n} a_{m,k}\phi_k(t)$
  - $\{s_1, s_2, \ldots\} \to \sum_l \boldsymbol{b}_{\boldsymbol{s_l}}(t - lT)$

M-ary Detection with Arbitrary Modulation in WGN

- Arbitrary modulation scheme
  - Signal set $\mathcal{A} = \{\boldsymbol{a_0}, \dots, \boldsymbol{a_{M-1}}\}$, $\boldsymbol{a_m} = \left(a_{m,1}, \dots, a_{m,n}\right)^T \in \mathbb{R}^n$
  - Choose orthonormal functions $\{\phi_k(t); k \geq 1\}$, span the space of real $\mathcal{L}_2$ waveforms
  - $\boldsymbol{a_m} \to \boldsymbol{b_m}(\boldsymbol{t}) = \sum_{k=1}^{n} a_{m,k}\phi_k(t)$
  - $\{s_1, s_2, \dots\} \to \sum_l \boldsymbol{b}_{\boldsymbol{s_l}}(t - lT)$
  - the successive transmitted signal waveforms are all orthogonal to each other
    - $\{\phi_k(t - lT), k, l \in \mathbb{Z}\}$ are all orthonormal
  - PAM: $n = 1$, $\phi_1(t) = p(t)$ (BB), $\phi_1(t) = \sqrt{2}p(t)\cos 2\pi f_c t$ (PB)
  - QAM: $n = 2$, $\phi_1(t) = \sqrt{2}p(t)\cos 2\pi f_c t$, $\phi_2(t) = -\sqrt{2}p(t)\sin 2\pi f_c t$ (PB)

M-ary Detection with Arbitrary Modulation in WGN

- Arbitrary modulation scheme
  - $X(t)$ is a choice from M waveforms $\{\boldsymbol{b_m}(t)\}_{m=1}^{M}$
  - $X(t) = \sum_{k=1}^{n} X_k \phi_k(t)$
  - Received random waveform
    - $Y(t) = \sum_{k=1}^{l} Y_k \phi_k(t) = \sum_{k=1}^{n} (X_k + Z_k)\, \phi_k(t) + \underline{\sum_{k=n+1}^{l} Y_k \phi_k(t)}$

Signal Noise in signal space

Noise perpendicular to the signal space and Contribution of signal waveforms other than X (successive signals, signals from other users)

M-ary Detection with Arbitrary Modulation in WGN

- Arbitrary modulation scheme
  - $X(t)$ is a choice from M waveforms $\{\boldsymbol{b_m}(t)\}_{m=1}^{M}$
  - $X(t) = \sum_{k=1}^{n} X_k \phi_k(t)$
  - Received random waveform
    - $Y(t) = \sum_{k=1}^{l} Y_k \phi_k(t) = \sum_{k=1}^{n} (X_k + Z_k)\, \phi_k(t) + \sum_{k=n+1}^{l} Y_k \phi_k(t)$
  - $Y(t) \rightarrow \boldsymbol{Y} = (Y_1, \dots, Y_n)^T$ and $\boldsymbol{Y}' = (Y_{n+1}, \dots, Y_l)^T$
  - $\mathrm{X(t)} \rightarrow \boldsymbol{X} = (X_1, \dots, X_n)^T$
  - $\mathrm{WGN}\, Z(t) \rightarrow \boldsymbol{Z} = (Z_1, \dots, Z_n)^T$ and $\boldsymbol{Z}' = (Z_{n+1}, \dots, Z_l)^T$
  - $V(t)$ (contributions from other signals)$\rightarrow \boldsymbol{V}' = (V_{n+1}, \dots, V_l)^T$
  - $\boldsymbol{Y} = \boldsymbol{X} + \boldsymbol{Z}, \boldsymbol{Y}' = \boldsymbol{Z}' + \boldsymbol{V}'$
  - Assumption:
    - $\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{Z}', \boldsymbol{V}'$ are statistically independent.
    - $\boldsymbol{Z}'$ and $\boldsymbol{V}'$ are orthogonal to $\boldsymbol{X}$ and $\boldsymbol{Z}$

M-ary Detection with Arbitrary Modulation in WGN

- Arbitrary modulation scheme
  - $\boldsymbol{Y} = \boldsymbol{X} + \boldsymbol{Z}, \boldsymbol{Y}' = \boldsymbol{Z}' + \boldsymbol{V}'$
  - Likelihood:

$$f_{\boldsymbol{Y}\,\boldsymbol{Y}'|\boldsymbol{X}}(\boldsymbol{y}\boldsymbol{y}'|\boldsymbol{a}_m) = f_{\boldsymbol{Z}}(\boldsymbol{y} - \boldsymbol{a}_m) f_{\boldsymbol{Y}'}(\boldsymbol{y}') \quad \text{(independence)}$$

  - Likelihood ratio:

$$\Lambda_{m,m'}(\boldsymbol{y}) = \frac{f_{\boldsymbol{Z}}(\boldsymbol{y} - \boldsymbol{a}_m)}{f_{\boldsymbol{Z}}(\boldsymbol{y} - \boldsymbol{a}_{m'})}$$

  - Y is sufficient statistic for MAP on X, Y′ is irrelevant
  - Theorem of irrelevance: Assume that $\boldsymbol{Y}'$ is statistically independent of the pair $\boldsymbol{X}, \boldsymbol{Z}$. Then the MAP detection of $\boldsymbol{X}$ from the observation of $(\boldsymbol{Y}, \boldsymbol{Y}')$ depends only on $\boldsymbol{Y}$. That is, the observed sample value of $\boldsymbol{Y}'$ is irrelevant.
  - Reduce the problem to a finite dimensional problem. The other signals can be view as part of $\boldsymbol{Y}'$, assuming they are orthogonal and independent of $\boldsymbol{X}$.

Summary:

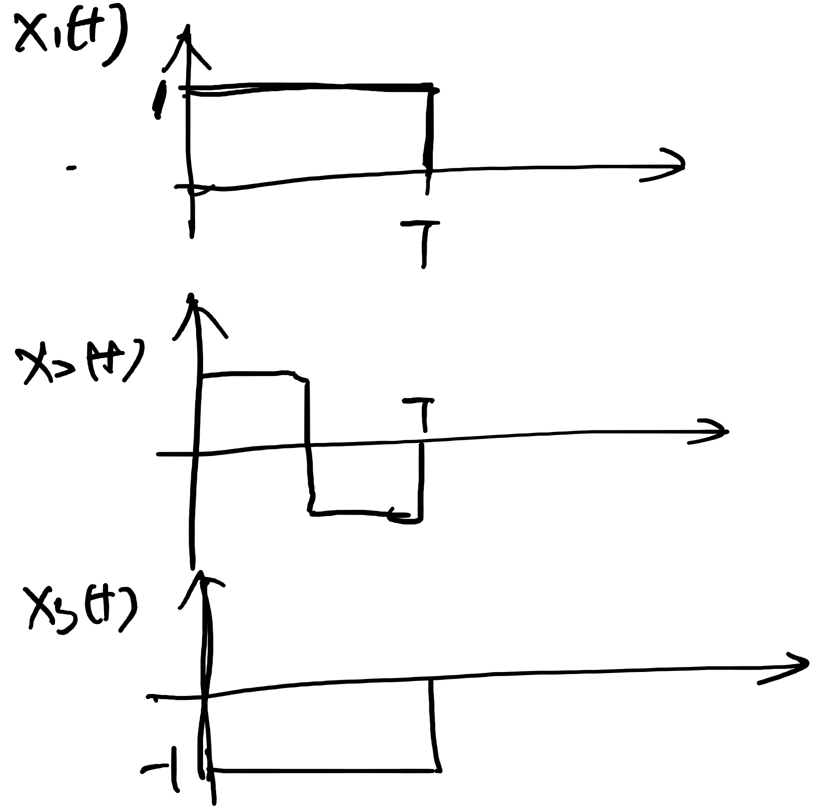
Example:

$$a_m \in \mathbb{R}^n \xrightarrow{\{\phi_k(t)\}_{k=1}^n} \underline{x_m(t)} = \sum_{k=1}^{n} a_{m,k}\phi_k(t)$$ waveform Detection

$\Updownarrow$

a_m symbol Detection

$x_m(t) \longrightarrow a_m \longrightarrow$ symbol Detection



Q: MAP Detection & Pe

① Find the orthonormal Basis of signal space $\{\phi_k(t)\}$

Gram-schmidt orthonormalization

$$x_1(t) \longrightarrow \frac{x_1(t)}{\|x_1(t)\|} = \phi_1(t)$$

$$\frac{x_2(t) - \langle x_2(t), \phi_1(t)\rangle \phi_1(t)}{\| \qquad\qquad \|} = \phi_2(t)$$

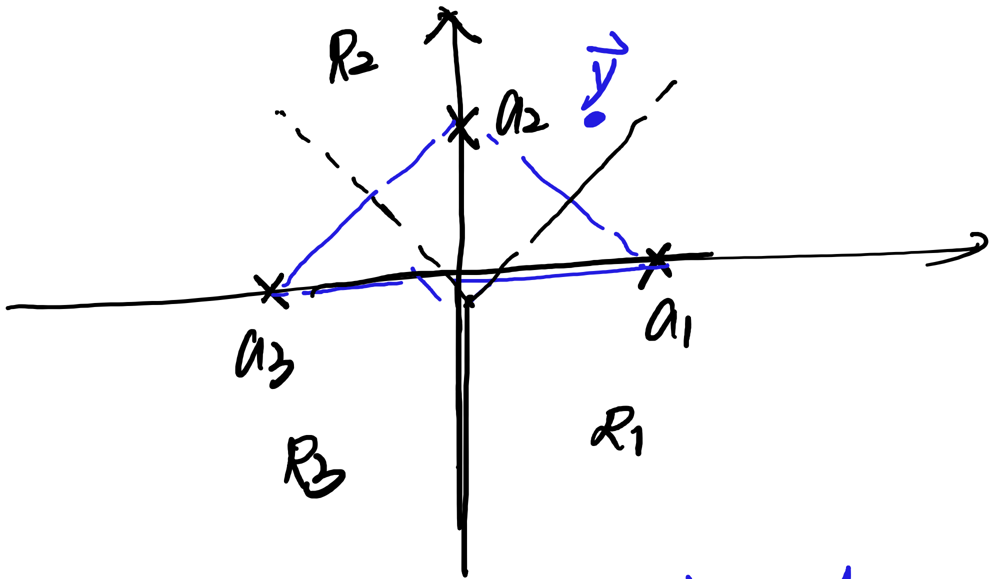
② $\{\phi_1(t), \phi_2(t)\}$

$y(t) \longrightarrow \vec{y} = [y_1, y_2]$

$x_1(t) \longrightarrow a_1 = [a_{1,1}, a_{1,2}]$

$x_2(t) \longrightarrow a_2 = [a_{2,1}, a_{2,2}]$

$x_3(t) \xrightarrow{\{\phi_1(t),\ \phi_2(t)\}} \vec{a}_3 = [a_{3,1},\ a_{3,2}]$



① Draw the decision boundary

or Binary Detection

or **If ML,** minimum Distance Detection $= \arg\min_m \| \vec{y} - \underline{a_m} \|$

② Calculation Detection error probability

$P_e = P_1 P(e \mid u = a_1) + P_2 P(e \mid u = a_2) + P_3 P(e \mid u = a_3)$

$\leq$ ______ (union bound) depends on symbol Distance.

Summary:

1. prior distribution $P(U=a_m)=P_m$,

posterior probability $P_{U|V}(a_m|v)$

Likelihood probability $P_{V|U}(v|a_m)$

MAP: $\tilde{u}(v) = \arg\max_m P_{U|V}(a_m|v)$

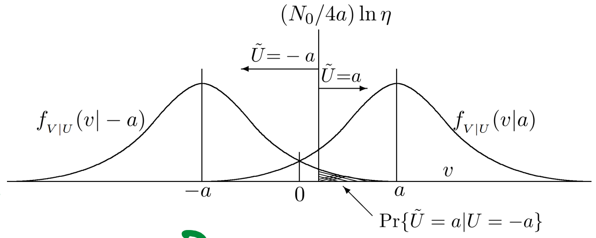
ML: $\tilde{u}(v) = \arg\max_m P_{V|U}(v|a_m)$

equal prior

2. Detection (MAP/ML, Pe)

① Binary detection

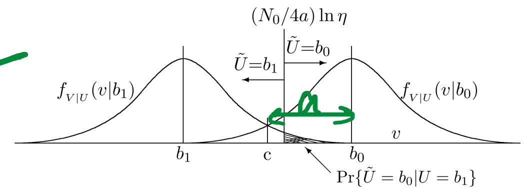
- Scalar
  - Antipodal



$E_b=a^2$

$$\boxed{\Pr\{e\} = \Pr\{e\,|\,U=-a\} = \Pr\{e\,|\,U=a\} = Q\left(\sqrt{\frac{2E_b}{N_0}}\right)} \text{ (ML)}$$

  - NonAntipodal

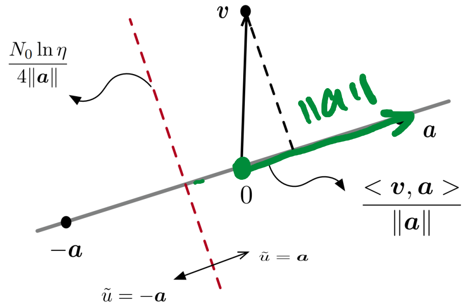


$$\Pr\{e\,|\,U=-a\} = Q\left(\frac{a}{\sqrt{N_0/2}} + \frac{\sqrt{N_0/2}\ln\eta}{2a}\right)$$

- vector
  - real vector
  - complex vector

vector

real vector =



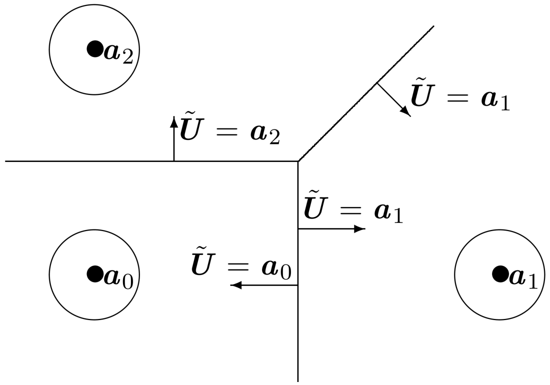
$$\Pr\{e \mid U = -a\} = Q\left(\sqrt{\frac{2\|a\|^2}{N_0}} + \frac{\ln \eta}{2\sqrt{2\|a\|^2/N_0}}\right)$$

$$\Pr\{e\} = Q\left(\sqrt{\frac{2E_b}{N_0}}\right)$$

complex vector $\longrightarrow$

$$\frac{\Re[\langle v, a\rangle]}{\|a\|} \ \underset{<_{\tilde{U}=-a}}{\geq^{\tilde{U}=a}} \ \frac{N_0 \ \ln(\eta)}{4\|a\|}$$

② M-ary Detection



$$\Pr[e|U = a_m]$$
$$= \Pr\left[\cup_{m' \neq m} \left(\tilde{U}(v) = a_{m'} | U = a_m\right)\right]$$
$$\leq \sum_{m' \neq m} \Pr\left(\tilde{U}(v) = a_{m'} \mid U = a_m\right)$$

③ M-ary QAM =

$$V(t)=\sum_{k=1}^{\infty} V_k\phi_k(t)=\sum_{k=1}^{n}(u_k+Z_k)p(t-kT)+\sum_{k>n} Z_k\phi_k(t)$$

$$\mathrm{LLR}_{\boldsymbol{u},\boldsymbol{u}'}(\boldsymbol{v}) = \frac{-\|\boldsymbol{v}-\boldsymbol{u}\|^2+\|\boldsymbol{v}-\boldsymbol{u}'\|^2}{N_0}$$

ML sequence detector with M^n hypothesis detects each U_k by minimizing $(v_k-u_k)^2$ over M hypothesis for that U_k.

④ M-ary Arbitrary Modulation:

$$\boldsymbol{a_m} \to \boldsymbol{b_m(t)} = \sum_{k=1}^{n} a_{m,k}\phi_k(t)$$

$$\{s_1, s_2, \dots\} \to \sum_{l} \boldsymbol{b}_{\boldsymbol{s_l}}(t-lT)$$

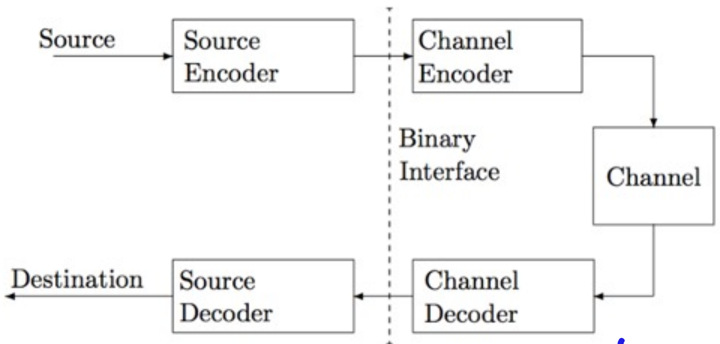
$$Y(t)=\sum_{k=1}^{l} Y_k\phi_k(t)$$

$$=\sum_{k=1}^{n}(X_k+Z_k)\,\phi_k(t)+\sum_{k=n+1}^{l} Y_k\phi_k(t)$$

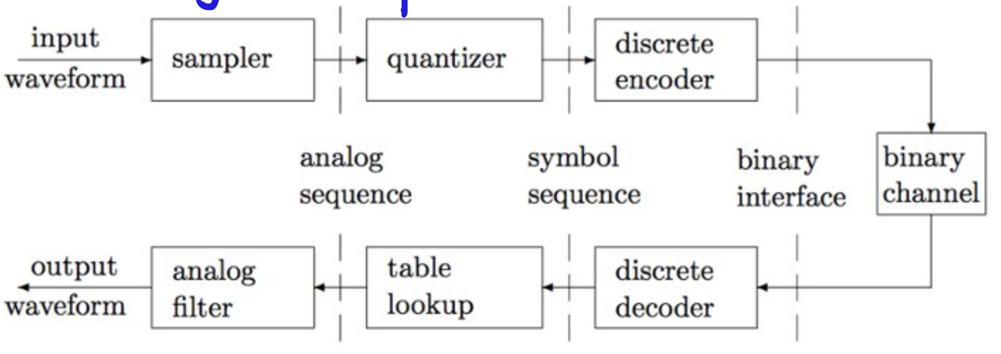
$$\Lambda_{m,m'}(\boldsymbol{y})=\frac{f_Z(\boldsymbol{y}-\boldsymbol{a}_m)}{f_Z(\boldsymbol{y}-\boldsymbol{a}_{m'})}$$

waveform Detection ⟺ symbol Detection

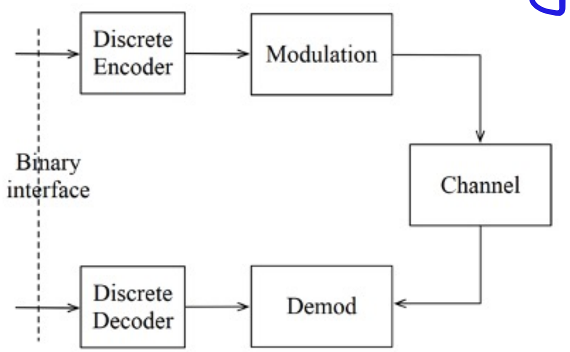
Digital Communication

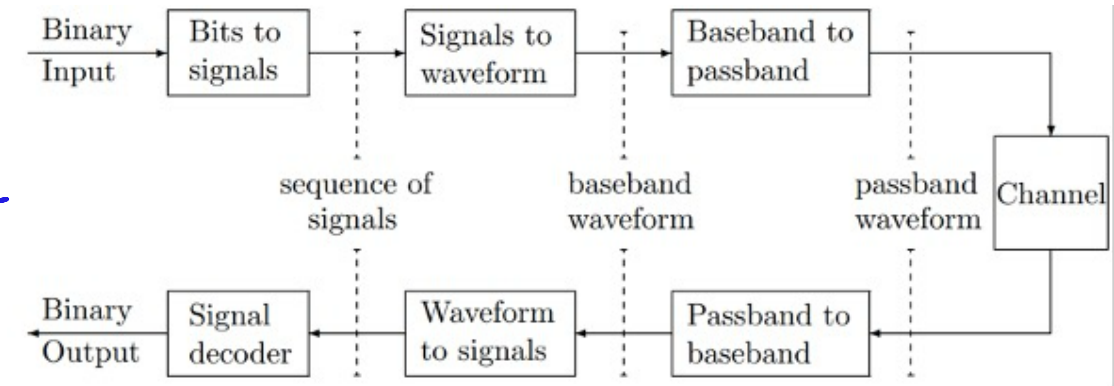


general framework



source coding

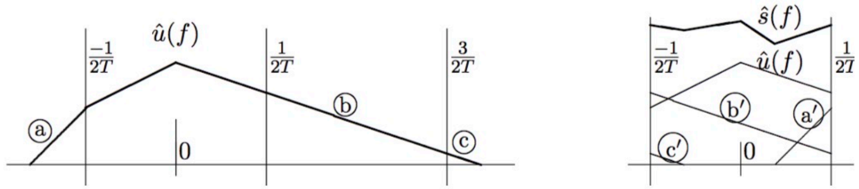




channel coding

Source Coding:

① Sampling: $\begin{cases} u(t) \to \{u_k\}, \text{ orthogonal Expansion} \\ \text{sampling theorem: } x(t) = \sum_{k=-\infty}^{+\infty} x\left(\frac{k}{2W}\right) \operatorname{sinc}(2Wt-k) \\ \text{Aliasing:} \end{cases}$



② Quantization $\begin{cases} \text{Analog sequences } \{u_k\} \to \boxed{Q} \to \text{Discrete sequence } \{v_k\} \\ \text{MSE: } \begin{cases} E[|U-V|^2] \\ E_V E_{U|V}[|U-V|^2] \end{cases} \\ \min_{\{R_j\}\{a_j\}} \text{MSE} = E[|U-V|^2] \quad \text{s.t. } M \\ \min \text{MSE} \quad \text{s.t. } \underline{H(V) = R} \end{cases}$

→ **Lloyd-Max Algorithm**

→ Entropy-coded quantization (High rate, uniform)

MSE vs. $\bar{L}$ Tradeoff ←

③ Discrete Encoder:

- Lossless (uniquely decodable)
- $\bar{L}_{min}$

Fixed-length code: $\log_2 M \le L < \log_2 M + 1$

fixed to fixed length code: $\log_2 M \le \bar{L} < \log_2 M + \frac{1}{n}$

variable-length code:

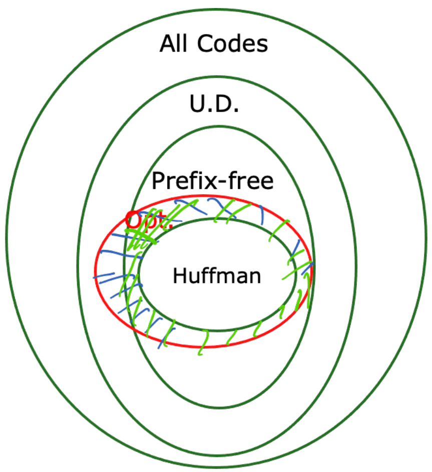
- prefix-free code
  ↓
- kraft-Inequality
  ↓
- Huffman-code

$H(X) \le \bar{L}_{min} < H(X) + 1$

(entropy bound of P.F. code)

variable to variable length code:

$H(X) \le \bar{L}_{min,n} < H(X) + \frac{1}{n}$



Channel Encoder

↓

$\boxed{\text{Detection}}$

PAM
(Constellation, Es, Mod, DeM.)
QAM
(Constellation, Es, Mod, DeM.)

bits to signal mapping

↓

signal to BB waveform

$u(t) = \sum_k u_k p(t-kT)$

↓

BB → PB mapping

↓ channel

P.B. → BB

↓

BB → signals
(Nyquist criterion)

↓

Signal → bits
(Detection)

Nyquist criterion

Time

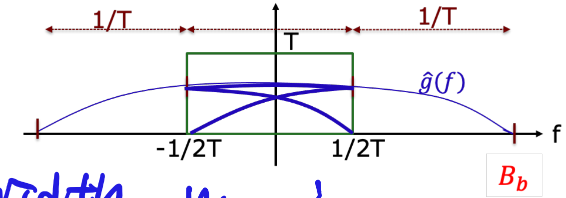
$g(kT)=1, k=0$

$g(kT)=0, k\neq 0,$

freq:

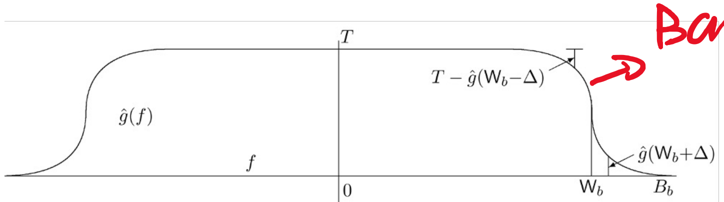
$\sum \hat{g}(f+\frac{k}{T})\,\mathrm{rect}(fT)$

$= T\,\mathrm{rect}(fT)$



Nyquist Bandwidth: $W_b = \frac{1}{2T}$

$2W_b > B_b \geq W_b$



→ Band edge symmetry

Matched Filter: $q(f) = P^*(f) \Leftrightarrow \{p(t-kT)\}$ orthonormal functions

Digital Communication

Thanks for your kind attention!

Questions?