

**Subject** : **Digital Communication**  
**Code** : **UEC 639**  
**Credit** : **4**

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# Signal space analysis

## ➤ Received signal

### ❑ Time domain

$$r(t) = s(t) + n(t)$$

### ❑ Vector form

$$\underline{r} = \underline{s} + \underline{n}$$

## ➤ How to choose a transmitted signal from an observation of $\underline{r}$

## ➤ MAP Maximize “a posteriori” probability

### ❑ ML Maximize the Likelihood

## ➤ **We need to analyze the noise ...**

# Signal space

$$r(t) = \sum_{j=1}^{\infty} r_j \psi_j(t) \quad \underline{r} = [r_1 \ r_2 \ \dots r_n \ r_{n+1} \ \dots]$$

$$n(t) = \sum_{j=1}^{\infty} n_j \psi_j(t) \quad \underline{n} = [n_1 \ n_2 \ \dots n_n \ n_{n+1} \ \dots]$$

$$s_i(t) = \sum_{j=1}^{\infty} s_{ij} \psi_j(t) \quad \underline{s}_i = [s_{i,1} s_{i,2} \ \dots s_{i,n} \ 0 \ 0 \ \dots]$$

$$\begin{aligned} \Pr(r(t) | s_i(t)) &= \Pr(r(t) = s_i(t) + n(t)) \\ &= \Pr(\underline{r} = \underline{s}_i + \underline{n}) \end{aligned}$$

## Vocabulaire/notation

### Échantillons

- ▢  $n$  pour  $n(T)$
- ▢  $z$  pour  $z(T)$
- ▢  $a_i$  pour  $a_i(T)$

### Densité conditionnelle

- ▢  $p_z(z | \text{événement})$  densité de la statistique du test quand la donnée " $z$ " a été envoyée
- ▢  $p_z(z | \mathcal{H}_0)$  et  $p_z(z | \mathcal{H}_1)$  par exemple

# Noise in signal space

- Noise vector

$$\underline{n} = [n_1 \ n_2 \ \dots] \quad n_j = \int_0^T n(t) \psi_j(t) dt$$

Coefficients of noise vector

- Recall  $n(t)$  Gaussian process

- $En(t) = 0$  ← Mean

Variance

- $\text{PSD}[n(t)] = G_N(f) = \frac{N_0}{2}$

$$\forall f \quad R_N(\tau) = \frac{N_0}{2} \delta(\tau)$$

Autocorrelation

- $En(t)n(t+\tau) = 0 \quad \tau \neq 0$

- $n(t)$  Gaussian

$\Rightarrow n_j$  Gaussian (integration is a linear operation)

# Noise analysis

## ➤ Expected value

$$\begin{aligned} En_j &= E \int_0^T n(t) \psi_j(t) dt \\ &= \int_0^T E \{ n(t) \} \psi_j(t) dt \\ &= \int_0^T 0 \psi_j(t) dt = 0 \end{aligned}$$

# Noise analysis

## ➤ Variance

$$\text{Var}[X] \stackrel{\text{def}}{=} E[(X - E[X])^2]$$

$$\begin{aligned} En_j^2 &= E \int_0^T n(t) \psi_j(t) dt \cdot \int_0^T n(z) \psi_j(z) dz \\ &= E \int_0^T \int_0^T n(t) n(z) \psi_j(t) \psi_j(z) dz dt \\ &= \int_0^T \int_0^T E \{ n(t) n(z) \} \psi_j(t) \psi_j(z) dz dt \\ &= \int_0^T \int_0^T \frac{N_0}{2} \delta(t - z) \psi_j(t) \psi_j(z) dz dt \\ &= \frac{N_0}{2} \int_0^T \psi_j^2(t) dt = \frac{N_0}{2} \end{aligned}$$



In statistics, a **variance** is the **spread of a data** set around its mean value, while a **covariance** is the measure of the **directional relationship** between two random variables.

## Independence of coefficients

➤ Covariance, *i.e.*, suppose  $i \neq j$

$$\begin{aligned} E n_i n_j &= E \int_0^T \int_0^T n(t) n(z) \psi_i(t) \psi_j(z) dt dz \\ &= \int_0^T \int_0^T E \{ n(t) n(z) \} \psi_i(t) \psi_j(z) dt dz \\ &= \int_0^T \int_0^T \frac{N_0}{2} \delta(t-z) \psi_i(t) \psi_j(z) dt dz \\ &= \frac{N_0}{2} \int_0^T \psi_i(t) \psi_j(t) dt \\ &= \frac{N_0}{2} \langle \psi_i(t) \psi_j(t) \rangle = 0 \end{aligned}$$

The  $\delta(t-z)$  only valid at  $t=z$

# Independence of coefficients

- The coefficients are not correlated for white noise in an orthonormal base

- $$En_i n_j = \frac{N_0}{2} \langle \psi_i(t) \psi_j(t) \rangle = 0$$

- For Gaussian random variables, uncorrelated  $\Rightarrow$  Independent



# Noise Summary

- Gaussian of zero mean

- $$n_j \sim N\left(0, \frac{N_0}{2}\right) \quad \sigma^2 = \frac{N_0}{2}$$

- Independent  $En_j n_i = 0$  for  $j \neq i$

- Vector density  
= joint density of coefficients

**iid:** Independent Identically Distributed.

# Noise density

For two or more independent signals / vectors the joint *pdf* is expressed as product of the *pdf* of all the signals / vectors.

➤ By independence

➤ 
$$P_{\underline{n}}(\underline{n}) = \prod_{j=1}^{\infty} P_{n_j}(n_j) = \prod_{j=1}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-n_j^2/2\sigma^2}$$

$$\begin{aligned} p(r(t)|s_i(t)) &= p(r(t) = s_i(t) + n(t)) \\ &= p(\underline{r} = \underline{s}_i + \underline{n}) \\ &= p(\underline{n} = \underline{r} - \underline{s}_i) \\ &= \prod_{j=1}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-(r_j - s_{j,i})^2/2\sigma^2} \end{aligned}$$

$$\underline{s}_i = \begin{bmatrix} s_{1,i} & s_{2,i} & s_{3,i} & \cdots \end{bmatrix}$$

# Detectors

## ➤ ML (Likelihood)

- ❑ Maximize the likelihood, i.e. choosing the  $s_i(t)$  which maximizes the likelihood of receiving  $r(t)$

$$s_i(t) \text{ such that } \arg \max_j P(\underline{r} | \underline{s}_j) = i$$

## ➤ MAP (*a posteriori*)

- ❑ Choose transmitted signal to maximize the "*a posteriori*" probability

$$s_i \text{ such that } \arg \max_j P(\underline{r} | \underline{s}_j) \boxed{P(\underline{s}_j)} = i$$

*a priori probability*

# MAP choice

$$\begin{aligned} \text{Arg max}_j P(\underline{r}|\underline{s}_j)P(\underline{s}_j) &= \text{Arg max}_j P(\underline{r} = \underline{s}_j + \underline{n})P(\underline{s}_j) \\ &= \text{Arg max}_j P(\underline{n} = \underline{r} - \underline{s}_j)P(\underline{s}_j) \\ &= \text{Arg max}_j \prod_{k=1}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-(r_k - s_{j,k})/2\sigma^2} P(\underline{s}_j) \\ &= \text{Arg max}_j \prod_{k=1}^{\infty} e^{-(r_k - s_{j,k})^2/2\sigma^2} P(\underline{s}_j) \\ &= \text{Arg max}_j e^{-\frac{1}{2\sigma^2} \sum_{k=1}^{\infty} (r_k - s_{j,k})^2} P(\underline{s}_j) \end{aligned}$$

We can discard  $\sqrt{2\pi}\sigma$ , as it is a constant and does not contribute any information

In two or more exponential functions power multiplication can be replaced by addition

# MAP choice

$$\text{Arg max}_j P(\underline{r}|\underline{s}_j) P(\underline{s}_j) = \text{Arg max}_j e^{-\frac{1}{2\sigma^2} \sum_{k=1}^{\infty} (r_k - s_{j,k})^2} P(\underline{s}_j)$$

Taking Log

$$= \text{Arg max}_j \ln \left[ e^{-\frac{1}{2\sigma^2} \sum_{k=1}^{\infty} (r_k - s_{j,k})^2} P(\underline{s}_j) \right]$$

$$= \text{Arg max}_j \left[ -\frac{1}{2\sigma^2} \sum_{k=1}^{\infty} (r_k - s_{j,k})^2 + \ln P(\underline{s}_j) \right]$$

We can discard  $2\sigma^2$ , as it is a constant and does not contribute any information

$$= \text{Arg max}_j \left[ -\sum_{k=1}^{\infty} (r_k - s_{j,k})^2 + 2\sigma^2 \ln P(\underline{s}_j) \right]$$

Convert function from max to min

$$= \text{Arg min}_j \left[ \sum_{k=1}^{\infty} (r_k - s_{j,k})^2 - 2\sigma^2 \ln P(\underline{s}_j) \right]$$



# MAP choice

➤ We want

$$\text{Arg min}_j \left[ \sum_{k=1}^{\infty} (r_k - s_{j,k})^2 - 2\sigma^2 \ln P(\underline{s}_j) \right]$$

➤

➤ Theorem of irrelevance

□  $s_{j,k} = 0 \quad \forall \quad k > N$

□ Elements for  $k > N$  in the sum  
do not change the  
minimization

$$\begin{aligned} & \text{Arg min}_j \left[ \sum_{k=1}^{\infty} (r_k - s_{j,k})^2 - 2\sigma^2 \ln P(\underline{s}_j) \right] \\ &= \text{Arg min}_j \left[ \sum_{k=1}^N (r_k - s_{j,k})^2 - 2\sigma^2 \ln P(\underline{s}_j) \right] \end{aligned}$$

Represent energy ←

norm in the finite basis  
of the signal space

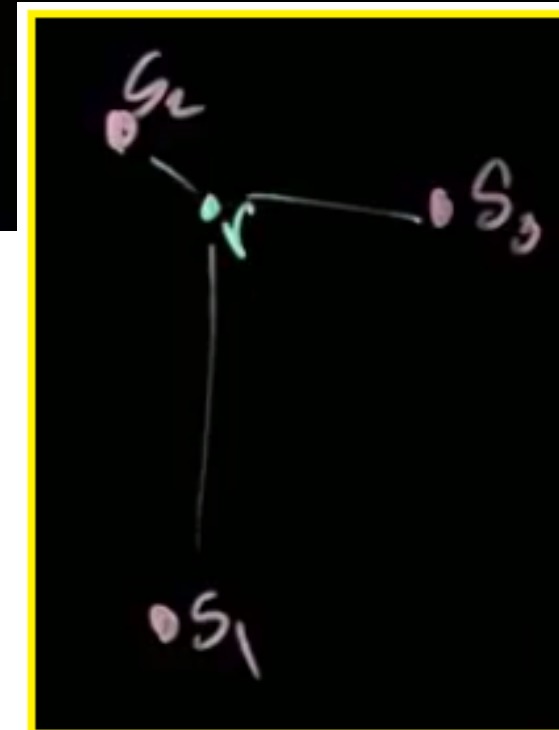
$$= \text{Arg min}_j \left[ \|\underline{r} - \underline{s}_j\|^2 - 2\sigma^2 \ln P(\underline{s}_j) \right]$$

# MAP choice

Choose the signal that is closer to the received signal modulo a weighting for a priori probability

$$\text{Arg} \min_j \left[ \|r - \underline{s}_j\|^2 - 2\sigma^2 \ln P(\underline{s}_j) \right]$$

**Explanation:**



## MAP choice

Choose the signal that is closer to the received signal modulo a weighting for a priori probability

$$\text{Arg min}_j \left[ \|r - \underline{s}_j\|^2 - 2\sigma^2 \ln P(\underline{s}_j) \right]$$

## ML choice

Choose the signal closest to the received signal

$$\text{Arg min}_j \left[ \|r - \underline{s}_j\|^2 \right]$$

# Vector space receiver

## ➤ MAP

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$

## ➤ ML

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2$

*What is the structure of the test statistics??*

# Vector space receiver

## ➤ MAP

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$$

## ➤ ML

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2$$



# Vector space

doesn't change the minimization  
—  
identical for all  $i$

## ➤ MAP

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$$

## ➤ ML

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2$$

# Vector space re

known: calculated in advance  
- not at each reception

## ➤ MAP

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$$

## ➤ ML

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2$$

# Vector space receiver

only calculated at the receiver

## ➤ MAP

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$$

## ➤ ML

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2$$

# Vector space receiver

correlator

## ➤ MAP

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2 - N_0 \ln P(\mathbf{s}_i)$$

## ➤ ML

□  $i$  that minimizes  $\|\mathbf{r} - \mathbf{s}_i\|^2$

$$\|\mathbf{r}\|^2 - 2\langle \mathbf{r}, \mathbf{s}_i \rangle + \|\mathbf{s}_i\|^2$$

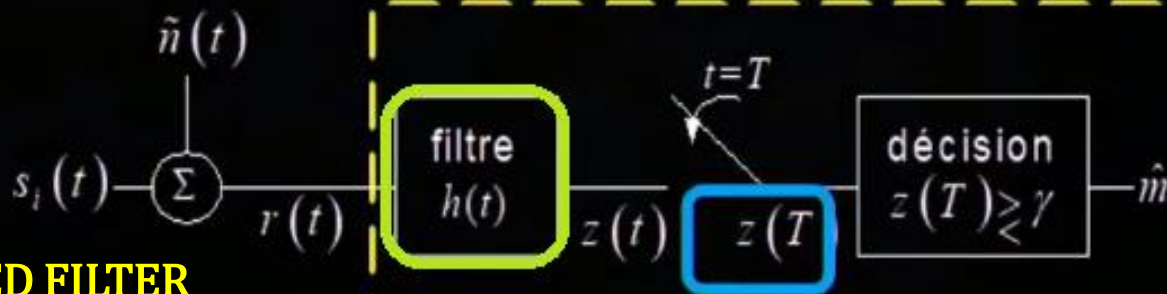


# Two approaches

- Linear sampling receiver
  - ❑ fix the type of receiver
  - ❑ probability theory for decision rule
  - ❑ maximize the SNR with a **matched filter**
- Signal space analysis
  - ❑ representation in a vector space
  - ❑ probability theory for decision rule
  - ❑ structure is a **correlator**

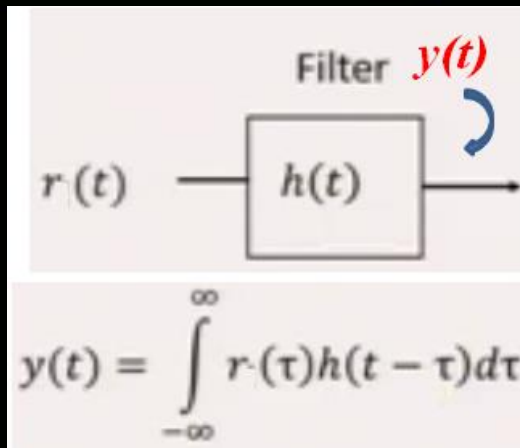


# Sampling receiver



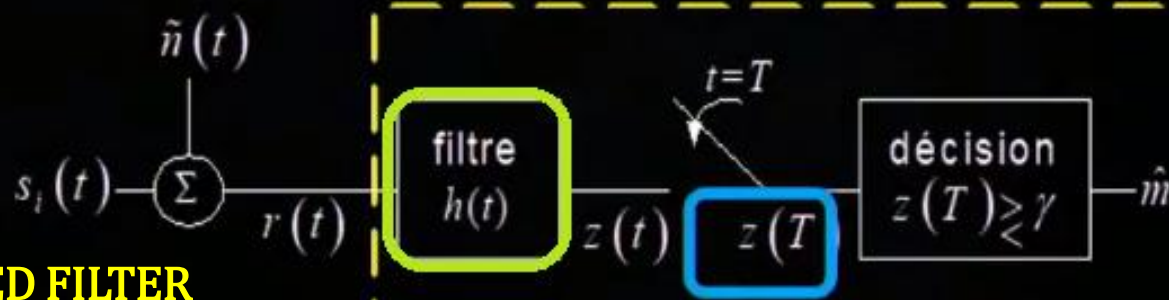
**MATCHED FILTER**

$$h(t) = \begin{cases} ks(T-t) & 0 \leq t \leq T \\ 0 & \text{elsewhere} \end{cases}$$



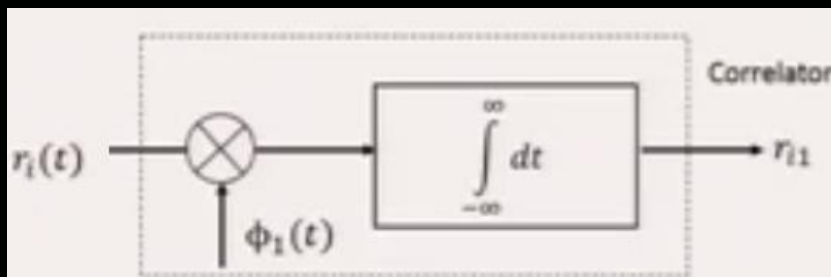
$$\begin{aligned} & [r(t) * ks_i(T-t)]_{t=T} \\ & \int_0^T r(z)s_i(T-(t-z))dz \Big|_{t=T} \\ & \int_0^T r(z)s_i(z)dz \Big|_{t=T} \\ & \int_0^T r(z)s_i(z)dz \end{aligned}$$

# Sampling receiver



**MATCHED FILTER**

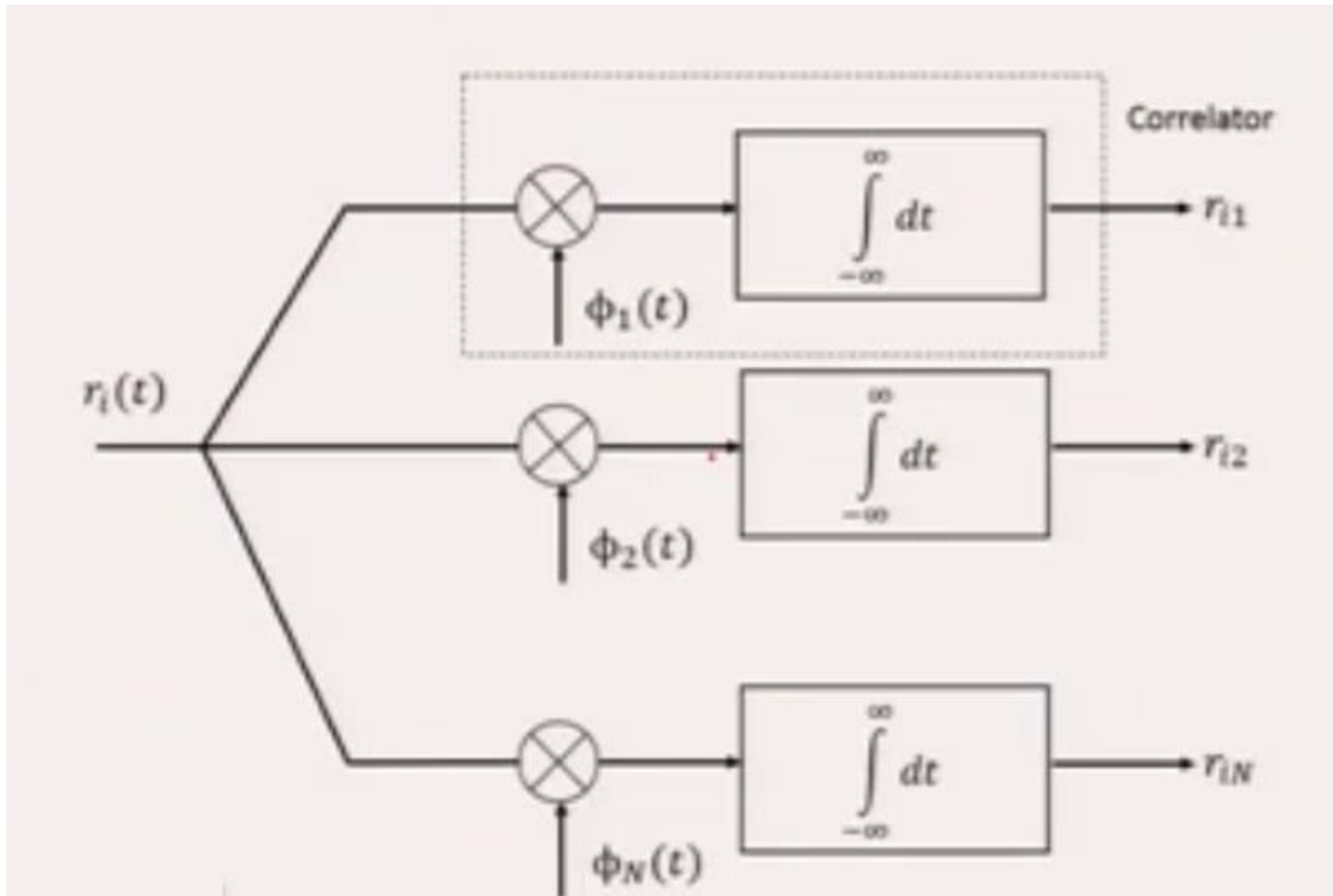
$$h(t) = \begin{cases} ks(T-t) & 0 \leq t \leq T \\ 0 & \text{elsewhere} \end{cases}$$



**Convolution converted to correlation**

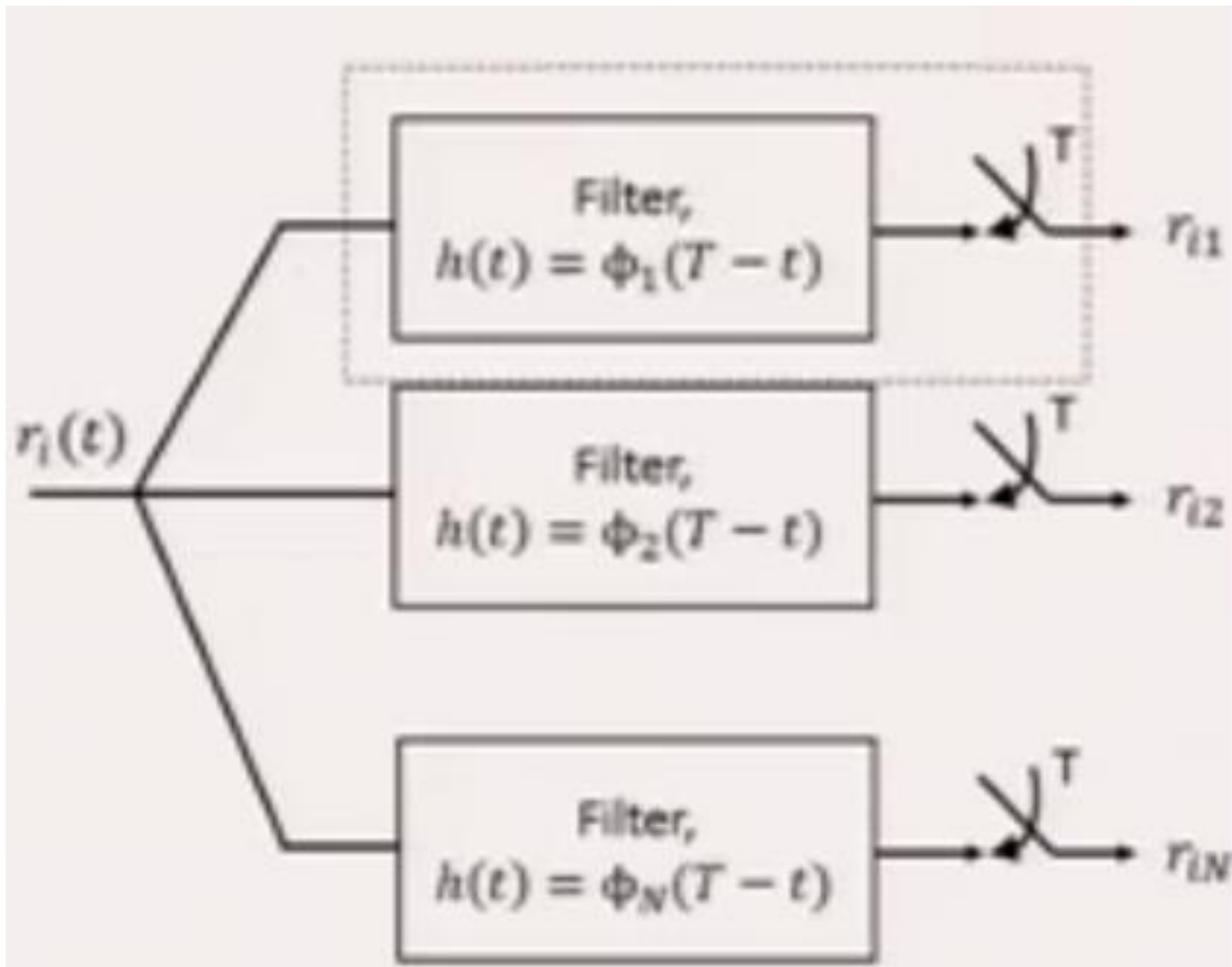
$$\begin{aligned} & \left[ r(t) * ks_i(T-t) \right]_{t=T} \\ & \int_0^T r(z) s_i(T-(T-z)) dz \Big|_{t=T} \\ & \int_0^T r(z) s_i(z) dz \Big|_{t=T} \\ & \int_0^T r(z) s_i(z) dz \end{aligned}$$

**Elaborate further?**



## Correlator

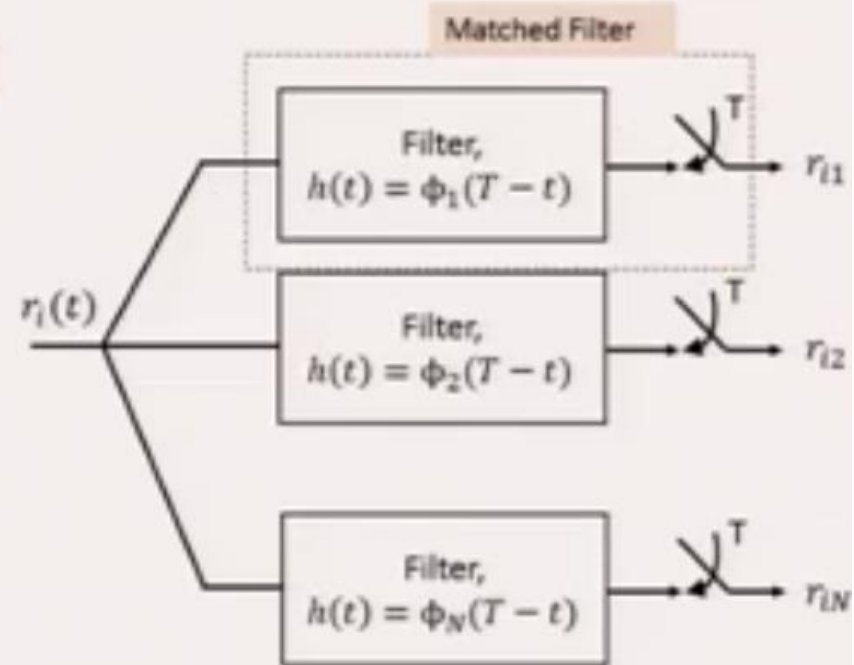
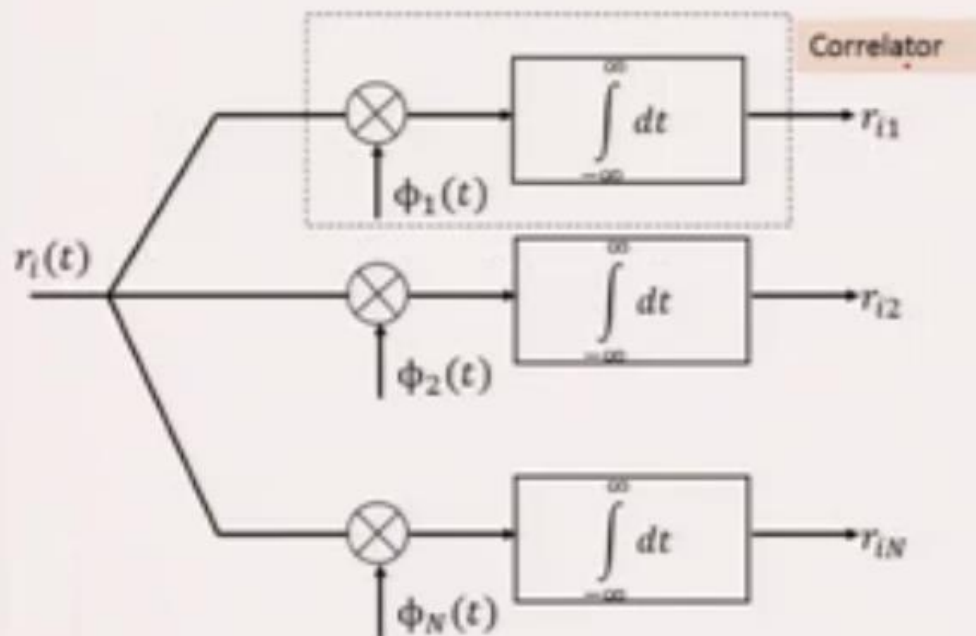
$$r_{i1} = \int_{-\infty}^{\infty} r_i(t) \phi_1(t) dt$$



## Matched Filter

$$r_{i1} = y(T) = \int_{-\infty}^{\infty} r_i(\tau) \phi_1(\tau) d\tau$$

# Correlator vs. Matched Filter



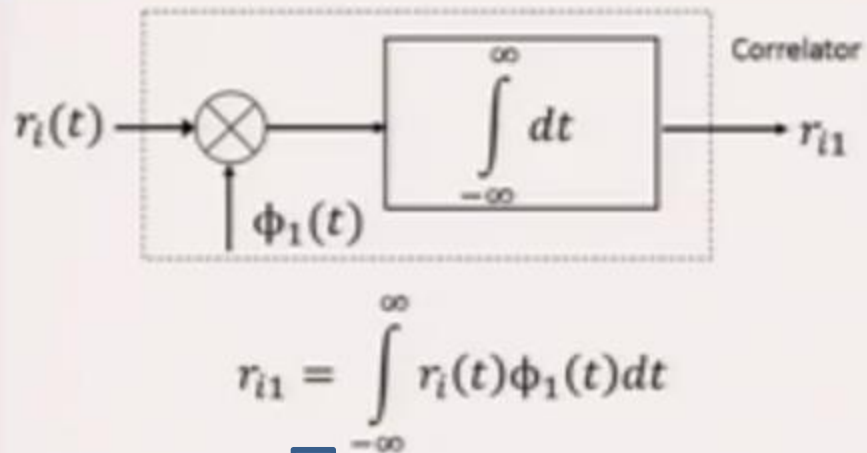
$$r_{i1} = \int_{-\infty}^{\infty} r_i(t) \phi_1(t) dt$$

$$r_{i1} = y(T) = \int_{-\infty}^{\infty} r_i(\tau) \phi_1(\tau) d\tau$$

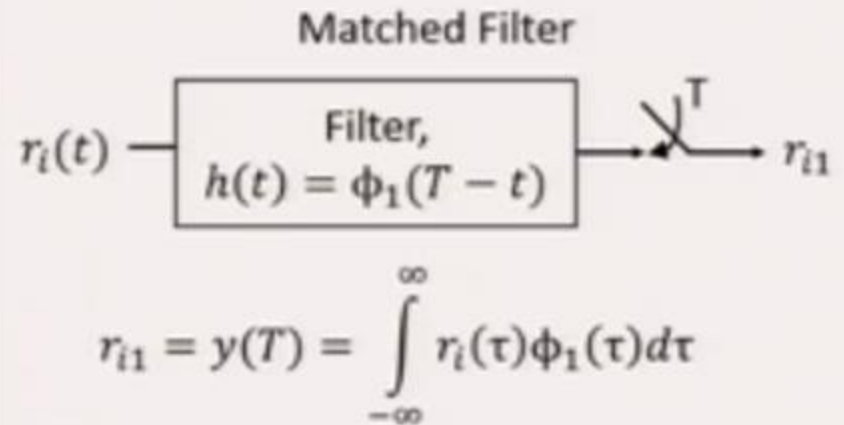


# Correlator vs. Matched filter

Correlator



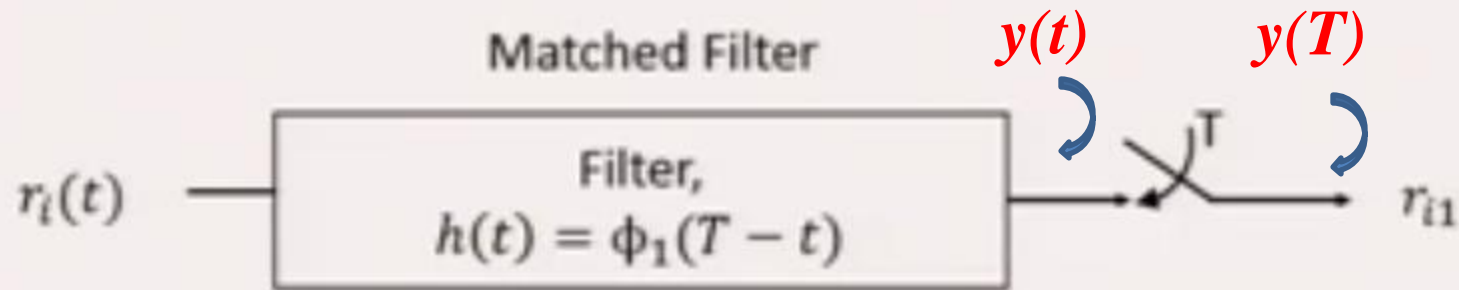
Matched filter



Equivalent

How?

# Matched filter



$$y(t) = \int_{-\infty}^{\infty} r_i(\tau) h(t - \tau) d\tau$$

From the convolution formula

$$= \int_{-\infty}^{\infty} r_i(\tau) \phi_1(T - (t - \tau)) d\tau$$

$$= \int_{-\infty}^{\infty} r_i(\tau) \phi_1(T - t + \tau) d\tau$$

At  $t=T$ ,

$$r_{i1} = y(T) = \int_{-\infty}^{\infty} r_i(\tau) \phi_1(\tau) d\tau$$

The result is same as Correlator filter

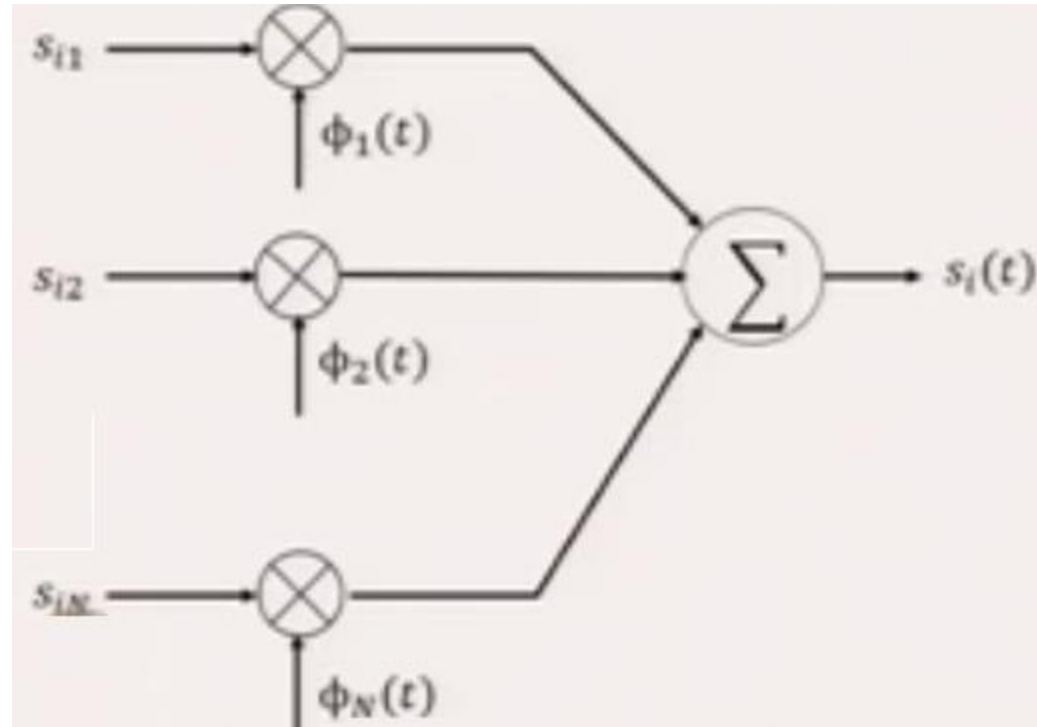
# Transmitter Design (Sequence to waveforms)



Sequence of symbols:

Real numbers **or**  
Quantized real  
numbers

**Transmitter**



$$s_i(t) = \begin{bmatrix} s_{i1} & s_{i2} & s_{i3} & \cdots & s_{iN} \\ s_{21} & s_{22} & s_{23} & \cdots & s_{2N} \\ s_{31} & s_{32} & s_{33} & \cdots & s_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{M1} & s_{M2} & s_{M3} & \cdots & s_{MN} \end{bmatrix} \begin{bmatrix} \phi_1 \\ \phi_2 \\ \phi_2 \\ \vdots \\ \phi_N \end{bmatrix}$$

$$s_1(t) = s_{11}\phi_1(t) + s_{12}\phi_2(t) \dots \dots \dots + s_{1N}\phi_N(t)$$

$$s_2(t) = s_{21}\phi_1(t) + s_{22}\phi_2(t) \dots \dots \dots + s_{2N}\phi_N(t)$$

$$s_M(t) = s_{M1}\phi_1(t) + s_{M2}\phi_2(t) \dots \dots \dots + s_{MN}\phi_N(t)$$

# Receiver Design (Waveform to sequences)

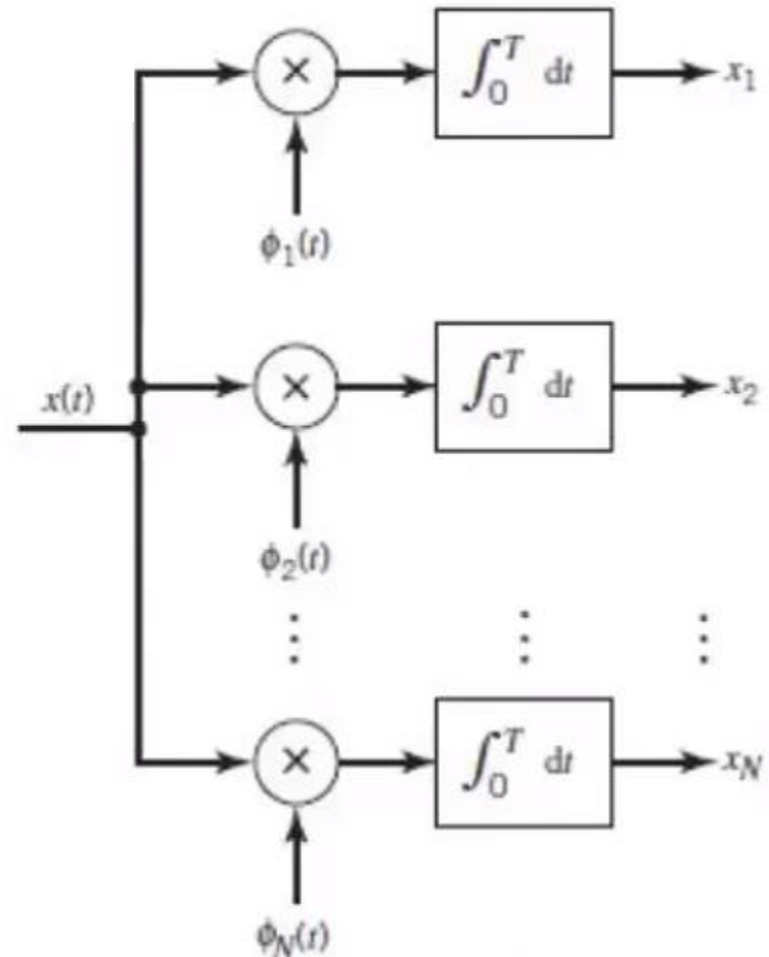
- Correlation receiver contains two parts:

Detector

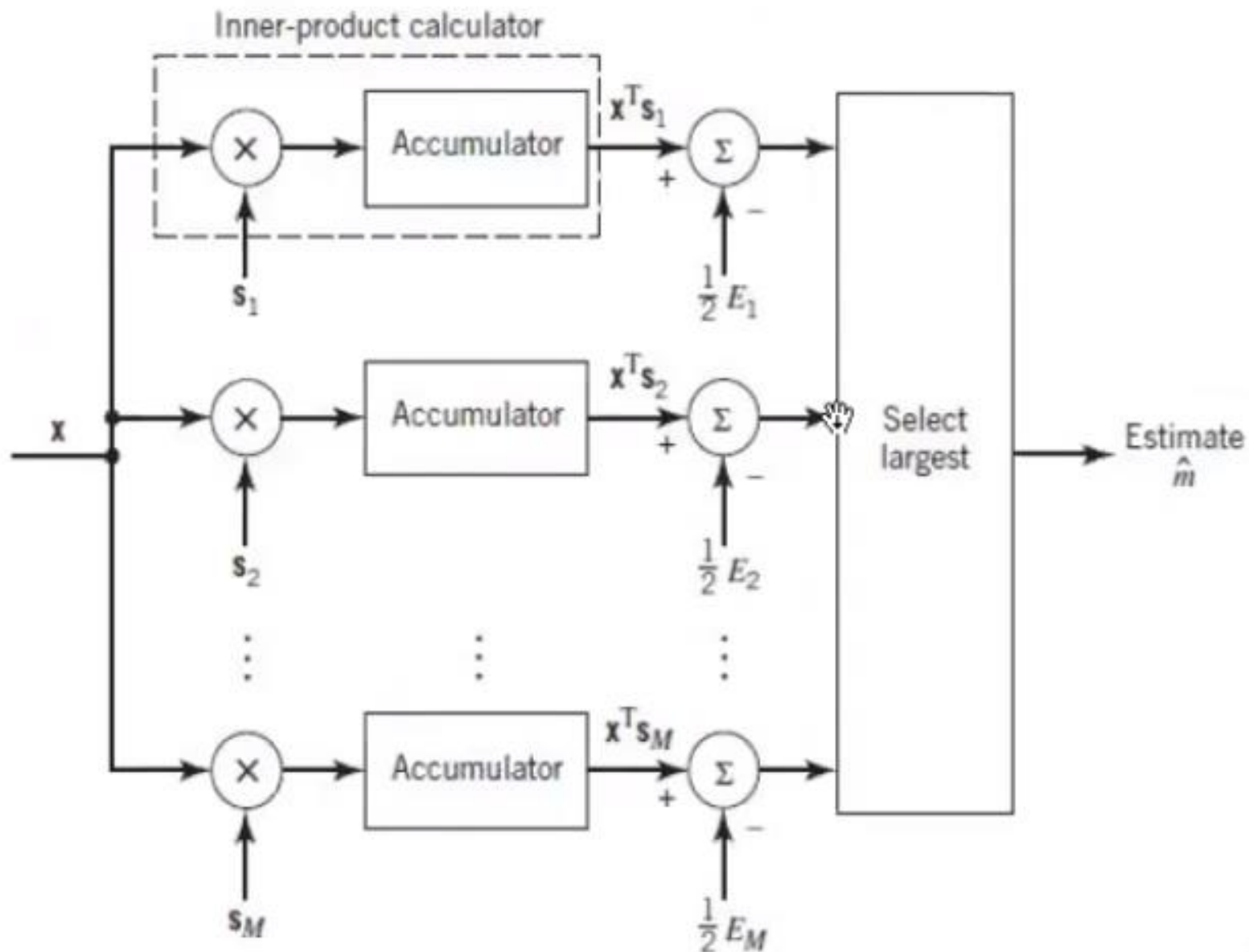
Vector Receiver

- Detector converts signal  $x(t)$  to observation vector  $x$  as per the equation

$$X_j = \int_0^T X(t) \phi_j(t) dt$$



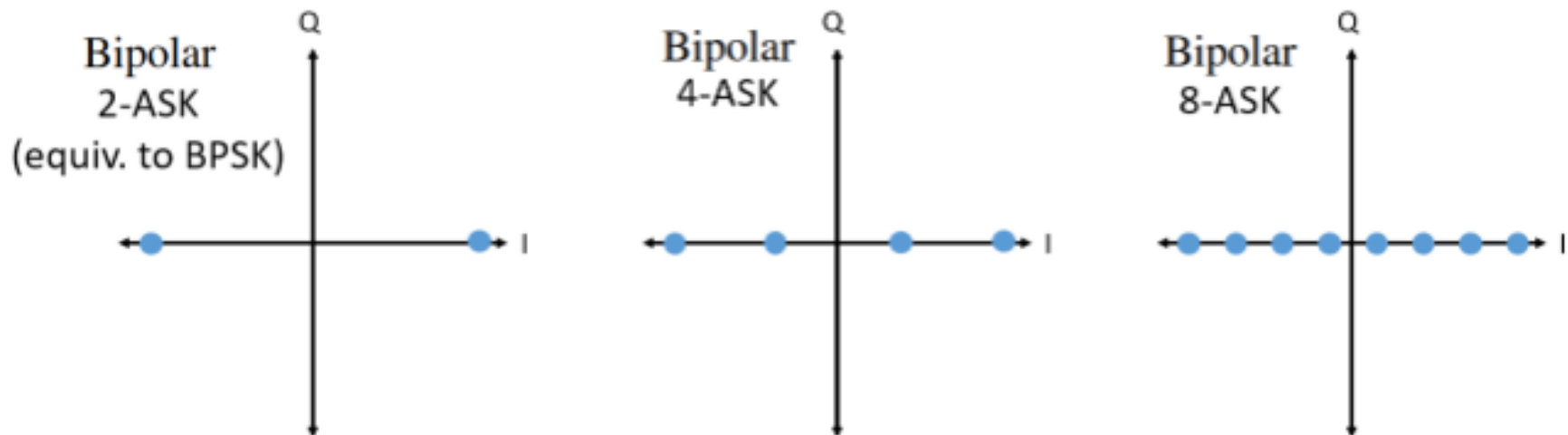
- Vector receiver converts  $\mathbf{x}$  to estimate  $\hat{m}$

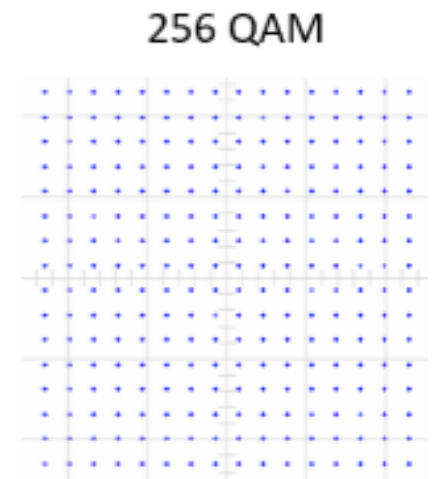
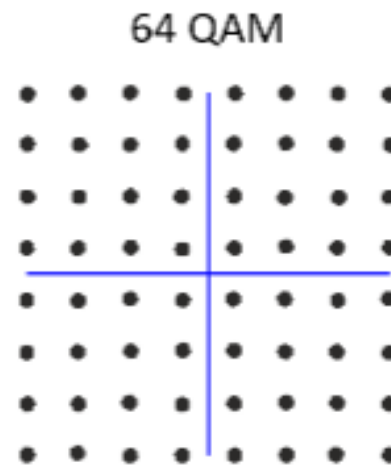
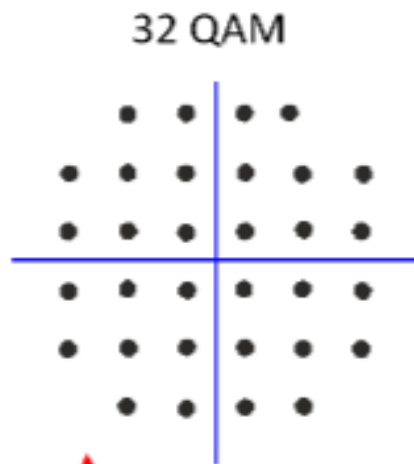
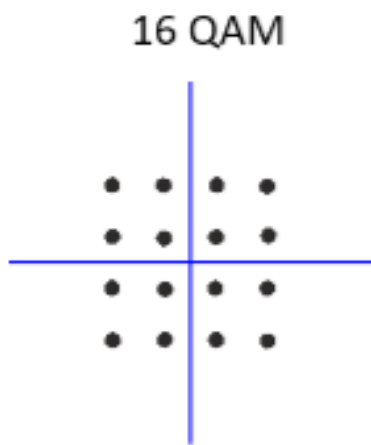
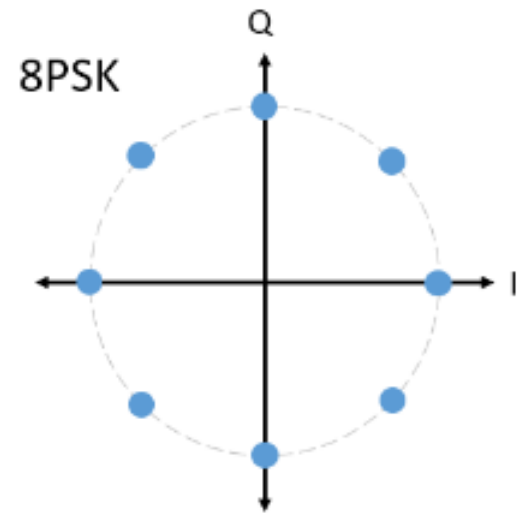
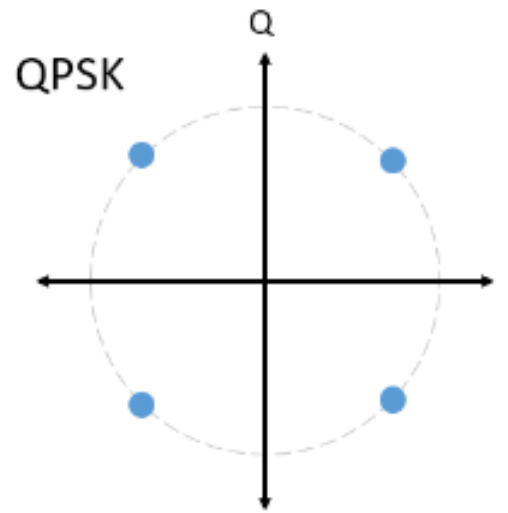
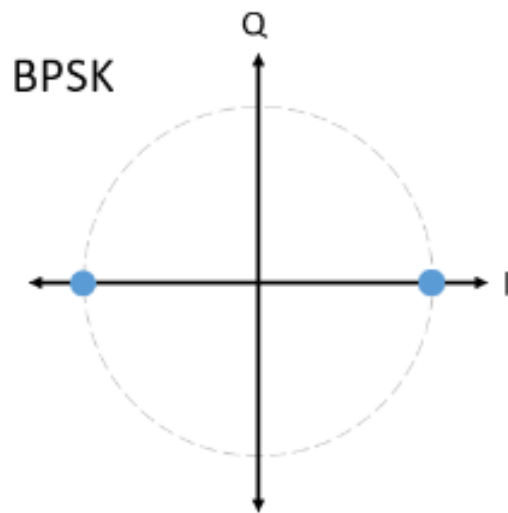




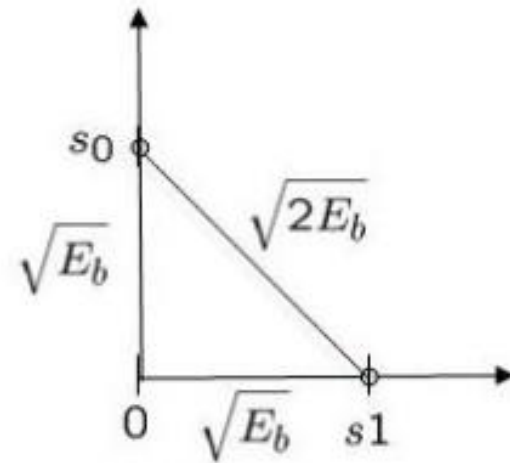
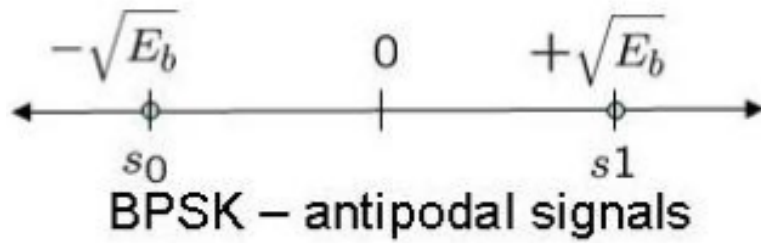
# Signal Constellation

A signal constellation is the physical diagram used to describe all the possible symbols used by a signaling system to transmit data and is an aid to designing better communications systems.





QAM doesn't have to be a square



FSK – orthogonal signals

Thanks !