



# Chapter 5

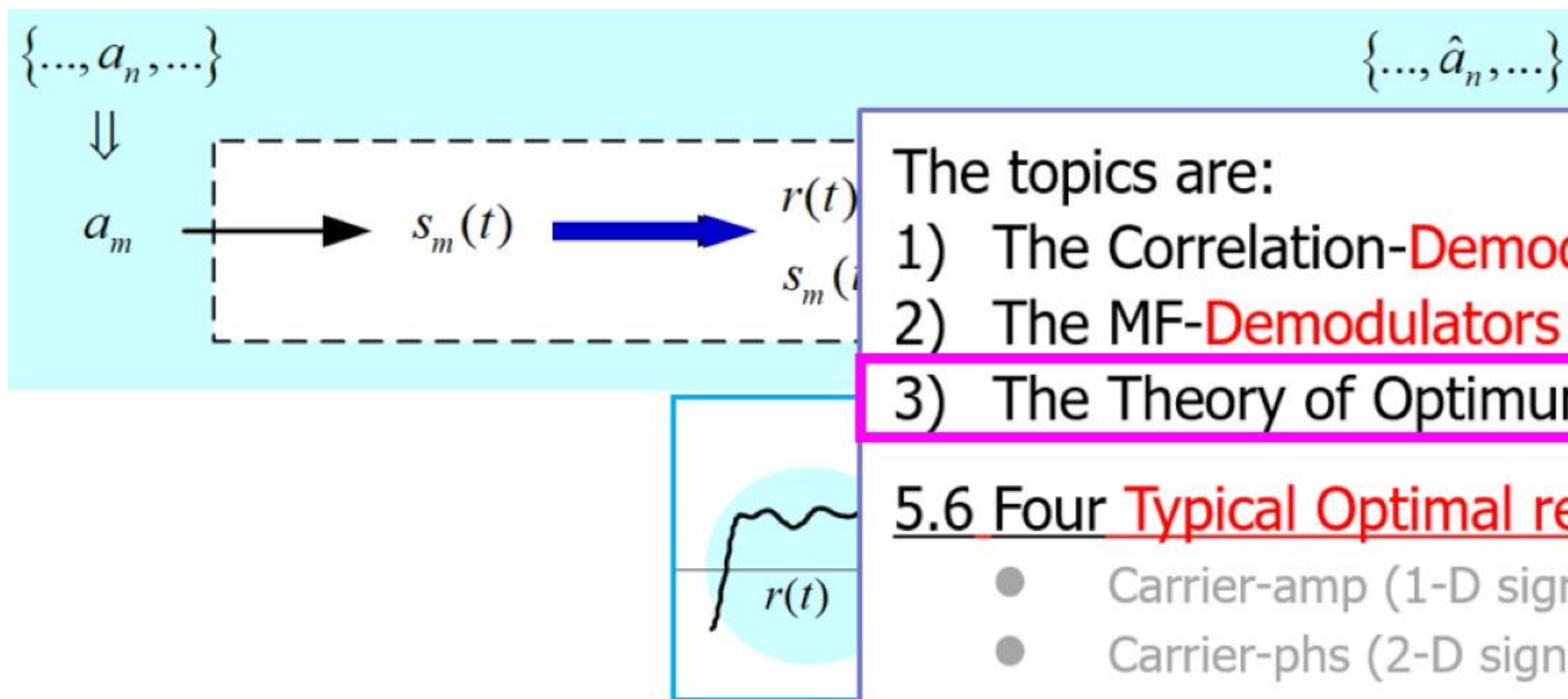
## Digital transmission through the AWGN channel

— by Prof. XIAOFENG LI  
SICE, UESTC

- Introduction
- Geometric rep. of the sig waveforms
- Pulse amplitude modulation
- 2-d signal waveforms
- M-d signal waveforms
- Opt. reception for the sig. In AWGN
- Optimal receivers and probs of err

## 5.5 Opt. reception for the sig. In AWGN

In the  $n$ th interval, the process is as follows,



The topics are:

- 1) The Correlation-**Demodulators**
- 2) The MF-**Demodulators**
- 3) The Theory of Optimum **Detector**

### 5.6 Four **Typical Optimal receivers**

- Carrier-amp (1-D signals)
- Carrier-phs (2-D signals)
- QAM (2-D signals)
- FSK (M-D orthogonal signals)

It is convenient to divide the receiver into two parts:

- 1) **Demodulator**: produce an **obs**
- 2) **Detector**: estimate the **sym** from the observation

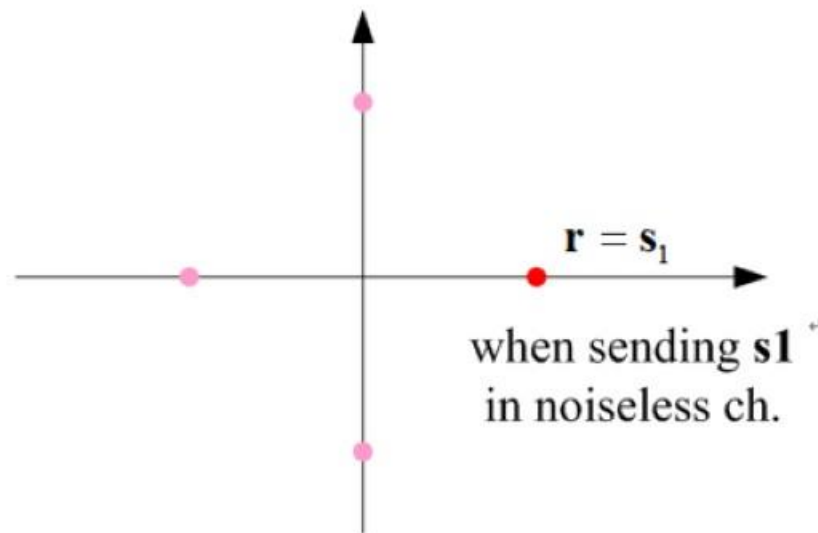
## 5.5.2 The optimum detector

**Detector:** estimate the **sym** from the observation

What is the problem in the detector ?

With observation  $\mathbf{r} = (r_1, \dots, r_N)$  in hand, we recall that

$\mathbf{r} = \mathbf{s}_m + \mathbf{n}$  and picture it.



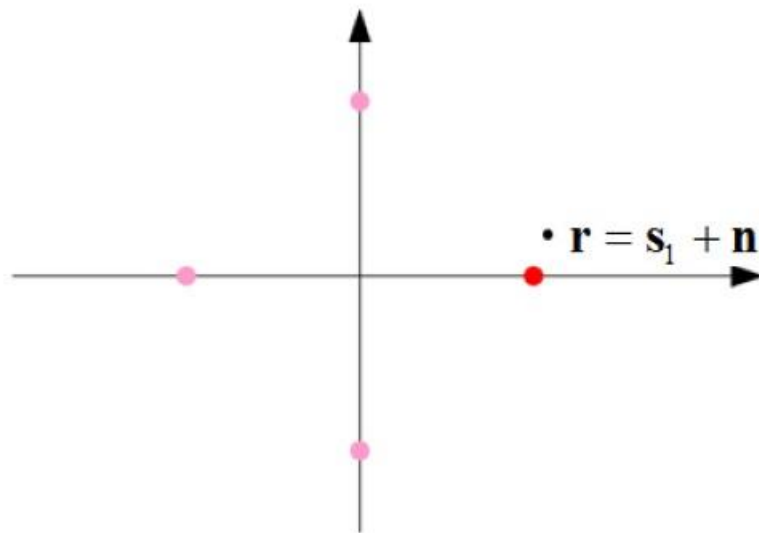
## 5.5.2 The optimum detector

**Detector:** estimate the **sym** from the observation

What is the problem in the detector ?

With observation  $\mathbf{r} = (r_1, \dots, r_N)$  in hand, we recall that

$\mathbf{r} = \mathbf{s}_m + \mathbf{n}$  and picture it.





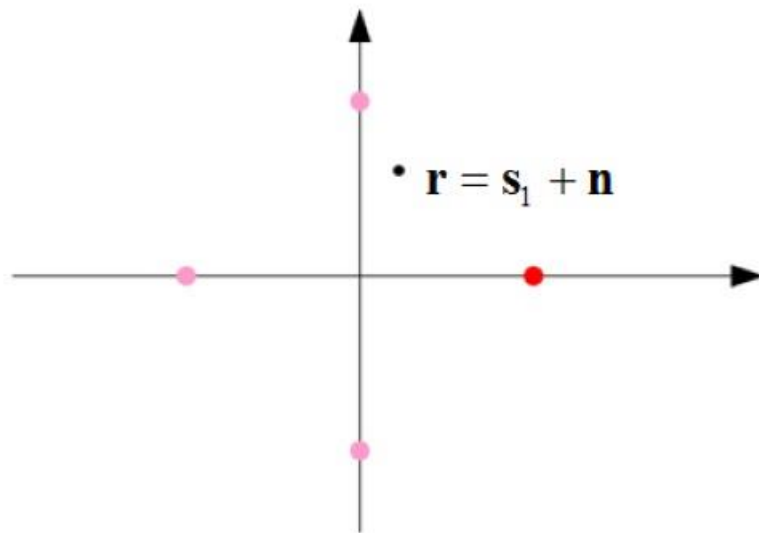
## 5.5.2 The optimum detector

**Detector:** estimate the **sym** from the observation

What is the problem in the detector ?

With observation  $\mathbf{r} = (r_1, \dots, r_N)$  in hand, we recall that

$\mathbf{r} = \mathbf{s}_m + \mathbf{n}$  and picture it.



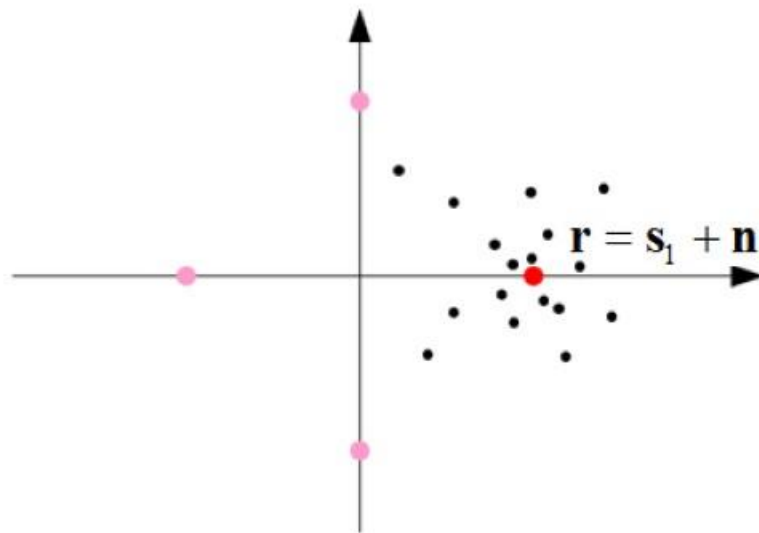
## 5.5.2 The optimum detector

**Detector:** estimate the **sym** from the observation

What is the problem in the detector ?

With observation  $\mathbf{r} = (r_1, \dots, r_N)$  in hand, we recall that

$\mathbf{r} = \mathbf{s}_m + \mathbf{n}$  and picture it.

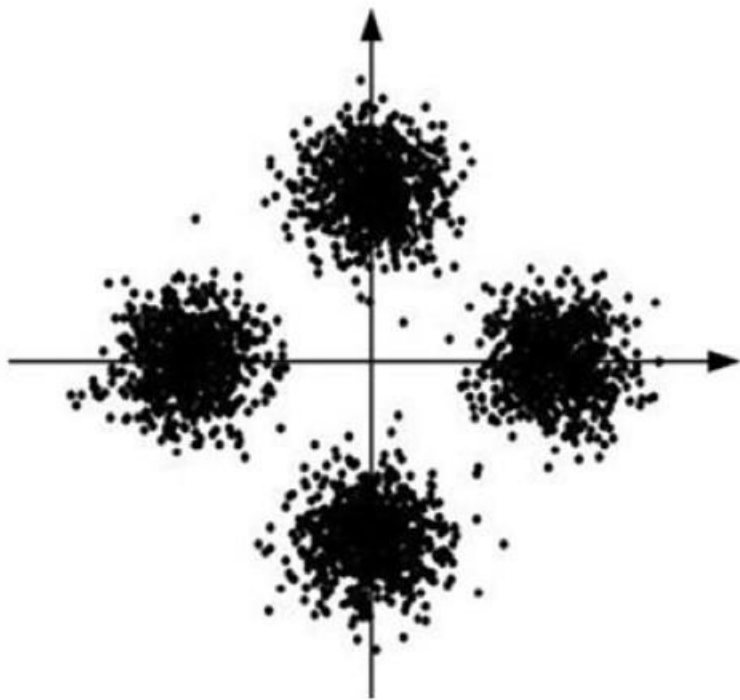


## 5.5.2 The optimum detector

**Detector:** estimate the  $\text{sym}$  from the observation

All the possibilities form a **cloud centered at  $\mathbf{s}_1$** .

The dense of the cloud is higher at the center, and becomes less as departing from the center. The dense indicates basically the **probability density** or  $\mathbf{r}$ .



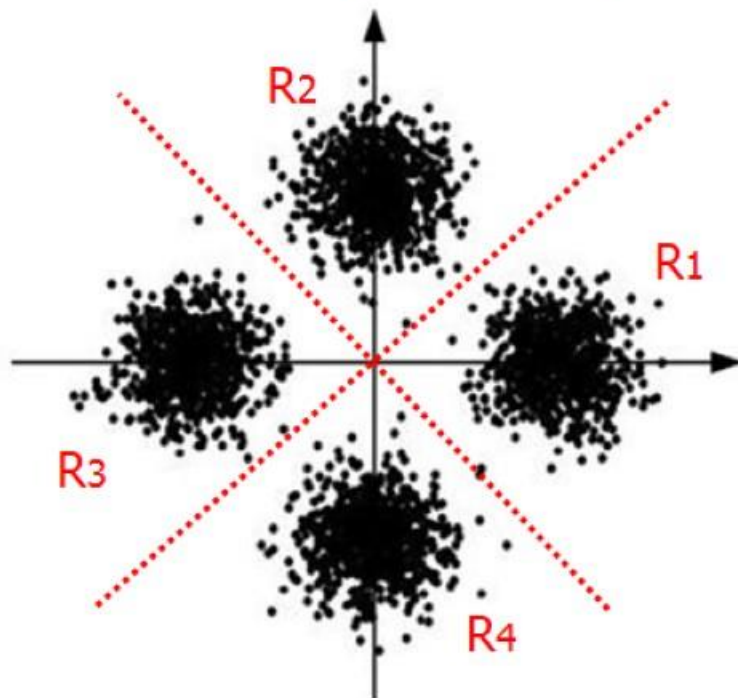


## 5.5.2 The optimum detector

**Detector:** estimate the  $\text{sym}$  from the observation

All the possibilities form a **cloud centered at  $\mathbf{s}_1$** .

The dense of the cloud is higher at the center, and becomes less as departing from the center. The dense indicates basically the **probability density** or  $\mathbf{r}$ .



## 5.5.2 The optimum detector

What is a good detector ? ---- Make error as less as possible

How to measure error ? ---- **Probability of error**

Let  $R_m$  be the region in the space for which we select  $\mathbf{s}_m$ ,  
 $R_m^c$  be the complement of  $R_m$ . They are decided by the criterion.

The average probability of errors is,

$$P_e = P(e) = 1 - \sum_{m=1}^M \int_{R_m} P(\mathbf{s}_m | \mathbf{r}) f(\mathbf{r}) d\mathbf{r}$$

where,  $P(\mathbf{s}_m | \mathbf{r})$  is the prob that  $\mathbf{s}_m$  has been transmitted  
on the reception of  $\mathbf{r}$

$f(\mathbf{r})$  is the unconditional pdf of  $\mathbf{r}$ .

## 5.5.2 The optimum detector

What is a good detector ? ---- Make error as less as possible

How to measure error ? ---- **Probability of error**

Let  $R_m$  be the region in the space for which we select  $\mathbf{s}_m$ ,  
 $R_m^c$  be the complement of  $R_m$ . They are decided by the criterion.

The average probability of errors is,

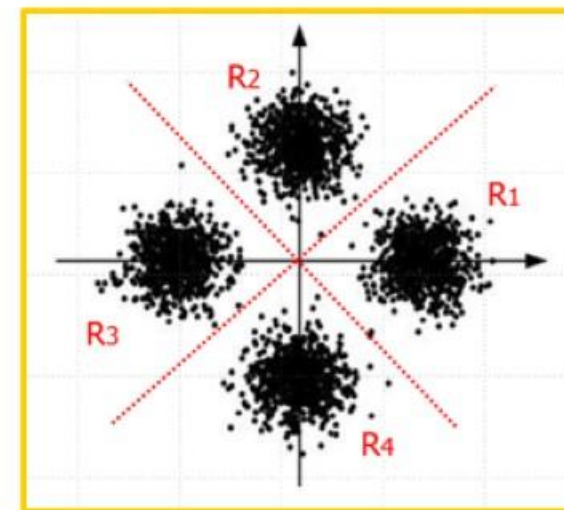
$$P_e = P(e) = 1 - \sum_{m=1}^M \int_{R_m} P(\mathbf{s}_m | \mathbf{r}) f(\mathbf{r}) d\mathbf{r}$$

$$P(\text{success} | \mathbf{s}_1) = \int_{R_1} P(\mathbf{s}_1 | \mathbf{r}) f(\mathbf{r}) d\mathbf{r}$$

where,  $P(\mathbf{s}_m | \mathbf{r})$  is the prob that  $\mathbf{s}_m$  has been transmitted

on the reception of  $\mathbf{r}$

$f(\mathbf{r})$  is the unconditional pdf of  $\mathbf{r}$ .





## 5.5.2 The optimum detector

What is the best detector ?

$P_e$  is **minimum** when  $R_m$  corresponds to  $\max P(\mathbf{s}_m | \mathbf{r})$ .

That lead to MAP criterion as follows.

$$P_e = P(e) = 1 - \sum_{m=1}^M \int_{R_m} P(\mathbf{s}_m | \mathbf{r}) f(\mathbf{r}) d\mathbf{r}$$

**Maximum a posterior probability (MAP)**

$\mathbf{s}_m$  that max the  $P(\mathbf{s}_m | \mathbf{r})$ . Denoted by,

$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} \{P(\mathbf{s}_m | \mathbf{r})\}$$

Note that  $P(\mathbf{s}_m | \mathbf{r})$  is often called **a posterior probability**.

**The Optimum Detector:**

**MAP:** Maximum a posterior probability

**ML :** Maximum-likelihood

**Min-Dist :** Minimum-distance

**Max-Corr:** Maximum Correlation

### 5.5.3 The optimum detector

Using Bayes' rule,

$$P(\mathbf{s}_m | \mathbf{r}) = \frac{f(\mathbf{r} | \mathbf{s}_m)P(\mathbf{s}_m)}{f(\mathbf{r})}$$

where,  $f(\mathbf{r} | \mathbf{s}_m)$  is the **condi pdf** of  $\mathbf{r}$  given  $\mathbf{s}_m$ ;

$P(\mathbf{s}_m)$  is prob of transmitting  $\mathbf{s}_m$ , called **priori probability**

Let  $PM(\mathbf{r}, \mathbf{s}_m) = f(\mathbf{r} | \mathbf{s}_m)P(\mathbf{s}_m)$

**MAP is equivalent to:**  $\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} PM(\mathbf{r}, \mathbf{s}_m)$

**Maximum a posterior probability (MAP):** to select the  $\mathbf{s}_m$  that max the  $P(\mathbf{s}_m | \mathbf{r})$ . Denoted by,

$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} \{P(\mathbf{s}_m | \mathbf{r})\}$$

Note that  $P(\mathbf{s}_m | \mathbf{r})$  is often called **a posterior probability**.



### 5.5.3 The optimum detector

Note that  $f(\mathbf{r} | \mathbf{s}_m)$  is usually called **likelihood function**.

**Maximum-likelihood (ML):** to select the  $\mathbf{s}_m$  that max the  $f(\mathbf{r} | \mathbf{s}_m)$ .

Denoted by, 
$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} \{f(\mathbf{r} | \mathbf{s}_m)\}$$

Obviously, when the **symbols are equally probable**, we have, **ML=MAP**  
Equally-probable case is very common, thus ML is widely used in practical.

Let  $PM(\mathbf{r}, \mathbf{s}_m) = f(\mathbf{r} | \mathbf{s}_m)P(\mathbf{s}_m)$

**MAP is equivalent to:** 
$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} PM(\mathbf{r}, \mathbf{s}_m)$$

**Maximum a posterior probability (MAP):** to select the  $\mathbf{s}_m$  that max the  $P(\mathbf{s}_m | \mathbf{r})$ . Denoted by,

$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} \{P(\mathbf{s}_m | \mathbf{r})\}$$

Note that  $P(\mathbf{s}_m | \mathbf{r})$  is often called **a posterior probability**.

### 5.5.3 The optimum detector

Note that  $f(\mathbf{r} | \mathbf{s}_m)$  is usually called **likelihood function**.

**Maximum-likelihood (ML):** to select the  $\mathbf{s}_m$  that max the  $f(\mathbf{r} | \mathbf{s}_m)$ .

Denoted by, 
$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} \{f(\mathbf{r} | \mathbf{s}_m)\}$$

**Minimum-distance (Min-Dist):** to select the  $\mathbf{s}_m$  that is nearest to  $\mathbf{r}$ ,

that is 
$$\hat{\mathbf{s}}_m = \arg \min_{\mathbf{s}_m} D(\mathbf{r}, \mathbf{s}_m) \quad \text{and,} \quad D(\mathbf{r}, \mathbf{s}_m) = \|\mathbf{r} - \mathbf{s}_m\|^2$$

Recall that, 
$$f(\mathbf{r} | \mathbf{s}_m) = \left( \frac{1}{\sqrt{\pi N_0}} \right)^N \exp \left[ -\frac{\|\mathbf{r} - \mathbf{s}_m\|^2}{N_0} \right]$$

It is more convenient to work with, 
$$\ln f(\mathbf{r} | \mathbf{s}_m) = -\frac{N}{2} \ln(\pi N_0) - \frac{1}{N_0} \|\mathbf{r} - \mathbf{s}_m\|^2$$

Clearly, max of  $f(\mathbf{r} | \mathbf{s}_m)$  is same as min of  $\|\mathbf{r} - \mathbf{s}_m\|^2$ , which is the distance bwtween  $\mathbf{r}$  and  $\mathbf{s}_m$



### 5.5.3 The optimum detector

Note that  $f(\mathbf{r} | \mathbf{s}_m)$  is usually called **likelihood function**.

**Maximum-likelihood (ML):** to select the  $\mathbf{s}_m$  that max the  $f(\mathbf{r} | \mathbf{s}_m)$ .

Denoted by, 
$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} \{f(\mathbf{r} | \mathbf{s}_m)\}$$

**Minimum-distance (Min-Dist):** to select the  $\mathbf{s}_m$  that is nearest to  $\mathbf{r}$ ,

that is 
$$\hat{\mathbf{s}}_m = \arg \min_{\mathbf{s}_m} D(\mathbf{r}, \mathbf{s}_m) \quad \text{and,} \quad D(\mathbf{r}, \mathbf{s}_m) = \|\mathbf{r} - \mathbf{s}_m\|^2$$

We can say more, 
$$D(\mathbf{r}, \mathbf{s}_m) = \|\mathbf{r}\|^2 - 2\mathbf{r} \bullet \mathbf{s}_m + \|\mathbf{s}_m\|^2$$

Note  $\|\mathbf{r}\|^2$  is common to all  $\mathbf{s}_m$ ,

$\mathbf{r} \bullet \mathbf{s}_m$  is the **correlation**

and,  $\|\mathbf{s}_m\|^2$  is the energy of the symbol.

### 5.5.3 The optimum detector

Note that  $f(\mathbf{r} | \mathbf{s}_m)$  is usually called **likelihood function**.

**Maximum-likelihood (ML):** to select the  $\mathbf{s}_m$  that max the  $f(\mathbf{r} | \mathbf{s}_m)$ .

Denoted by, 
$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} \{f(\mathbf{r} | \mathbf{s}_m)\}$$

**Minimum-distance (Min-Dist):** to select the  $\mathbf{s}_m$  that is 
$$\hat{\mathbf{s}}_m = \arg \min_{\mathbf{s}_m} D(\mathbf{r}, \mathbf{s}_m)$$

We can say more,  $D(\mathbf{r}, \mathbf{s}_m) = \|\mathbf{r}\|^2 - 2\mathbf{r} \bullet \mathbf{s}_m$

Let  $E_m = \|\mathbf{s}_m\|^2$  and  $C(\mathbf{r}, \mathbf{s}_m) = \mathbf{r} \bullet \mathbf{s}_m - E_m / 2$

**Maximum Correlation (Max-Corr):** to select the  $\mathbf{s}_m$  that is most correlated with  $\mathbf{r}$ , possibly compensated by some bias due to unequal energy, that is,

$$\hat{\mathbf{s}}_m = \arg \max_{\mathbf{s}_m} C(\mathbf{r}, \mathbf{s}_m)$$

#### The Optimum Detector:

**MAP:** Maximum a posterior probability

**ML :** Maximum-likelihood

**Min-Dist :** Minimum-distance

**Max-Corr:** Maximum Correlation



### 5.5.3 The optimum detector

ML is often very simple and common. It is nice to see that ,  
**ML=MinDist=MaxCorr.**

**Example 5.5.3 on page 285.**

- 1) The observation vector;
- 2) The pdfs
- 3) MAP, ML(Min-Dist), or Mac-Corr

#### **The Optimum Detector:**

- MAP:** Maximum a posterior probability  
**ML :** Maximum-likelihood  
**Min-Dist :** Minimum-distance  
**Max-Corr:** Maximum Correlation