

Digital Communications and Simulation
ECE 5654

Section 3 – Modulation

Module 2 – Optimum Receiver Structures

Set 2 – MAP and ML Receivers

Set 4 – Matched Filter Form of Optimum Receiver

Modulation

- We want to modulate digital data using signal sets which are:
 - bandwidth efficient
 - energy efficient
- A signal space representation is a convenient form for viewing modulation which allows us to:
 - design energy and bandwidth efficient signal constellations
 - *determine the form of the optimal receiver for a given constellation*
 - evaluate the performance of a modulation type

Problem Statement

- We transmit a signal $s(t) \in \{s_1(t), s_2(t), \dots, s_M(t)\}$, where $s(t)$ is nonzero only on $t \in [0, T]$.
- Let the various signals be transmitted with probability:

$$p_1 = \Pr[s_1(t)], \dots, p_M = \Pr[s_M(t)]$$

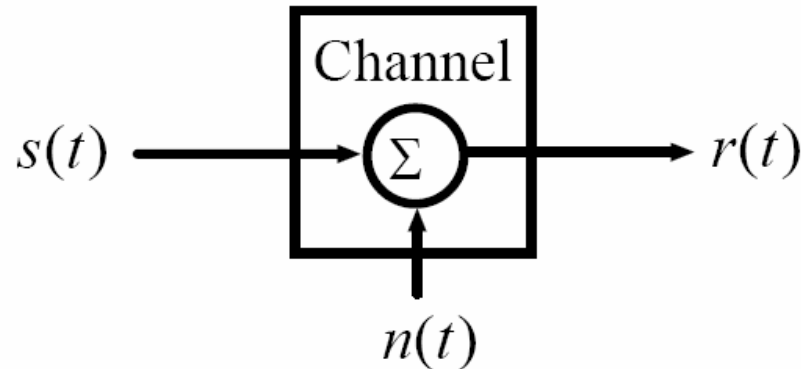
- The received signal is corrupted by noise:

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

- Given $r(t)$, the receiver forms an estimate $\hat{s}(t)$ of the signal $s(t)$ with the goal of minimizing symbol error probability $P_s = \Pr[\hat{s}(t) \neq s(t)]$

Noise Model

- The signal is corrupted by Additive White Gaussian Noise (AWGN) $n(t)$
- The noise $n(t)$ has autocorrelation $\phi_{nn}(\tau) = \frac{N_0}{2} \delta(\tau)$ and power spectral density $\Phi_{nn}(f) = N_0/2$
- Any linear function of $n(t)$ will be a Gaussian random variable





Signal Space Representation

- The transmitted signal can be represented as:

$$s_m(t) = \sum_{k=1}^K s_{m,k} f_k(t)$$

where $s_{m,k} = \int_0^T s_m(t) f_k(t) dt$

- The noise can be represented as:

where $n_k = \int_0^T n(t) f_k(t) dt$

and $n'(t) = n(t) - \sum_{k=1}^K n_k f_k(t)$

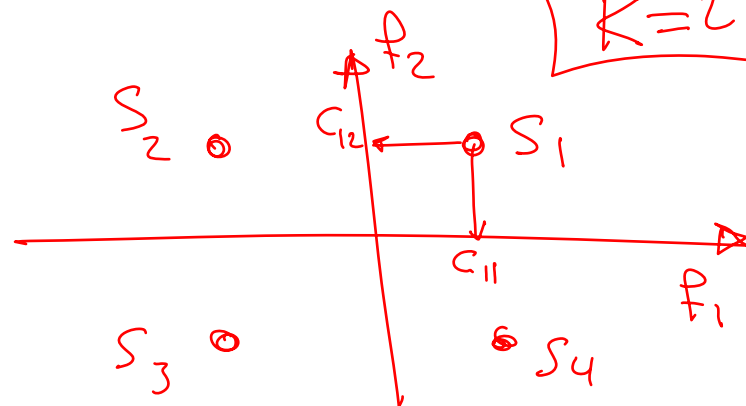
$$n(t) = n'(t) + \sum_{k=1}^K n_k f_k(t)$$

previous lecture

$f_k(t)$ are the basis functions

for example

$K=2$



$$S_i(t) = \sum_{k=1}^2 C_{km} f_k(t)$$

$$S_i(t) = C_{11} p_1 + C_{12} p_2$$

Signal Space Representation (continued)

- The received signal can be represented as:

$$\boxed{r(t)} = \sum_{k=1}^K s_{m,k} f_k(t) + \sum_{k=1}^K n_k f_k(t) + n'(t) = \boxed{\sum_{k=1}^K r_k f_k(t) + n'(t)}$$

where $r_k = s_{m,k} + n_k$

→ zero
prove

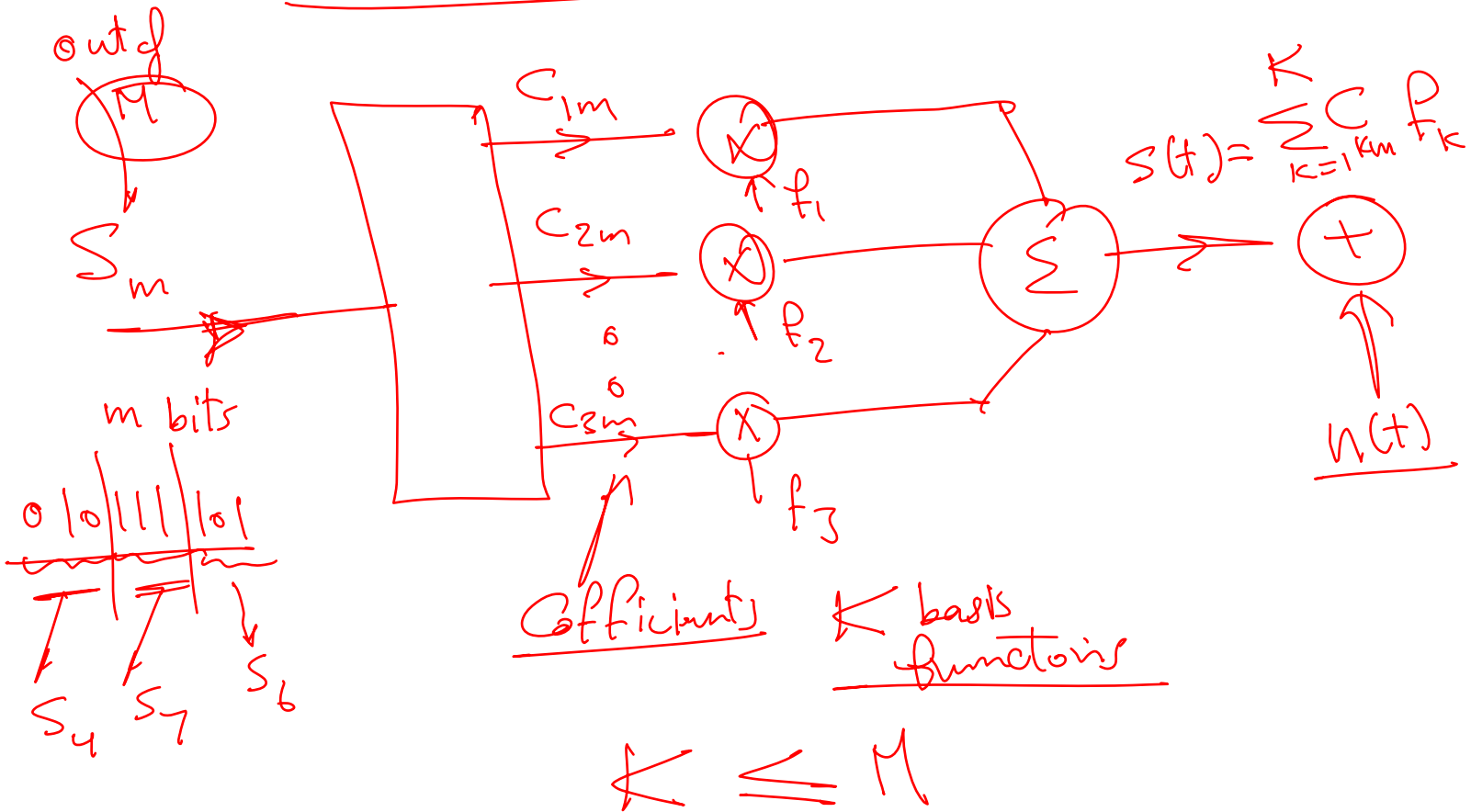
The Orthogonal Noise: $n'(t)$

- The noise $n'(t)$ can be disregarded by the receiver

$$\begin{aligned}\int_0^T s_m(t) n'(t) dt &= \int_0^T s_m(t) \left(n(t) - \sum_{k=1}^K n_k f_k(t) \right) dt \\&= \int_0^T \sum_{k=1}^K s_{m,k} f_k(t) \left(n(t) - \sum_{k=1}^K n_k f_k(t) \right) dt \\&= \sum_{k=1}^K s_{m,k} \int_0^T f_k(t) n(t) dt - \sum_{k=1}^K s_{m,k} n_k \int_0^T f_k^2(t) dt \\&= \sum_{k=1}^K s_{m,k} n_k - \sum_{k=1}^K s_{m,k} n_k = 0\end{aligned}$$

The generalized digital modulation

Transmitter



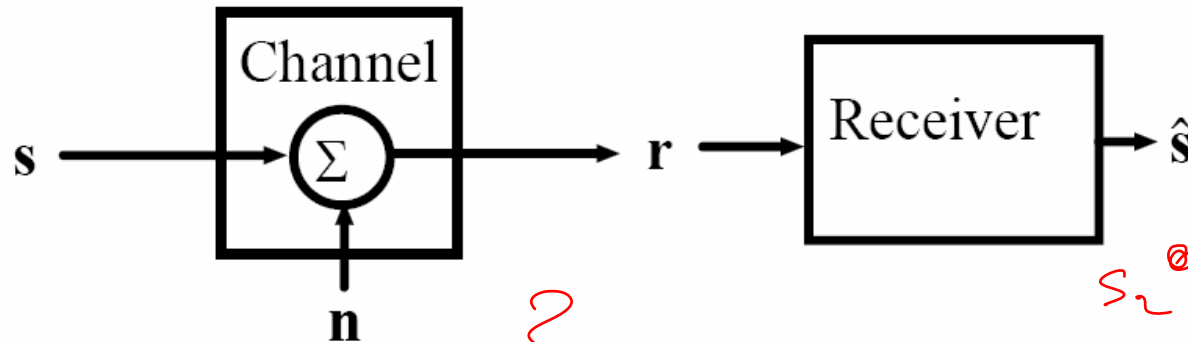
We can reduce the decision to a finite dimensional space!

- We transmit a K dimensional signal vector:

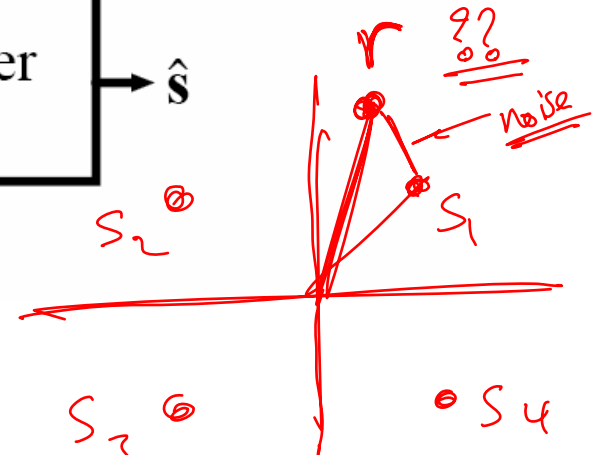
Coefficients $\mathbf{s} = [\underbrace{s_1}_{c_{m1}}, \underbrace{s_2}_{c_{m2}}, \dots, \underbrace{s_K}_{c_{mK}}] \in \{\mathbf{s}_1, \dots, \mathbf{s}_M\}$

- We receive a vector $\mathbf{r} = [r_1, \dots, r_K] = \mathbf{s} + \mathbf{n}$ which is the sum of the signal vector and noise vector $\mathbf{n} = [n_1, \dots, n_K]$

- Given \mathbf{r} , we wish to form an estimate $\hat{\mathbf{s}}$ of the transmitted signal vector which minimizes $P_s = \Pr[\hat{\mathbf{s}} \neq \mathbf{s}]$



*?
 $\hat{\mathbf{s}} \in \{s_1, s_2, s_3, s_4\}$*



$$\Pr(s_1|r) \geq \Pr(s_2|r) \quad \forall m \neq 1$$

s_3
 s_4

MAP (Maximum a posteriori probability) Decision Rule

- Suppose that signal vectors $\{s_1, \dots, s_M\}$ are transmitted with probabilities $\{p_1, \dots, p_M\}$ respectively, and the signal vector \mathbf{r} is received
- We minimize symbol error probability by choosing the signal s_m which satisfies: $\Pr(s_m|\mathbf{r}) \geq \Pr(s_i|\mathbf{r}), \forall m \neq i$
- Equivalently:
$$\frac{p(\mathbf{r}|s_m) \Pr(s_m)}{p(\mathbf{r})} \geq \frac{p(\mathbf{r}|s_i) \Pr(s_i)}{p(\mathbf{r})}, \forall m \neq i$$

or $p(\mathbf{r}|s_m) \Pr(s_m) \geq p(\mathbf{r}|s_i) \Pr(s_i), \forall m \neq i$

Maximum Likelihood (ML) Decision Rule

- If $p_1 = \dots = p_m$ or the a priori probabilities are unknown, then the MAP rule simplifies to the ML Rule
- We minimize symbol error probability by choosing the signal \mathbf{s}_m which satisfies $p(\mathbf{r}|\mathbf{s}_m) \geq p(\mathbf{r}|\mathbf{s}_i), \forall m \neq i$

Evaluation of Probabilities

- In order to apply either the MAP or ML rules, we need to evaluate: $p(\mathbf{r}|\mathbf{s}_m)$
- Since $\mathbf{r} = \mathbf{s}_m + \mathbf{n}$ where \mathbf{s}_m is constant, it is equivalent to evaluate: $p(\mathbf{n}) = p(n_1, \dots, n_K)$
- $n(t)$ is a Gaussian random process
 - Therefore $n_k = \int_0^T n(t) f_k(t) dt$ is a Gaussian random variable
 - Therefore $p(n_1, \dots, n_K)$ will be a Gaussian p.d.f.

Final Form of MAP Receiver

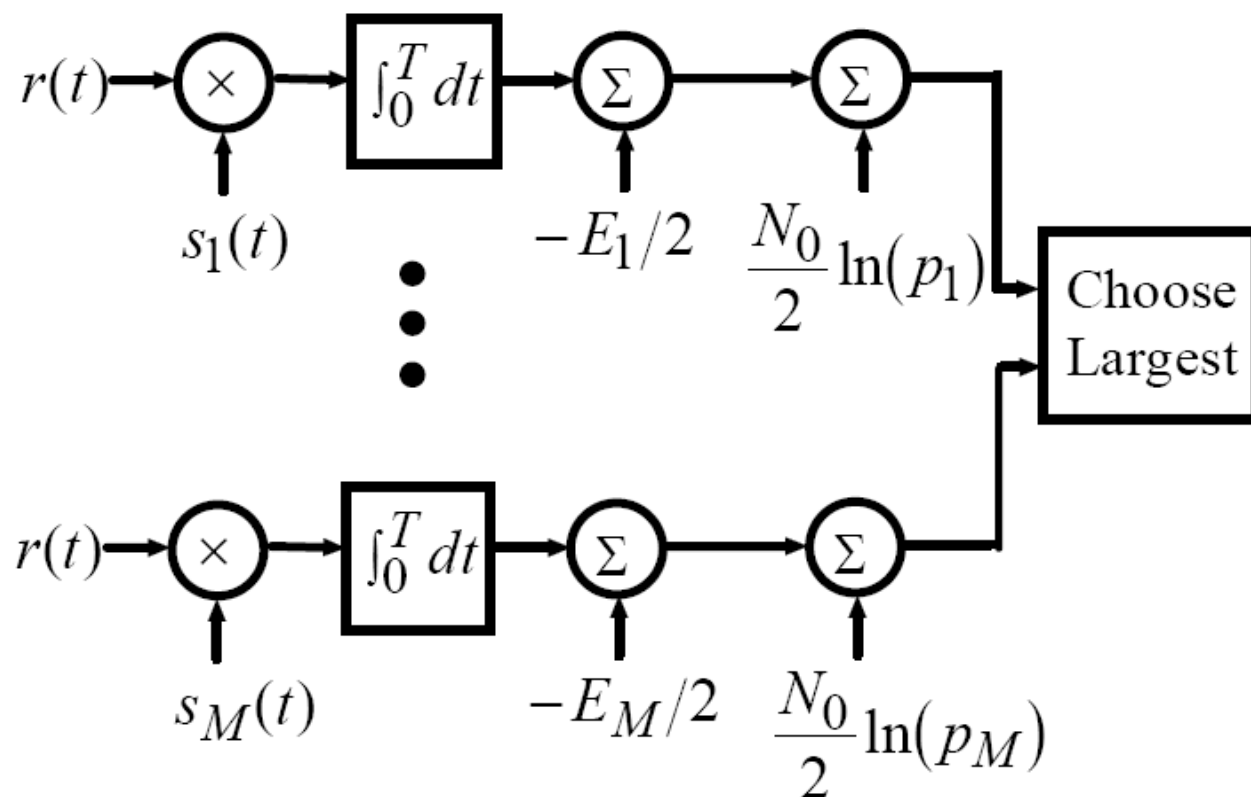
- Multiplying through by the constant $N_0/2$:

$$\hat{\mathbf{s}} = \underset{\{\mathbf{s}_1, \dots, \mathbf{s}_M\}}{\operatorname{argmax}} \frac{N_0}{2} \ln[p_m] + \sum_{k=1}^K r_k s_{m,k} - \frac{1}{2} \sum_{k=1}^K s_{m,k}^2$$

Interpreting This Result

- $\frac{N_0}{2} \ln[p_m]$ weights the a priori probabilities
 - If the noise is large, p_m counts a lot
 - If the noise is small, our received signal will be an accurate estimate and p_m counts less
- $\sum_{k=1}^K r_k s_{m,k} = \int_0^T s_m(t) r(t) dt$
 - represents the correlation with the received signal
- $\frac{1}{2} \sum_{k=1}^K s_{m,k}^2 = \frac{1}{2} \int_0^T s_m^2(t) dt = \frac{E_m}{2}$
 - represents signal energy

*An Implementation of the Optimal Receiver -
Correlation Receiver*

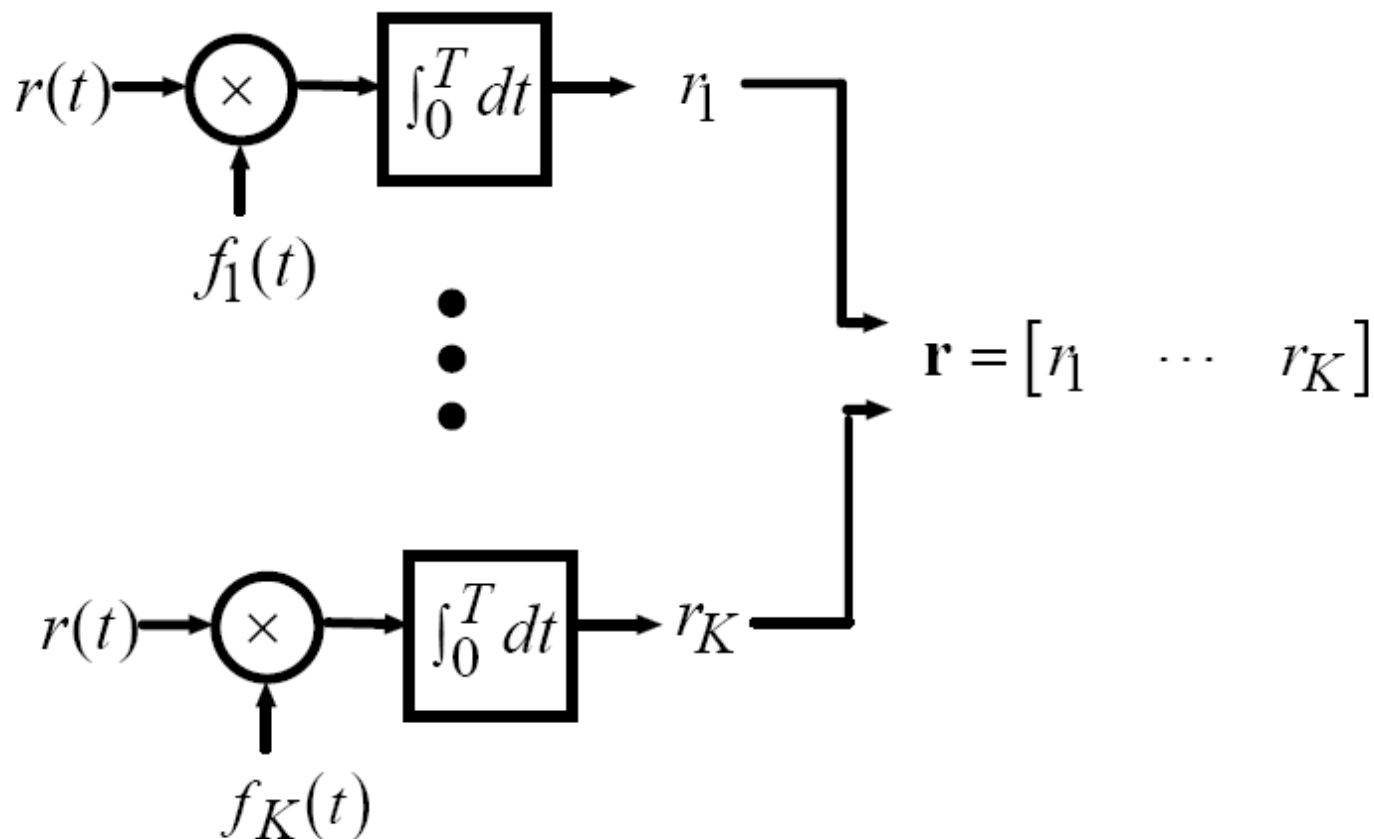


Simplifications for Special Cases

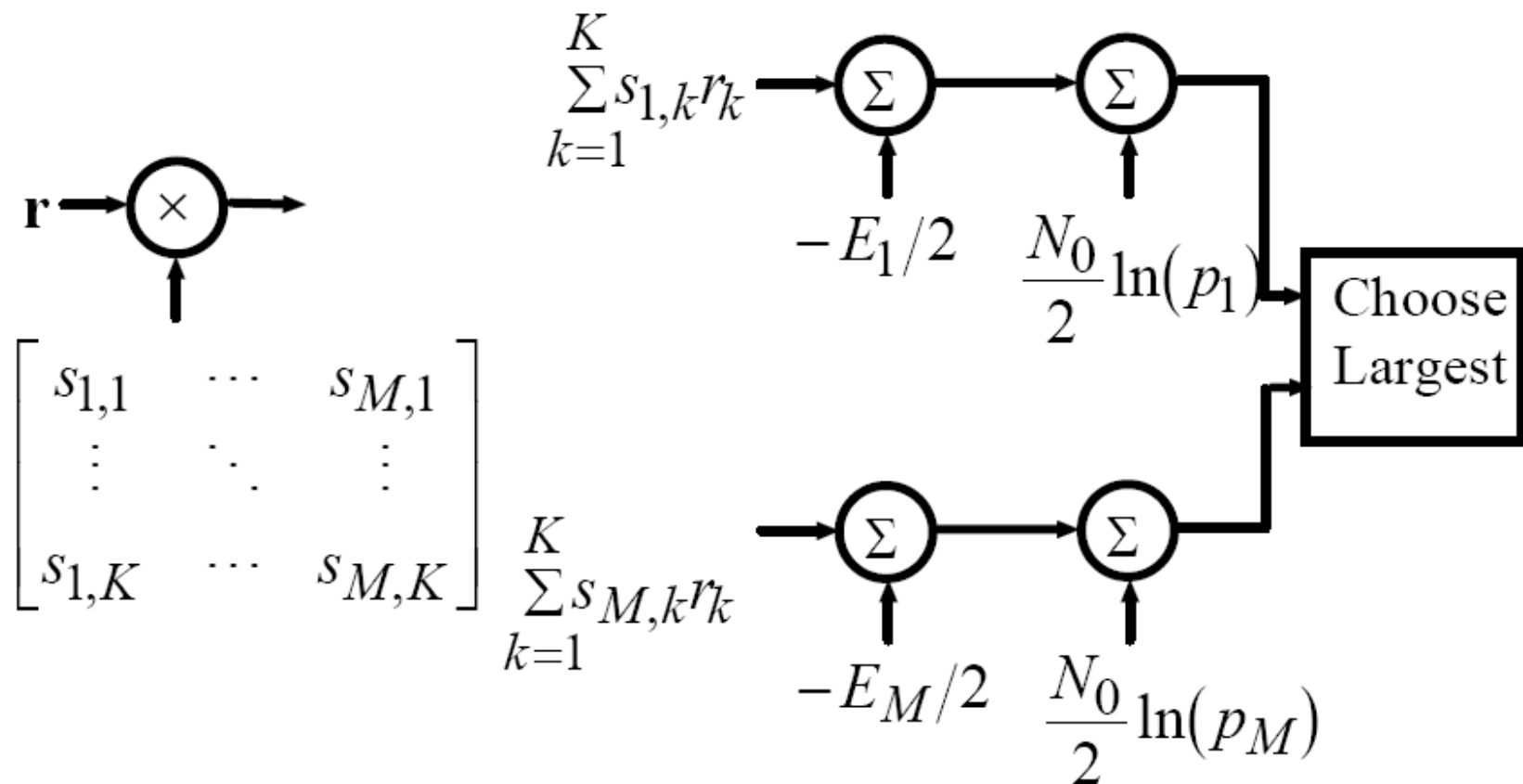
- ML case: All signals are equally likely ($p_1 = \dots = p_M$).
 - A priori probabilities can be ignored.
- All signals have equal energy ($E_1 = \dots = E_M$).
 - Energy terms can be ignored.
- We can reduce the number of correlations by directly implementing:

$$\hat{\mathbf{s}} = \arg \max_{\{\mathbf{s}_1, \dots, \mathbf{s}_M\}} \frac{N_0}{2} \ln[p_m] + \sum_{k=1}^K r_k s_{m,k} - \frac{1}{2} \sum_{k=1}^K s_{m,k}^2$$

*Reduced Complexity Implementation:
Correlation Stage*



Reduced Complexity Implementation - Processing Stage



Matched Filter Implementation

- Assume $f_k(t)$ is time-limited to $t \in [0, T]$, and let

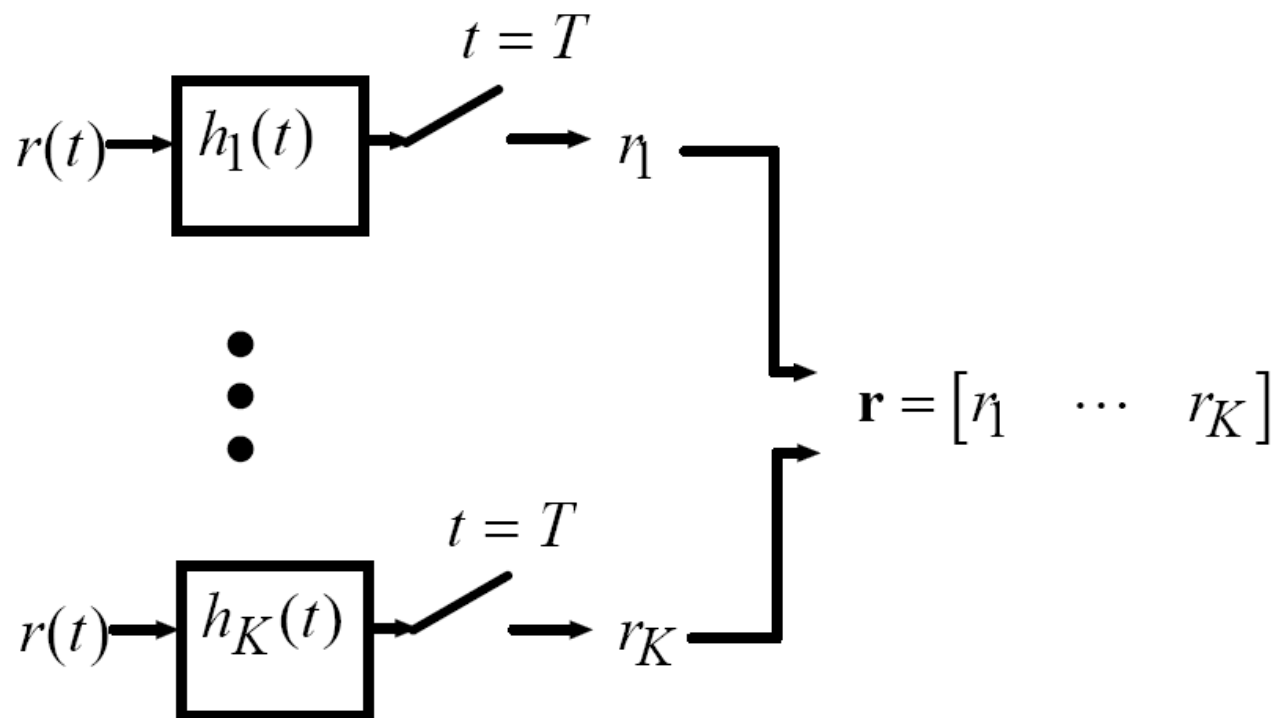
$$h_k(t) = f_k(T - t)$$

- Then
$$r_k = \int_0^T r(t) f_k(t) dt = \int_0^T r(t) f_k(T - (T - t)) dt$$
$$= \int_0^T r(t) h_k(T - t) dt = r(t) \otimes h_k(t) \Big|_{t=T}$$

where $r(t) \otimes h_k(t) \Big|_{t=T}$ denotes the convolution of the signals $r(t)$ and $h_k(t)$ evaluated at time T

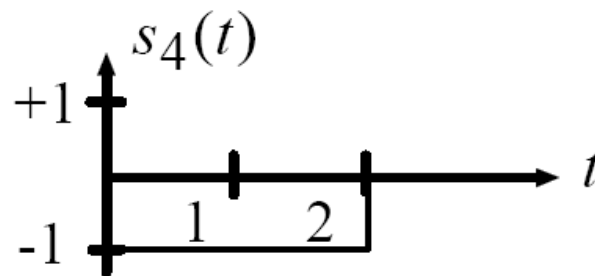
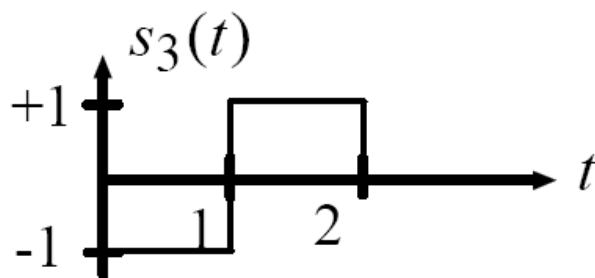
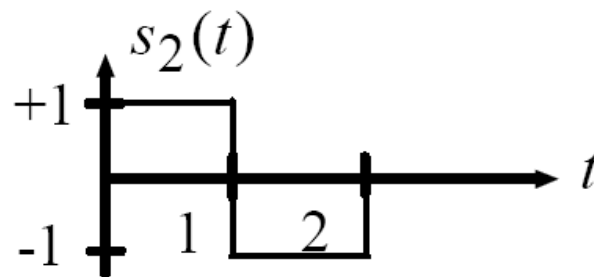
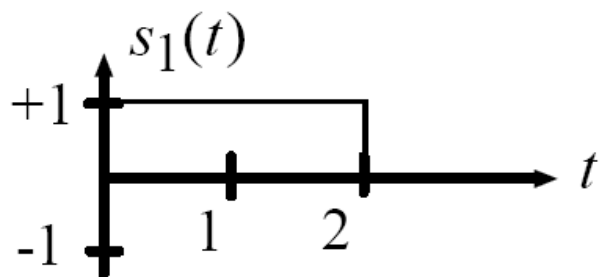
- We can implement each correlation by passing $r(t)$ through a filter with impulse response $h_k(t)$

Matched Filter Implementation of Correlation



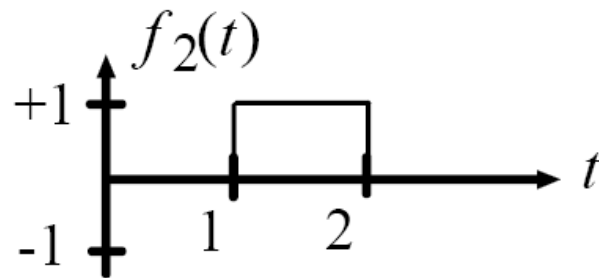
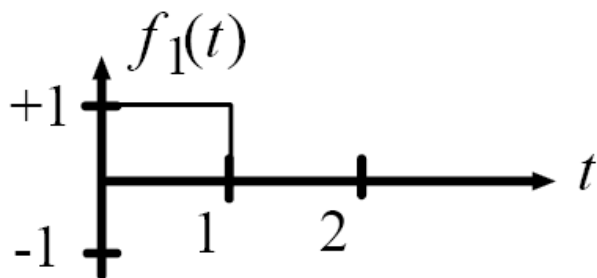
Example of Optimal Receiver Design

- Consider the signal set:



Example of Optimal Receiver Design (continued)

- Suppose we use the basis functions:



$$s_1(t) = 1 \cdot f_1(t) + 1 \cdot f_2(t)$$

$$s_2(t) = 1 \cdot f_1(t) - 1 \cdot f_2(t)$$

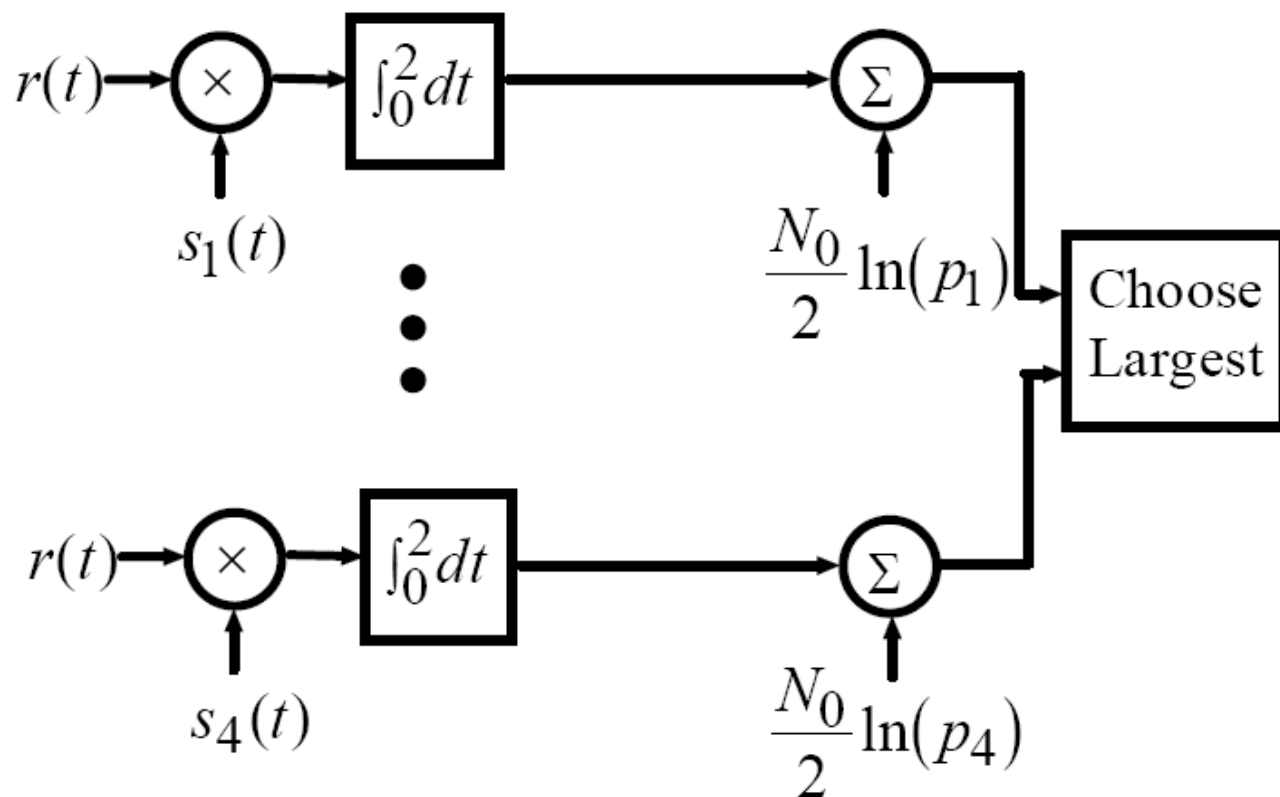
$$s_3(t) = -1 \cdot f_1(t) + 1 \cdot f_2(t)$$

$$s_4(t) = -1 \cdot f_1(t) - 1 \cdot f_2(t)$$

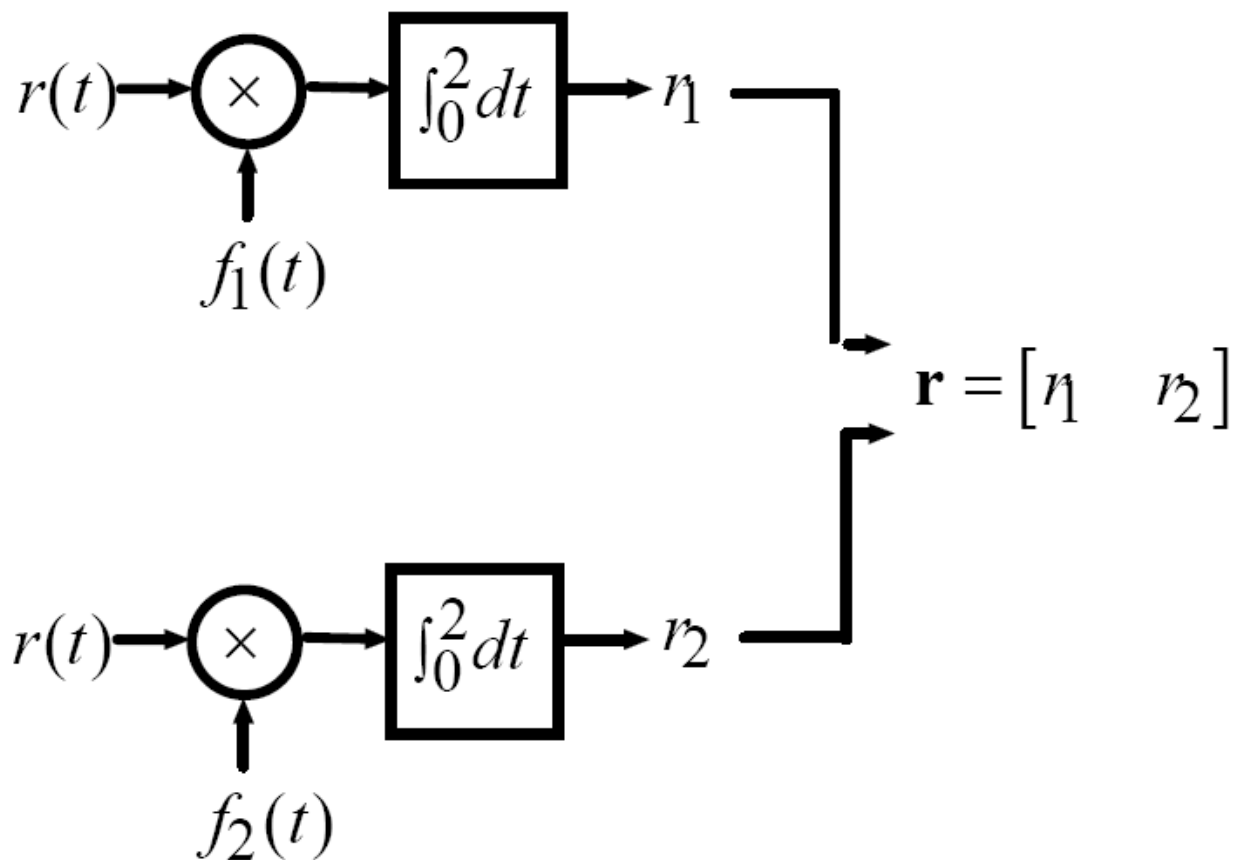
$$T = 2$$

$$E_1 = E_2 = E_3 = E_4 = 2$$

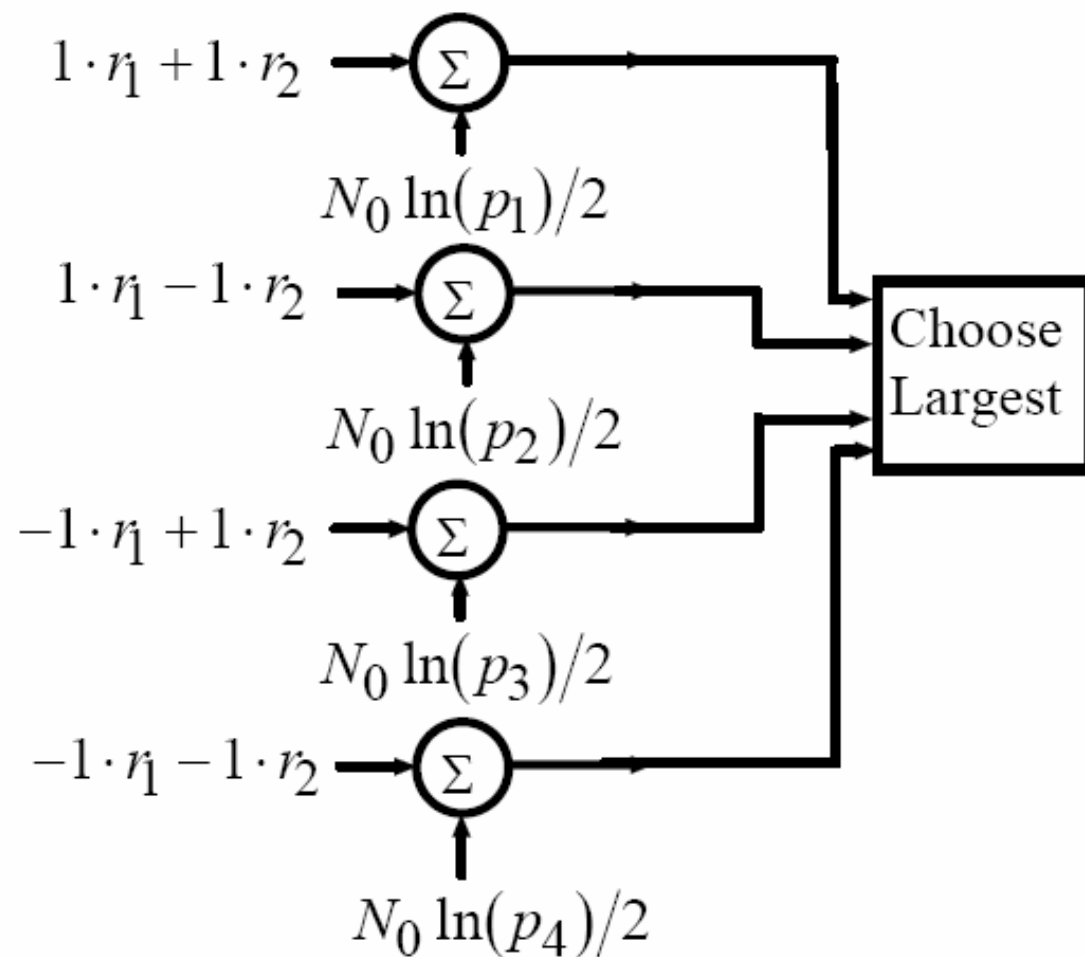
1st Implementation of Correlation Receiver



Reduced Complexity Correlation Receiver - Correlation Stage

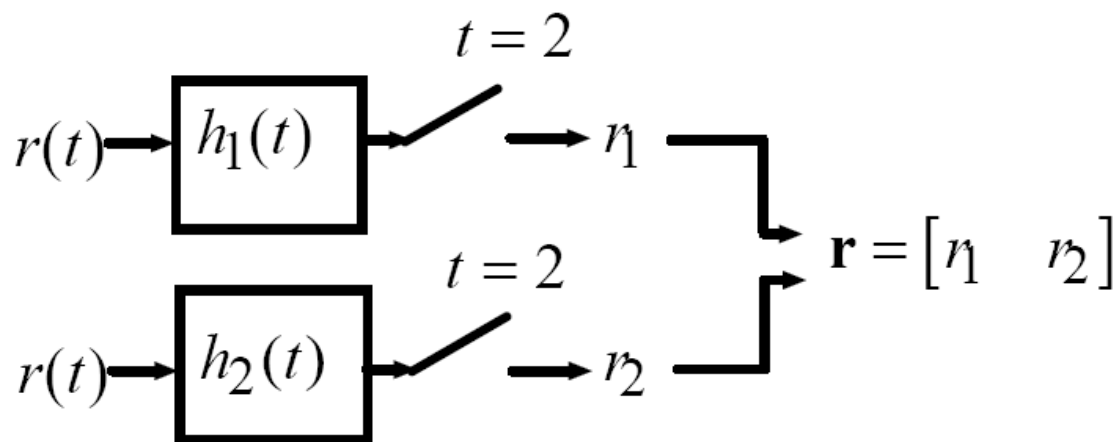
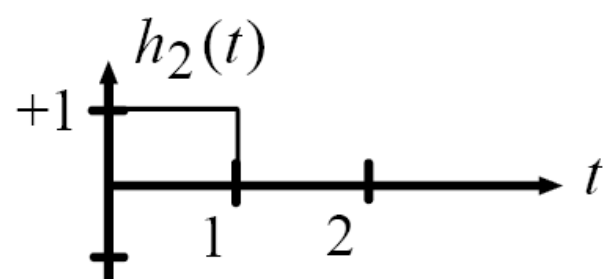
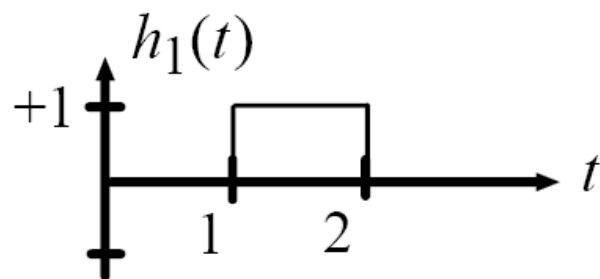


Reduced Complexity Correlation Receiver - Processing Stage



Matched Filter Implementation of Correlations

$$h_k(t) = f_k(2 - t)$$



Summary of Optimal Receiver Design

- Optimal coherent receiver for AWGN has three parts:
 - Correlates the received signal with each possible transmitted signal
 - Normalizes the correlation to account for energy
 - Weights the a priori probabilities according to noise power
- This receiver is completely general for any signal set
- Simplifications are possible under many circumstances