

Lecture 2: MAP receiver and signal space

Any bandpass signal can be written as follows (from dig com course, p.118)

$$s(t) = x_I(t) \cos(2\pi f_c t) - x_Q(t) \sin(2\pi f_c t)$$

where $x_I(t)$ and $x_Q(t)$ are: 1) real-valued, 2) low pass, 3) bandwidth $\ll f_c$

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Let us now choose $x_I(t)$ and $x_Q(t)$ as **PAM** signals, i.e.,

$$x_I(t) = A_\ell g(t)$$

$$x_Q(t) = B_\ell g(t) \quad \ell = 0, \dots, M - 1$$

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$$x_Q(t) = B_\ell g(t) \quad \ell = 0, \dots, M - 1$$

We get

$$s_\ell(t) = A_\ell g(t) \cos(2\pi f_c t) - B_\ell g(t) \sin(2\pi f_c t)$$

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Let us now rewrite this as

$$s_\ell(t) = A_\ell \sqrt{E_g/2} \phi_1(t) - B_\ell \sqrt{E_g/2} \phi_2(t)$$

where

$$\phi_1(t) = \frac{g(t) \cos(2\pi f_c t)}{\sqrt{E_g/2}} \quad \phi_2(t) = -\frac{g(t) \sin(2\pi f_c t)}{\sqrt{E_g/2}}$$

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Define

$$s_{\ell,1} = A_\ell \sqrt{E_g/2} \quad s_{\ell,2} = B_\ell \sqrt{E_g/2}$$

$$s_\ell(t) = A_\ell g(t) \cos(2\pi f_c t) - B_\ell g(t) \sin(2\pi f_c t)$$

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We get

$$s_\ell(t) = s_{\ell,1}\phi_1(t) + s_{\ell,2}\phi_2(t)$$

where

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Continuous waveform, representing message ℓ

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We get

Basis functions

$$s_\ell(t) = s_{\ell,1}\phi_1(t) + s_{\ell,2}\phi_2(t)$$

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$$\phi_1(t) = \frac{g(t) \cos(2\pi f_c t)}{\sqrt{E_g/2}} \quad \phi_2(t) = -\frac{g(t) \sin(2\pi f_c t)}{\sqrt{E_g/2}}$$

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Expansion coefficients, representing message ℓ

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Checkpoint: Is both $\phi_1(t)$ and $\phi_2(t)$ needed?

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Continuous waveform, representing message ℓ

Checkpoint: Is both $\phi_1(t)$ and $\phi_2(t)$ needed?

YES, since $\phi_1(t) \neq \alpha\phi_2(t)$

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We get

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Continuous waveform, representing message ℓ

Checkpoint: Is basis orthonormal ?

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Expansion coefficients, representing message ℓ

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Continuous waveform, representing message ℓ

Checkpoint: Is basis orthonormal ?

- 1) $\int \phi_1^2(t) dt = 1$
- 2) $\int \phi_2^2(t) dt = 1$

Prove this at home

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We get

$$s_\ell(t) = s_{\ell,1}\phi_1(t) + s_{\ell,2}\phi_2(t)$$

Basis functions

Expansion coefficients, representing message ℓ

where

$$\phi_1(t) = \frac{g(t) \cos(2\pi f_c t)}{\sqrt{E_g/2}} \quad \phi_2(t) = -\frac{g(t) \sin(2\pi f_c t)}{\sqrt{E_g/2}}$$

Continuous waveform, representing message ℓ

Checkpoint: Is basis orthonormal? Yes

- 1) $\int \phi_1^2(t) dt = 1$
- 2) $\int \phi_2^2(t) dt = 1$
- 3) $\int \phi_1(t)\phi_2(t) dt = 0$

Proofs requires usage of $f_c \gg 1$

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Generalization

$$s_{\ell}(t) = \sum_n^N s_{\ell,n} \phi_n(t) = s_{\ell,1} \phi_1(t) + \dots + s_{\ell,N} \phi_N(t)$$

In general, the signal set can require >2 basis functions

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In general, the signal set can require >2 basis functions

Question: For a signal set of below form, can $N > 2$?

$$s_\ell(t) = x_{I,\ell}(t) \cos(2\pi f_c t) - x_{Q,\ell}(t) \sin(2\pi f_c t)$$

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$$s_\ell(t) = x_{I,\ell}(t) \cos(2\pi f_c t) - x_{Q,\ell}(t) \sin(2\pi f_c t)$$

Yes! We only derived that for PAM components we get $N=2$

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Generalization

$$s_\ell(t) = \sum_n^N s_{\ell,n} \phi_n(t) = s_{\ell,1} \phi_1(t) + \dots + s_{\ell,N} \phi_N(t)$$

In general, the signal set can require >2 basis functions

Question: For a single signal of below form, can $N > 2$?

$$s(t) = x_I(t) \cos(2\pi f_c t) - x_Q(t) \sin(2\pi f_c t)$$

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Generalization

$$s_\ell(t) = \sum_n^N s_{\ell,n} \phi_n(t) = s_{\ell,1} \phi_1(t) + \dots + s_{\ell,N} \phi_N(t)$$

In general, the signal set can require >2 basis functions

Question: For a single signal of below form, can $N > 2$?

$$s(t) = x_I(t) \cos(2\pi f_c t) - x_Q(t) \sin(2\pi f_c t)$$

There is no need to!!!

We can write $s(t) = s\phi_1(t)$

where $\phi_1(t) = s(t)/\sqrt{E_s}$, $s = \sqrt{E_s}$

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Definition

The dimensionality of a signal set $\mathcal{S} = \{s_\ell(t)\}_{\ell=0}^{M-1}$ is the smallest number N such that each signal in \mathcal{S} can, for some orthonormal set of basis functions $\{\phi_n(t)\}_{n=1}^N$ be expressed as

$$s_\ell(t) = \sum_n^N s_{\ell,n} \phi_n(t) = s_{\ell,1} \phi_1(t) + \dots + s_{\ell,N} \phi_N(t)$$

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Why is it so important ?

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Why is it so important ? Because most properties are not dependent on the basis functions!

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Energy

$$E_\ell = \int s_\ell^2(t) dt =$$

By definition

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Energy

$$E_\ell = \int s_\ell^2(t) dt = \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right]^2 dt =$$

Use the basis expansion

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Energy

$$\begin{aligned} E_\ell &= \int s_\ell^2(t) dt = \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right]^2 dt \\ &= \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right] \left[\sum_{m=1}^N s_{\ell,m} \phi_m(t) \right] dt = \end{aligned}$$

Expand the power. Must use two different indices

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$$\begin{aligned} E_\ell &= \int s_\ell^2(t) dt = \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right]^2 dt \\ &= \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right] \left[\sum_{m=1}^N s_{\ell,m} \phi_m(t) \right] dt \\ &= \int \sum_{m=1}^N \sum_{n=1}^N s_{\ell,n} \phi_n(t) s_{\ell,m} \phi_m(t) dt = \end{aligned}$$

Reorder

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Energy

$$\begin{aligned} E_\ell &= \int s_\ell^2(t) dt = \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right]^2 dt \\ &= \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right] \left[\sum_{m=1}^N s_{\ell,m} \phi_m(t) \right] dt \\ &= \int \sum_{m=1}^N \sum_{n=1}^N s_{\ell,n} \phi_n(t) s_{\ell,m} \phi_m(t) dt \\ &= \sum_{m=1}^N \sum_{n=1}^N s_{\ell,n} s_{\ell,m} \int \phi_n(t) \phi_m(t) dt = \end{aligned}$$

Pull out constants not dependent on t

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Energy

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$= 0, \text{ if } n \neq m$
 $= 1, \text{ if } n = m$

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Lesson learned

1. Energy does not depend on basis functions
2. True only for orthonormal basis functions
3. All signal sets with equal expansion coefficients have same energies

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Why is it so important ? Because most properties are not dependent on the basis functions!

Euclidian distances

$$D_{i,j}^2 = \int (s_i(t) - s_j(t))^2 dt =$$

By definition

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Why is it so important ? Because most properties are not dependent on the basis functions!

Euclidian distances

$$D_{i,j}^2 = \int (s_i(t) - s_j(t))^2 dt = \int \left[\sum_{n=1}^N (s_{i,n} - s_{j,n}) \phi_n(t) \right]^2 dt$$

Basis expansion

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Why is it so important ? Because most properties are not dependent on the basis functions!

Euclidian distances

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Recall energy computation

$$E_\ell = \int s_\ell^2(t) dt = \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right]^2 dt = \sum_{n=1}^N s_{\ell,n}^2$$

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The same setup...

Recall energy computation

$$E_\ell = \int s_\ell^2(t) dt = \int \left[\sum_{n=1}^N s_{\ell,n} \phi_n(t) \right]^2 dt = \sum_{n=1}^N s_{\ell,n}^2$$

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Lessons learned

1. Euclidian distances do not depend on basis functions
2. True only for orthonormal basis functions
3. All signal sets with equal expansion coefficients have same distances

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Lessons learned

1. Euclidian distances do not depend on basis functions
2. True only for orthonormal basis functions
3. All signal sets with equal expansion coefficients have same distances
4. THEREFORE, SAME PERFORMANCE

Lecture 2: MAP receiver and signal space

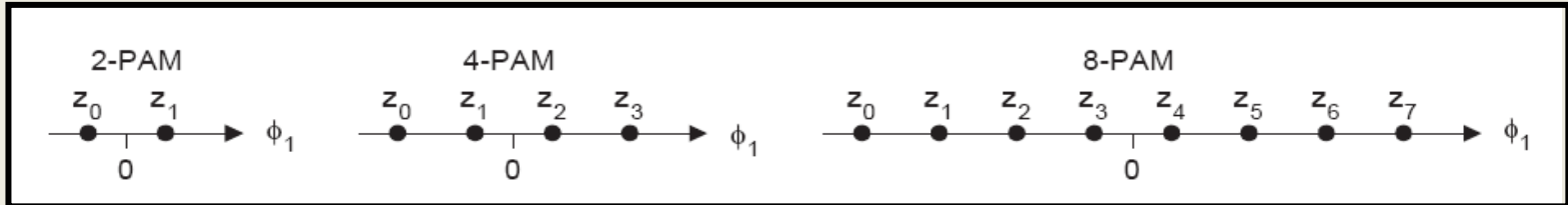
To study performance of a communication systems, it is sufficient to study its signal space decomposition

Lessons learned

1. Euclidian distances do not depend on basis functions
2. True only for orthonormal basis functions
3. All signal sets with equal expansion coefficients have same distances
4. THEREFORE, SAME PERFORMANCE

Lecture 2: MAP receiver and signal space

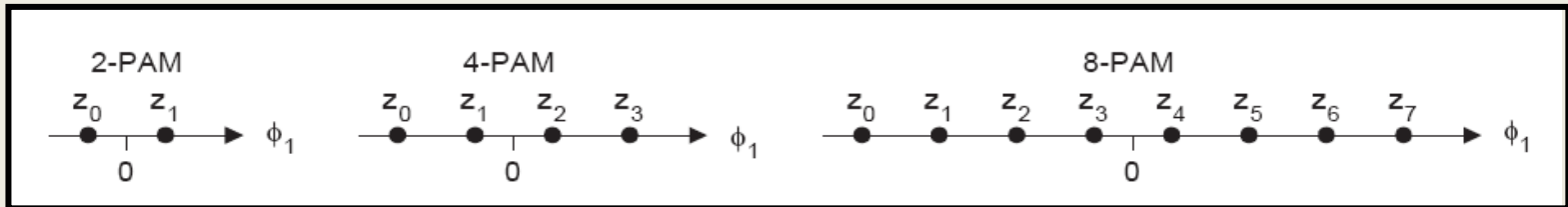
Examples



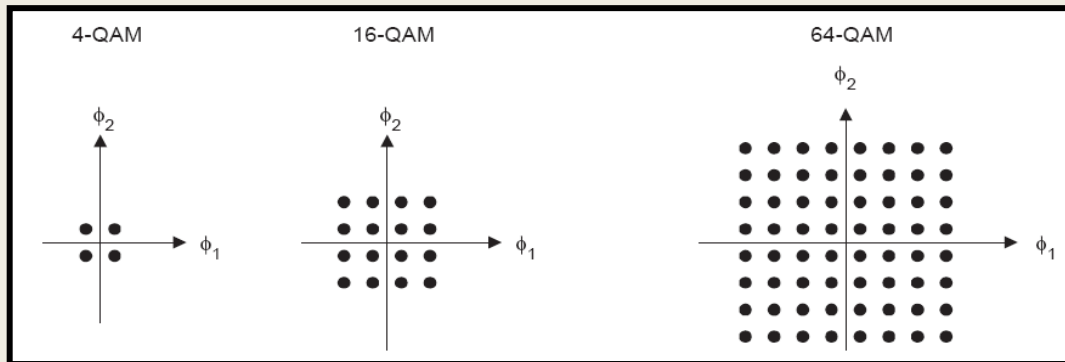
$N = ??$

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Examples



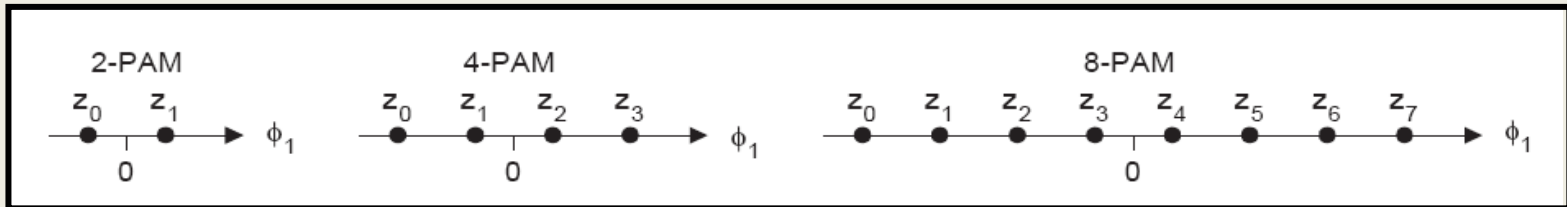
$N = 1$



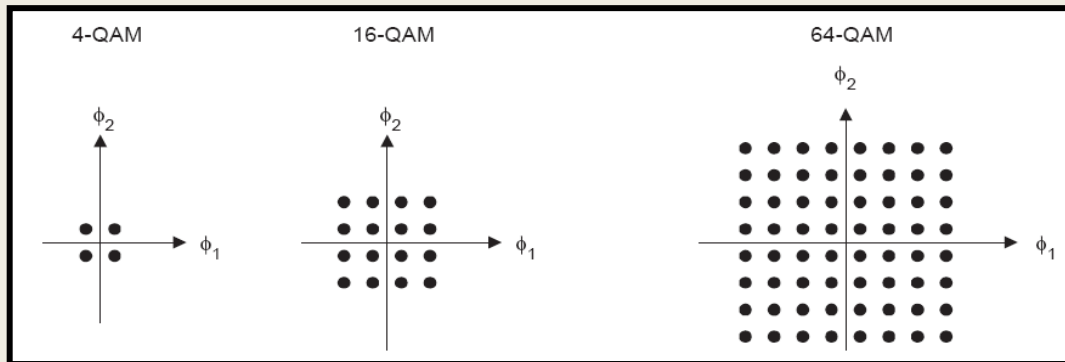
$N = ??$

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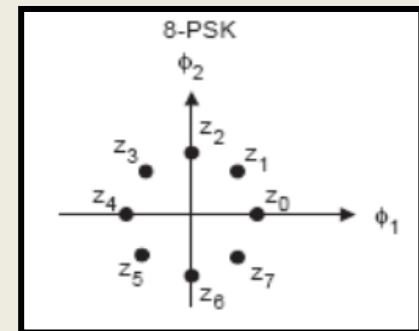
Examples



$N = 1$



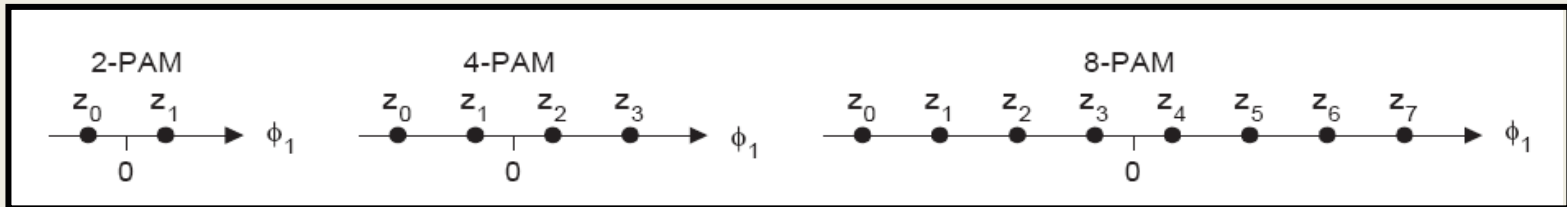
$N = 2$



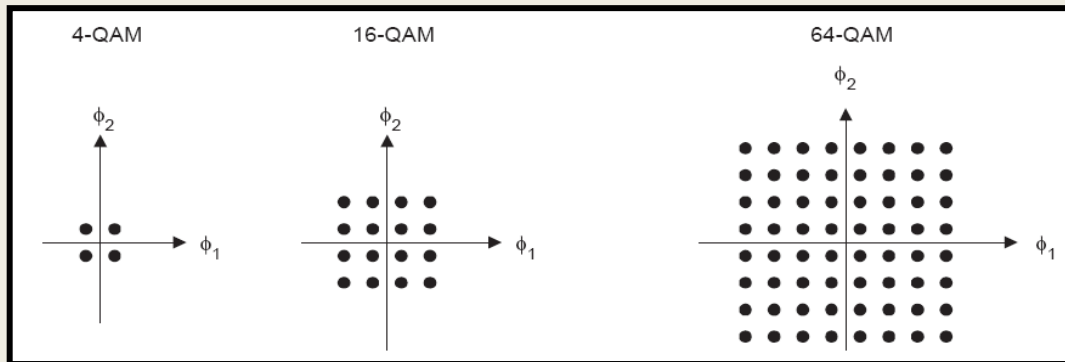
$N = ??$

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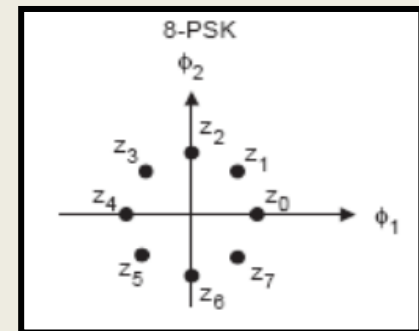
Examples



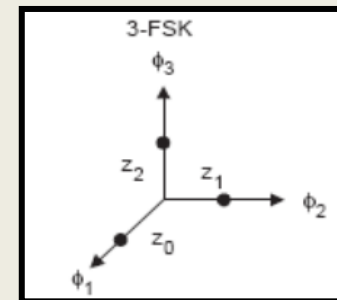
$N = 1$



$N = 2$



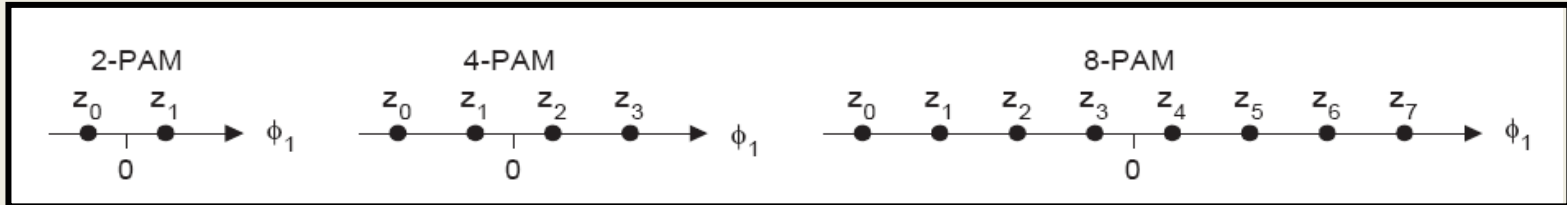
$N = 2$



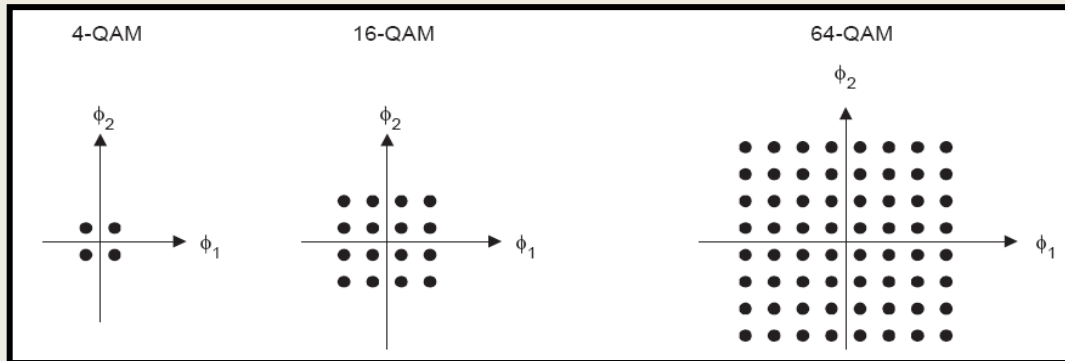
$N = ??$

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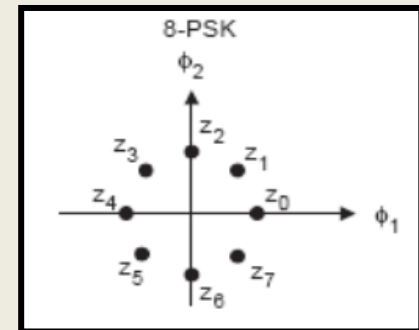
Examples



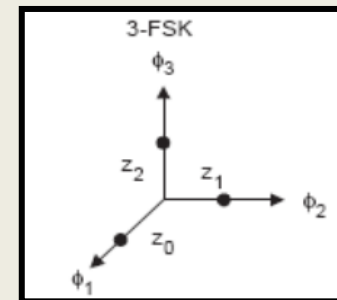
$N = 1$



$N = 2$



$N = 2$



$N = 3$

Lecture 2: MAP receiver and signal space

Definition

The signal $s_j(t)$ is expressed in signal space as the vector \mathbf{s}_j

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Property

The signal space vector (or point) \mathbf{s}_j carries all information relevant for performance evaluation

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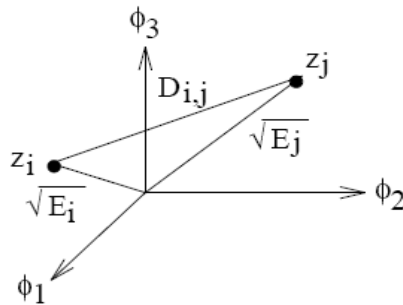


Figure 5.3: Illustrating E_ℓ and $D_{i,j}$ in signal space.

Lecture 2: MAP receiver and signal space

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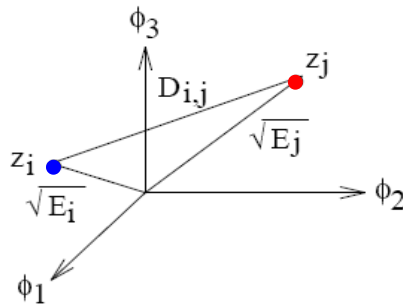
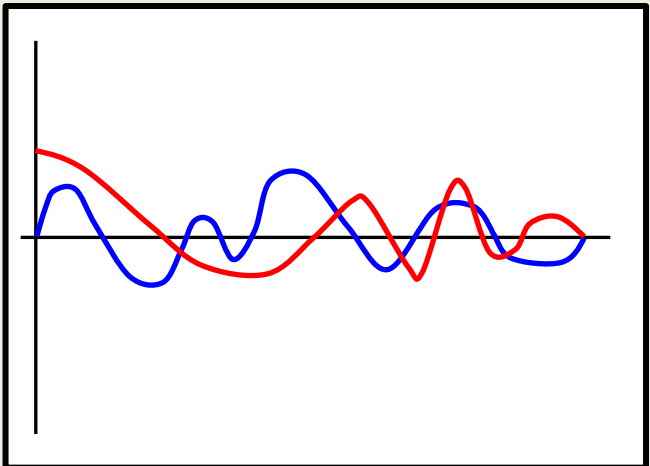


Figure 5.3: Illustrating E_ℓ and $D_{i,j}$ in signal space.



Lecture 2: MAP receiver and signal space

Towards the MAP receiver

Assume that we have a **noise free** signal $r(t)$ at the input of the receiver

We know that this is one of $\{s_\ell(t)\}_{\ell=1}^{M-1}$ but we don't know exactly which one

How to exploit signal space to find out?

Lecture 2: MAP receiver and signal space

Towards the MAP receiver

Assume that we have a **noise free** signal $r(t)$ at the input of the receiver

We know that this is one of $\{s_\ell(t)\}_{\ell=0}^{M-1}$ but we don't know exactly which one

How to exploit signal space to find out?

The energy of the signal $r(t)$ is along the directions of the basis functions $\{\phi_n(t)\}_{n=1}^N$

Lecture 2: MAP receiver and signal space

Towards the MAP receiver

Assume that we have a **noise free** signal $r(t)$ at the input of the receiver

We know that this is one of $\{s_\ell(t)\}_{\ell=0}^{M-1}$ but we don't know exactly which one

How to exploit signal space to find out?

The energy of the signal $r(t)$ is along the directions of the basis functions $\{\phi_n(t)\}_{n=1}^N$

“Look” in the dimensions

$$r_n = \int r(t)\phi_n(t)dt$$

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"Look" in the dimensions a is true message

$$r_n = \int r(t) \phi_n(t) dt = \int \left[\sum_{m=1}^N s_{a,m} \phi_m(t) \right] \phi_n(t) dt$$

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$$\begin{aligned} r_n &= \int r(t) \phi_n(t) dt = \int \left[\sum_{m=1}^N s_{a,m} \phi_m(t) \right] \phi_n(t) dt \\ &= \sum_{m=1}^N s_{a,m} \int \phi_m(t) \phi_n(t) dt \end{aligned}$$

A simple reordering...

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$$\begin{aligned} r_n &= \int r(t) \phi_n(t) dt = \int \left[\sum_{m=1}^N s_{a,m} \phi_m(t) \right] \phi_n(t) dt \\ &= \sum_{m=1}^N s_{a,m} \int \phi_m(t) \phi_n(t) dt = s_{a,n} \end{aligned}$$

due to orthonormality

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In vector notation $\mathbf{r} = \mathbf{S}_a$

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In vector notation $\mathbf{r} = \mathbf{S}_a$

Receiver: $\hat{a} = \arg \min_{\ell} \|\mathbf{r} - \mathbf{s}_\ell\|^2 = a$

↑
Guaranteed since no noise

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Assume that we have a **noisy signal** $r(t)$ at the input of the receiver

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Gaussian noise.
Variance $N_0/2$

Lecture 2: MAP receiver and signal space

Interlude: Gaussian random variables

Fact: Two Gaussian random variables are independent iff they are uncorrelated

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Question: Is w_i and w_j independent?

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$$E(w_i w_j) =$$

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Gaussian noise.
Variance $N_0/2$

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Question: Is w_i and w_j independent?

$$E(w_i w_j) = E \left(\int N(t) \phi_i(t) dt \int N(t) \phi_j(t) dt \right)$$

↑
Gaussian noise. Spectral density $N_0/2$

$$r_n = \int r(t) \phi_n(t) dt = s_{a,n} + w_n$$

Gaussian noise.
Variance $N_0/2$

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$$\begin{aligned} E(w_i w_j) &= E \left(\int N(t) \phi_i(t) dt \int N(t) \phi_j(t) dt \right) \\ &= E \left(\int \int N(t) \phi_i(t) N(\tau) \phi_j(\tau) dt d\tau \right) \end{aligned}$$

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The definition of white Gaussian noise

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By orthonormality

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Question: Is w_i and w_j independent? **YES!!!**

$$\begin{aligned} E(w_i w_j) &= E \left(\int N(t) \phi_i(t) dt \int N(t) \phi_j(t) dt \right) \\ &= E \left(\int \int N(t) \phi_i(t) N(\tau) \phi_j(\tau) dt d\tau \right) \\ &= \int \int E(N(t) N(\tau)) \phi_i(t) \phi_j(\tau) dt d\tau \\ &= \frac{N_0}{2} \int \phi_i(t) \phi_j(t) dt = \frac{N_0}{2} \delta[i - j] \end{aligned}$$

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We can still "look" along the basis functions $r_n = \int r(t)\phi_n(t)dt$

CRITICAL: Can we guarantee that this is optimal?

We get, $r_n = \int r(t)\phi_n(t)dt = s_{a,n} + w_n$

Gaussian noise.

Variance $N_0/2$

Independent over n

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$$r(t) = s_a(t) + N(t)$$

$$\hat{r}(t) = \sum_{n=1}^N r_n \phi_n(t) \quad \text{Attempt to reconstruct } r(t)$$

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$$\hat{r}(t) = \sum_{n=1}^N r_n \phi_n(t) = \sum_{n=1}^N (s_{a,n} + w_n) \phi_n(t) = s_a(t) + \sum_{n=1}^N w_n \phi_n(t)$$

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$$r(t) = s_a(t) + \hat{N}(t) \quad \text{Identical ?}$$

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$r(t) = s_a(t) + \hat{N}(t)$ **Identical ? NO. Basis functions are basis for signal, not for the noise**

$$\hat{r}(t) = \sum_{n=1}^N r_n \phi_n(t) = \sum_{n=1}^N (s_{a,n} + w_n) \phi_n(t) = s_a(t) + \sum_{n=1}^N w_n \phi_n(t) = s_a(t) + \hat{N}(t)$$

Lecture 2: MAP receiver and signal space

Towards the MAP receiver

To fix this, we can add more basis functions $\phi_n(t)$, $n > N$

We could guarantee optimality if we could retrieve $r(t)$ from r

$$r(t) = s_a(t) + \underbrace{N(t)}_{\text{Identical ? NO. Basis functions are basis for signal, not for the noise}}$$

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Lecture 2: MAP receiver and signal space

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To fix this, we can add more basis functions $\phi_n(t)$, $n > N$

Now, look again in all dimensions,

$$r_n = \int r(t) \phi_n(t) dt = \begin{cases} s_{a,n} + w_n & 1 \leq n \leq N \\ w_n & n > N \end{cases}$$

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With sufficiently many additional basis, we get

We could guarantee optimality if we could retrieve $r(t)$ from r

$$r(t) = s_a(t) + N(t) \quad \text{Identical ? YES}$$

$$\hat{r}(t) = \sum_{n=1}^{\infty} r_n \phi_n(t) = \sum_{n=1}^{\infty} (s_{a,n} + w_n) \phi_n(t) = s_a(t) + \sum_{n=1}^{\infty} w_n \phi_n(t) = s_a(t) + N(t)$$

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However, do we really need these extra basis functions *for detection?*

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NO, since we proved earlier that the noise in different dimensions is independent

Lecture 2: MAP receiver and signal space

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Although generated from the same noise $N(t)$, these values could just as well have been generated from

- 1.
- 2.

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1. A refrigerator somewhere in the Andromeda galaxy
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Clearly, a refrigerator in Andromeda cannot assist detection of systems on earth.

Lecture 2: MAP receiver and signal space

Towards the MAP receiver

So, for detection, it is sufficient to look in the N dimensions where the signal is

$$r_n = \int r(t) \phi_n(t) dt, \quad 1 \leq n \leq N$$

Lecture 2: MAP receiver and signal space

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Write in vector notation $\mathbf{r} = \mathbf{s}_a + \mathbf{w}$

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Probability density function

$$p(\mathbf{r}|\mathbf{s}_\ell) \propto \exp \left(-\frac{\|\mathbf{r} - \mathbf{s}_\ell\|^2}{N_0} \right)$$

Lecture 2: MAP receiver and signal space

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Probability density function $p(\mathbf{r}|\mathbf{s}_\ell) \propto \exp\left(-\frac{\|\mathbf{r} - \mathbf{s}_\ell\|^2}{N_0}\right)$

$$\text{ML} \quad \hat{m} = \arg \max_{\ell} \exp\left(-\frac{\|\mathbf{r} - \mathbf{s}_\ell\|^2}{N_0}\right) = \arg \min_{\ell} \|\mathbf{r} - \mathbf{s}_\ell\|^2$$

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$$r_n = \int r(t) \phi_n(t) dt, \quad 1 \leq n \leq N$$

Write in vector notation $\mathbf{r} = \mathbf{s}_a + \mathbf{w}$

Probability density function $p(\mathbf{r}|\mathbf{s}_\ell) \propto \exp\left(-\frac{\|\mathbf{r} - \mathbf{s}_\ell\|^2}{N_0}\right)$

$$\mathbf{ML} \quad \hat{m} = \arg \max_{\ell} \exp\left(-\frac{\|\mathbf{r} - \mathbf{s}_\ell\|^2}{N_0}\right) = \arg \min_{\ell} \|\mathbf{r} - \mathbf{s}_\ell\|^2$$

$$\mathbf{MAP} \quad \hat{m} = \arg \max_{\ell} P(\ell) \exp\left(-\frac{\|\mathbf{r} - \mathbf{s}_\ell\|^2}{N_0}\right)$$