

TSKS01 Digital Communication

Lecture 3

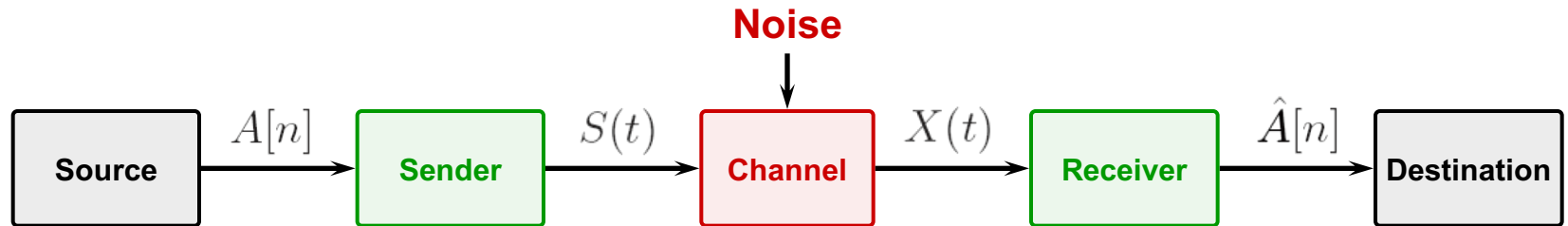
Signals as Vectors

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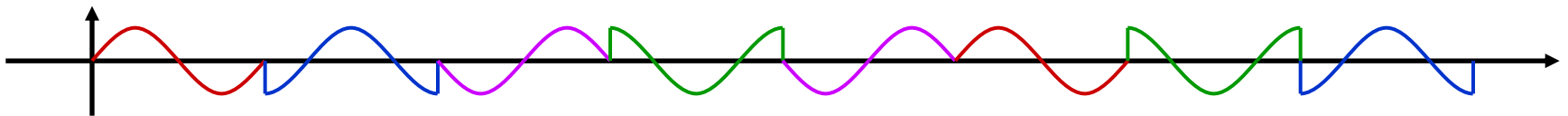
Situation: Additive Noise Channel



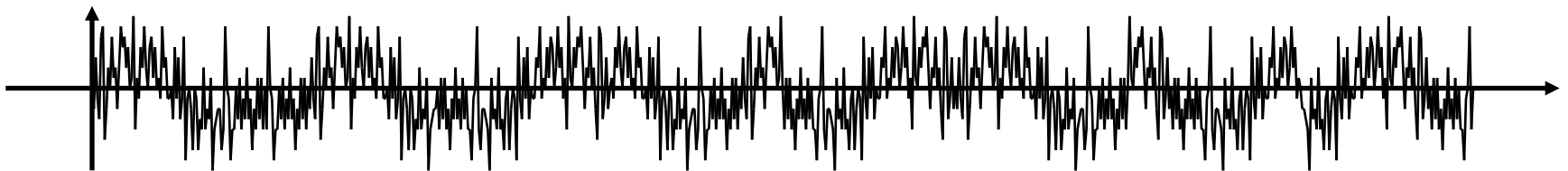
One message every T seconds.

00 10 11 01 11 00 01 10

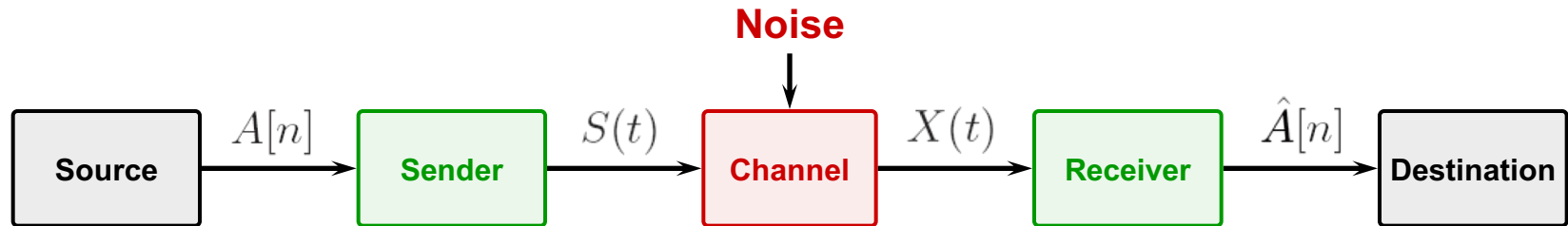
Represented using time-delimited signals. Duration T seconds ($T \sim 1/\text{bandwidth}$)



The channel adds noise to the signal.



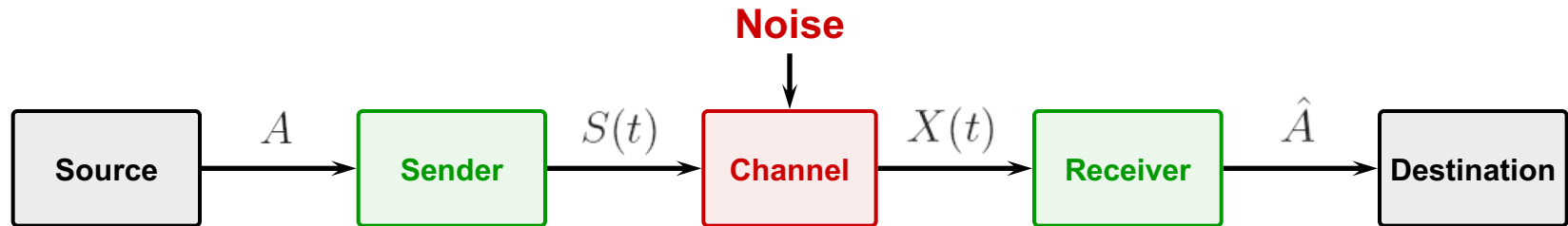
Analyze Only One Message at Time



Reasons:

- Different samples in $A[n]$ are assumed independent
⇒ No information gained about one sample from another.
- Pulse function satisfies Nyquist criterion
⇒ No intersymbol interference due to modulation.
- The channel does not filter the signal
⇒ No intersymbol interference due to filtering.
- Different samples of WGN are independent
⇒ Noise from non-overlapping intervals are independent.

Notation



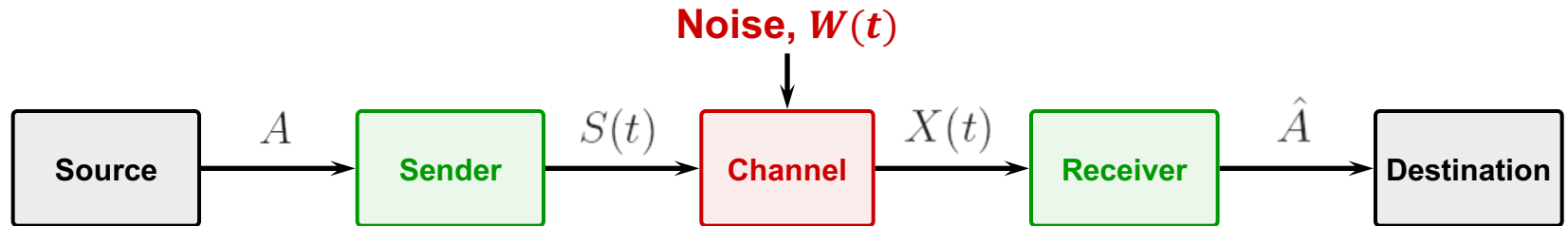
Message set: $\{a_i\}_{i=0}^{M-1}$ Size: M

Signal set: $\{s_i(t)\}_{i=0}^{M-1}$

Mapping: $a_i \rightarrow s_i(t)$ for $i \in \{0, 1, \dots, M-1\}$

Signal energy: $E_i = \int_{-\infty}^{\infty} s_i^2(t) dt < \infty, \quad i \in \{0, 1, \dots, M-1\}$

The Channel and the Receiver



AWGN channel: Additive White Gaussian Noise

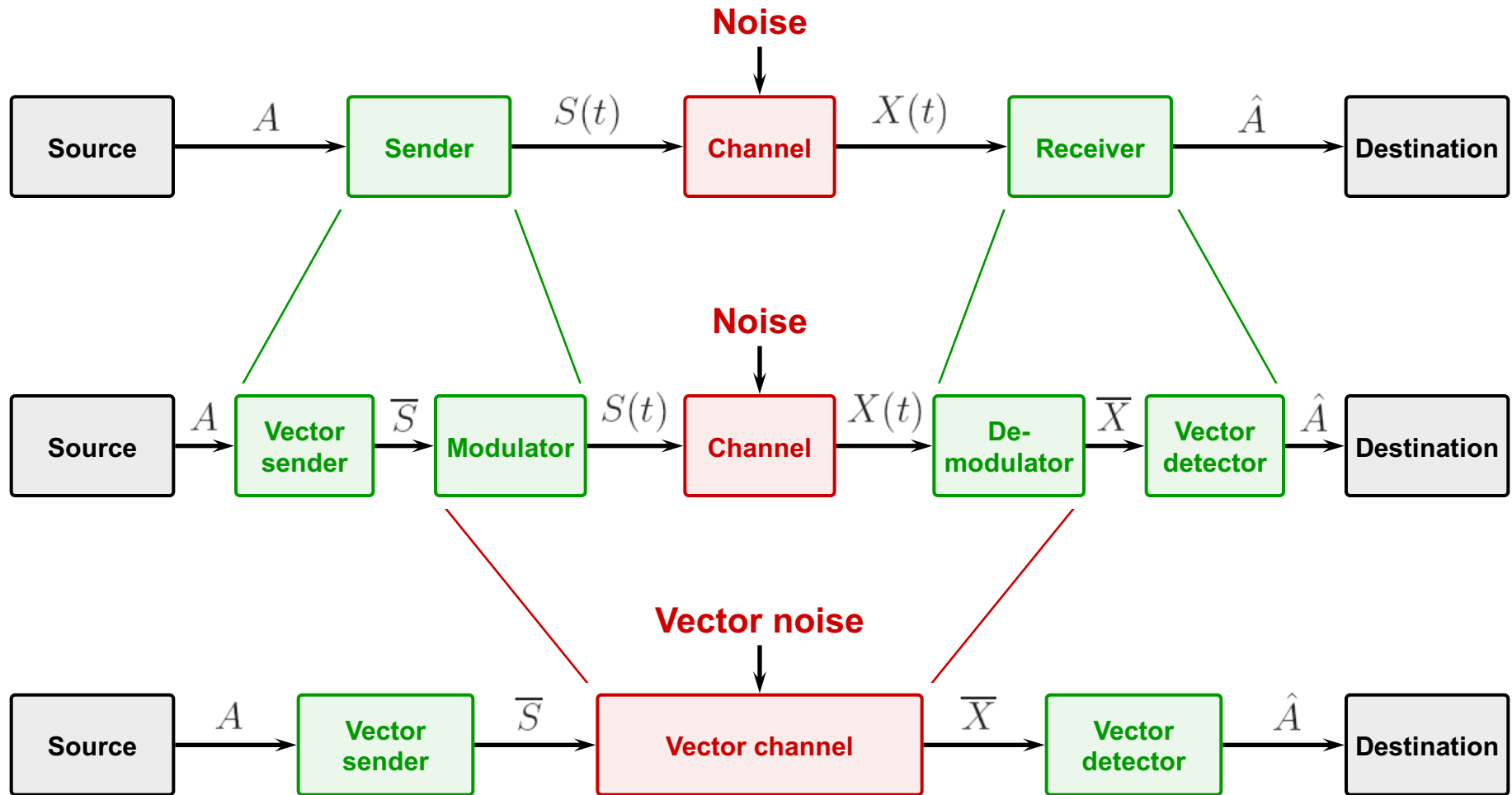
Channel output: $X(t) = s_i(t) + W(t)$

Receiver: Observes $X(t)$. Generates estimate $\hat{A}$.

Goal: Minimize $\Pr\{\hat{A} \neq A\}$.

This lecture concentrates on the sender

Where are we heading?



Function Spaces – Vector Spaces

M signals, $s_i(t)$, $i \in \{0, 1, \dots, M-1\}$ span N dimensions, $N \leq M$.

Ortho-normal (ON) basis: $\{\phi_j(t)\}_{j=0}^{N-1}$ (spans the same dimensions)

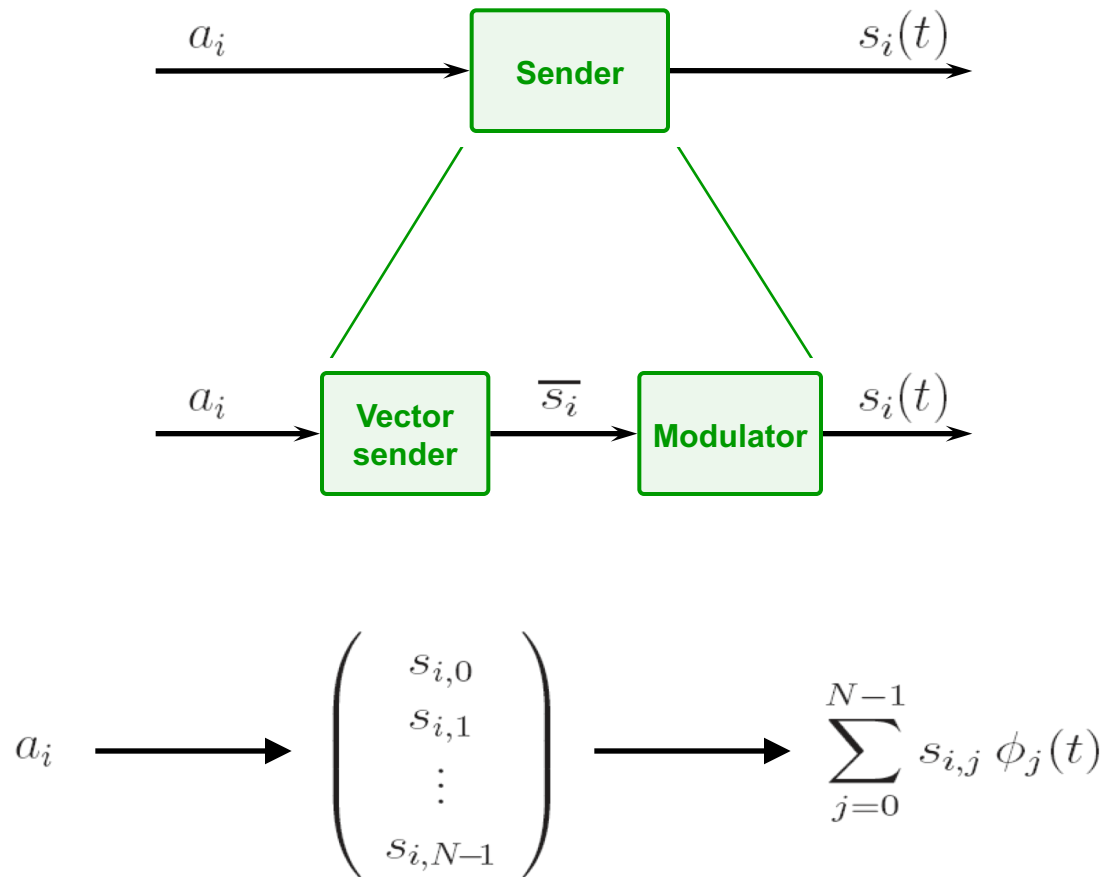
$$\int_{-\infty}^{\infty} \phi_i(t) \phi_j(t) dt = \delta_{i,j} \triangleq \begin{cases} 1, & i = j, \\ 0, & i \neq j. \end{cases}$$

The signals expressed using this basis:

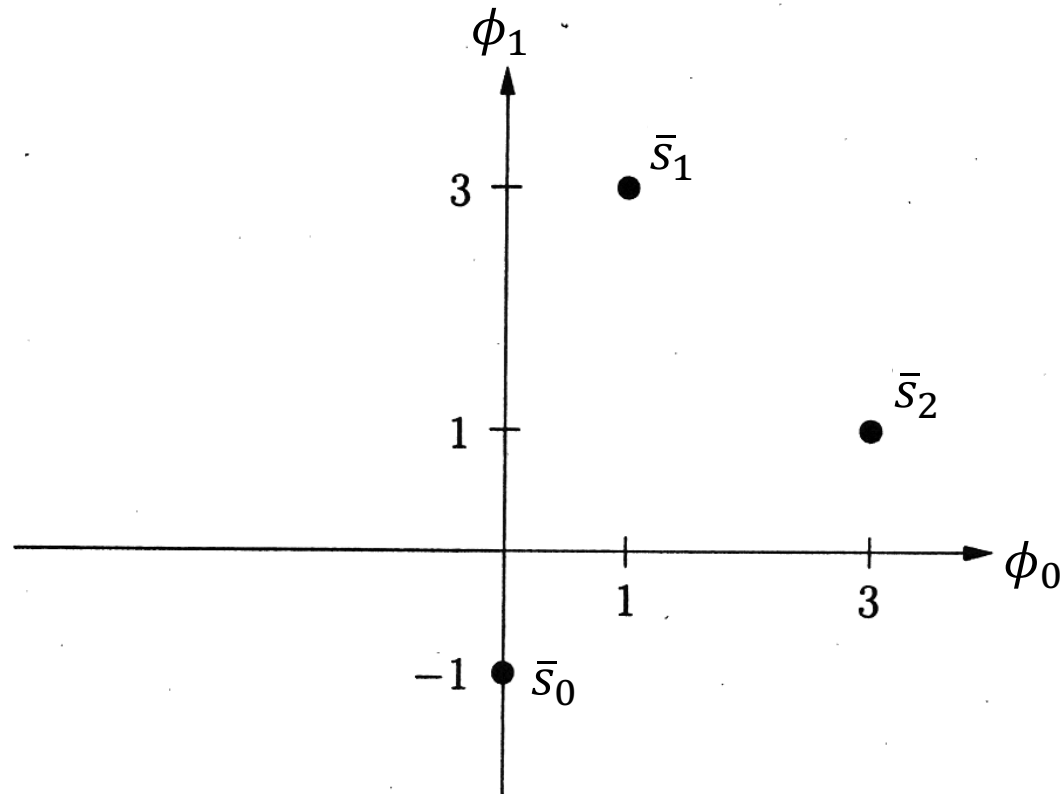
$$s_i(t) = \sum_{j=0}^{N-1} s_{i,j} \phi_j(t), \quad i \in \{0, 1, \dots, M-1\}$$

Corresponding vectors: $\overline{s_i} = \begin{pmatrix} s_{i,0} \\ s_{i,1} \\ \vdots \\ s_{i,N-1} \end{pmatrix}, \quad i \in \{0, 1, \dots, M-1\}$

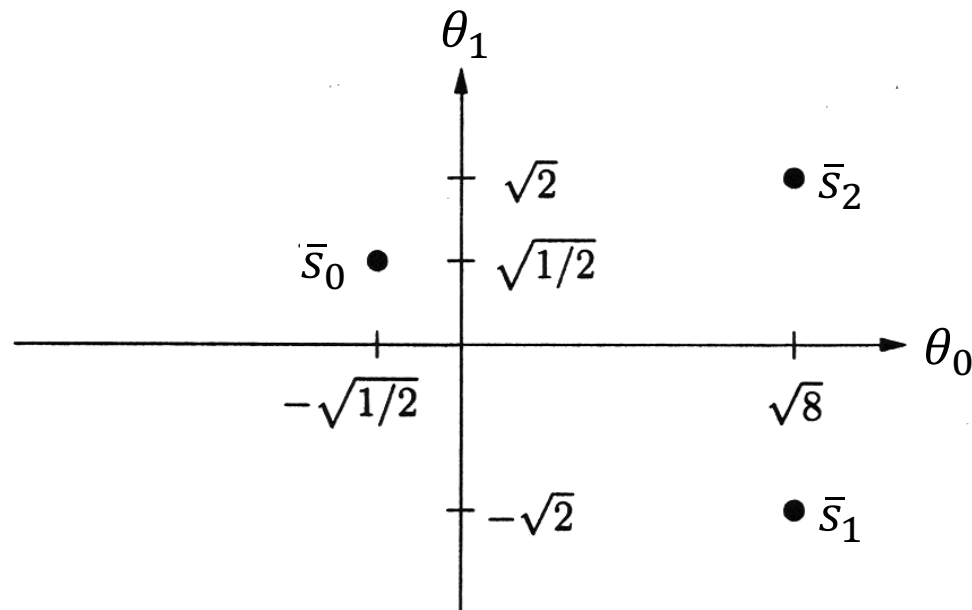
Result – Split the Sender



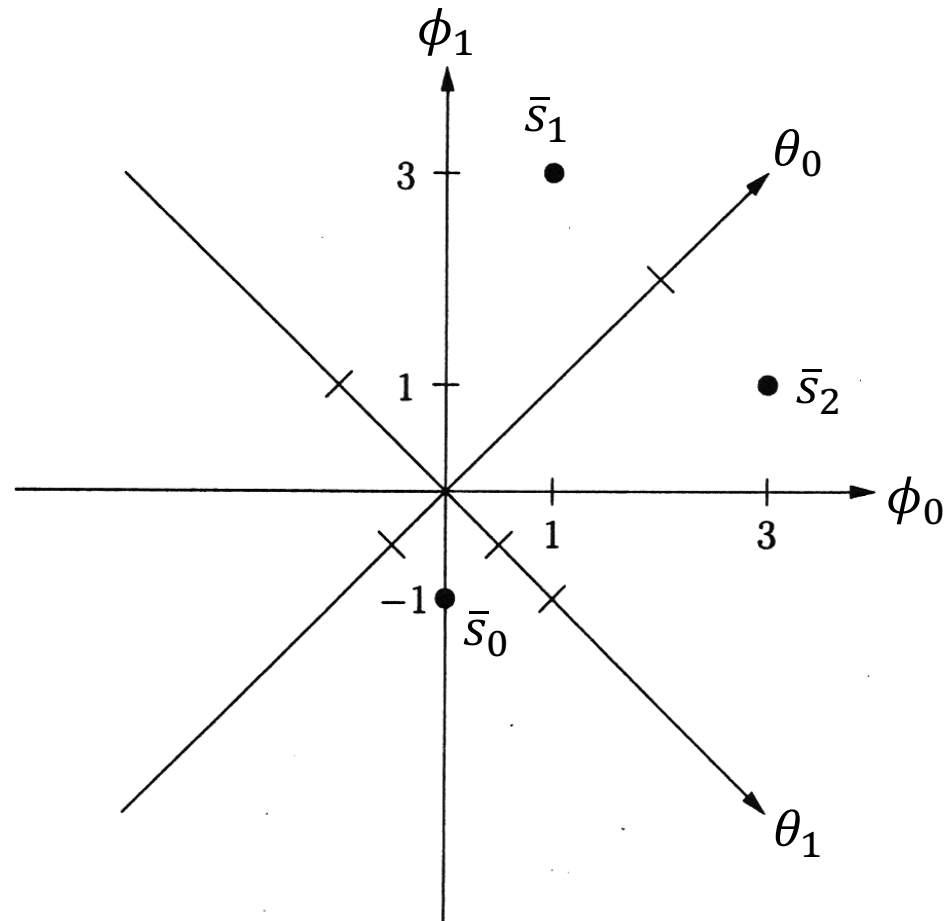
Example: Vector representation with respect to $\{\phi_0(t), \phi_1(t)\}$



Example: Vector representation with respect to $\{\theta_0(t), \theta_1(t)\}$



Example: Vector representation with respect to both bases



Geometric Interpretation

Signals: $a(t)$ and $b(t)$

ON-basis: $\{\phi_j(t)\}_{j=0}^{N-1}$

Vectors to represent signals: $\bar{a} = (a_0, a_1, \dots, a_{N-1})^T$
 $\bar{b} = (b_0, b_1, \dots, b_{N-1})^T$

Inner products: $(a, b) \triangleq \int_{-\infty}^{\infty} a(t)b(t)dt$ $\bar{a} \circ \bar{b} \triangleq \sum_{i=0}^{N-1} a_i b_i$

Claim: $(a, b) = \bar{a} \circ \bar{b}$

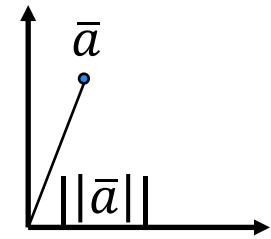
Geometric Interpretation

Claim: $(a, b) = \bar{a} \circ \bar{b}$

Proof:

$$\begin{aligned}(a, b) &= \int_{-\infty}^{\infty} a(t) b(t) dt = \int_{-\infty}^{\infty} \sum_{i=0}^{N-1} a_i \phi_i(t) \sum_{j=0}^{N-1} b_j \phi_j(t) dt \\&= \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} a_i b_j \int_{-\infty}^{\infty} \phi_i(t) \phi_j(t) dt \\&= \sum_{i=0}^{N-1} a_i \sum_{j=0}^{N-1} b_j \delta_{i,j} = \sum_{i=0}^{N-1} a_i b_i = \bar{a} \circ \bar{b}.\end{aligned}$$

Norms and Angles



Norms: $\|a\|$ of $a(t)$: $\|a\|^2 \triangleq (a, a)$

Signal energy.

$\|\bar{a}\|$ of $\bar{a}$: $\|\bar{a}\|^2 \triangleq \bar{a} \circ \bar{a}$,

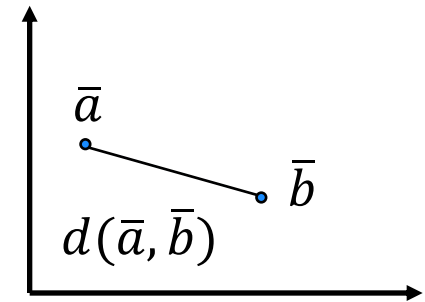
Squared length.

Relation: $(a, b) = \bar{a} \circ \bar{b} \Rightarrow \|a\| = \|\bar{a}\|$

From linear algebra: $\bar{a} \circ \bar{b} = \|\bar{a}\| \cdot \|\bar{b}\| \cdot \cos(\alpha)$

Angle between signals: $\cos(\alpha) = \frac{\bar{a} \circ \bar{b}}{\|\bar{a}\| \cdot \|\bar{b}\|} = \frac{(a, b)}{\|a\| \cdot \|b\|}$

Distances



Euclidean distances between vectors:

$$d^2(\bar{a}, \bar{b}) = \|\bar{a} - \bar{b}\|^2 = \sum_{j=0}^{N-1} (a_j - b_j)^2$$

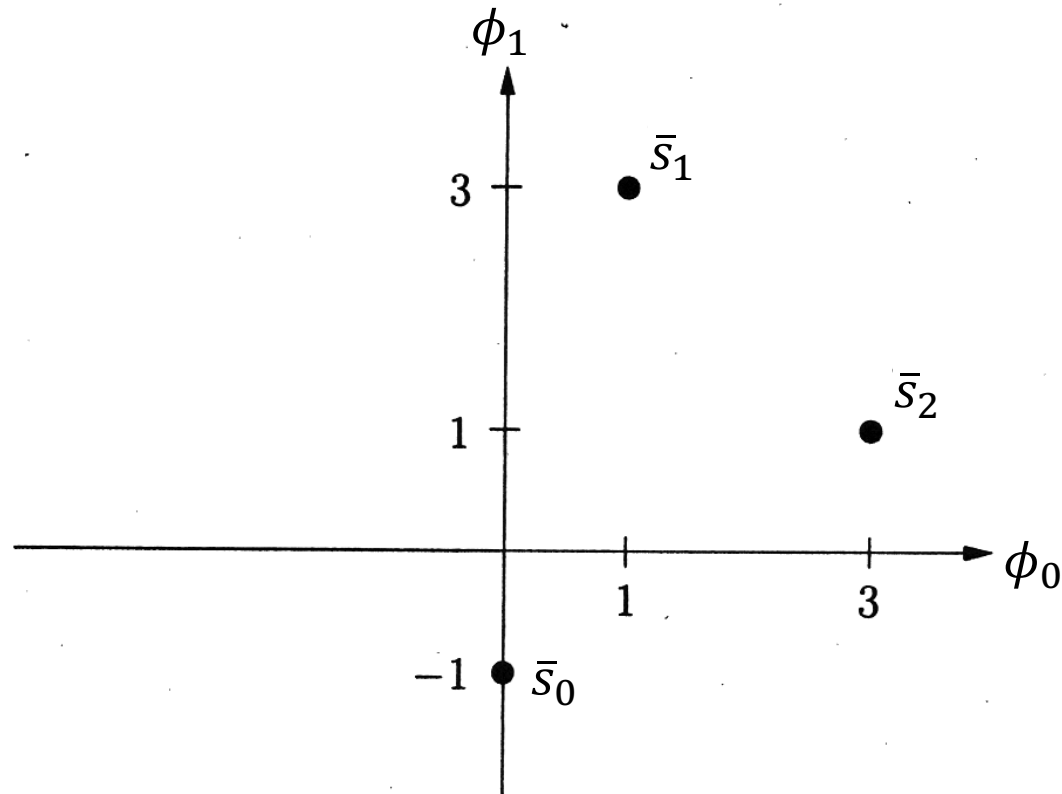
The Pythagorean relation in N dimensions.

Euclidean distances between signals:

$$d^2(\bar{a}, \bar{b}) = \|a - b\|^2 = \int_{-\infty}^{\infty} (a(t) - b(t))^2 dt$$

These computations are equivalent!

Example: Norms, Distances and Angles



Representing White Gaussian Noise 1(4)

Signal:
$$s_i(t) = \sum_{j=0}^{N-1} s_{i,j} \overset{\text{ON}}{\phi_j(t)}, \quad i \in \{0, 1, \dots, M-1\},$$

Noise: $W(t)$ WGN with PSD $R_W(f) = N_0/2$

Received: $X(t) = s_i(t) + W(t)$

Define: $W_j \triangleq (W, \phi_j)$

$\swarrow$ Gaussian variable $\Leftarrow$ Gaussian process
 Mean 0 $\Leftarrow$ Mean 0

Define: $X_j \triangleq (X, \phi_j)$

$\swarrow$ Gaussian variable $\Leftarrow$ Gaussian process
 Mean? $\Leftarrow$ Mean $s_i(t)$

Also determine:

- Variances?
- Correlations?
- Independence?
- Full statistical description?

Representing White Gaussian Noise 2(4)

Correlate:
$$(s_i, \phi_k) = \int_0^T s_i(t) \phi_k(t) dt = \int_0^T \sum_{j=0}^{N-1} s_{i,j} \phi_j(t) \phi_k(t) dt$$
$$= \sum_{j=0}^{N-1} s_{i,j} \int_0^T \phi_j(t) \phi_k(t) dt = \sum_{j=0}^{N-1} s_{i,j} \delta_{j,k} = s_{i,k}$$

Correlate:
$$X_j \triangleq (X, \phi_j) = ((s_i + W), \phi_j) = (s_i, \phi_j) + (W, \phi_j)$$
$$= s_{i,j} + W_j.$$

Result: X_j is Gaussian with mean $s_{i,j}$.

Next: Variance?

Time-limited basis functions to $[0, T)$

Representing White Gaussian Noise 3(4)

White noise: $r_W(u) = \frac{N_0}{2} \delta(u)$

Variance: $\sigma_{X_j}^2 = E\{(X_j - s_{i,j})^2\} = E\{W_j^2\} = E\{(W, \phi_j)^2\}$

$$= E \left\{ \int_0^T W(t) \phi_j(t) dt \int_0^T W(\tau) \phi_j(\tau) d\tau \right\} = E \left\{ \iint_0^T \phi_j(t) \phi_j(\tau) W(t) W(\tau) dt d\tau \right\}$$

$$= \iint_0^T \phi_j(t) \phi_j(\tau) E\{W(t)W(\tau)\} dt d\tau = \iint_0^T \phi_j(t) \phi_j(\tau) r_W(t - \tau) dt d\tau,$$

$$= \frac{N_0}{2} \iint_0^T \phi_j(t) \phi_j(\tau) \delta(t - \tau) dt d\tau = \frac{N_0}{2} \int_0^T \phi_j^2(t) dt = \frac{N_0}{2}$$

↑
White

↑
ON

Representing White Gaussian Noise 4(4)

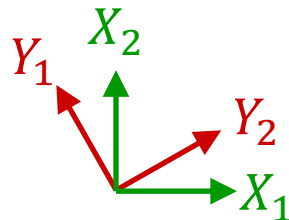
Covariance $j \neq k$:

$$\begin{aligned}\lambda_{X_j, X_k} &= E\{(X_j - s_{i,j})(X_k - s_{i,k})\} = E\{W_j W_k\} = E\{(W, \phi_j)(W, \phi_k)\} \\&= E\left\{\int_0^T W(t) \phi_j(t) dt \int_0^T W(\tau) \phi_k(\tau) d\tau\right\} = E\left\{\iint_0^T \phi_j(t) \phi_k(\tau) W(t) W(\tau) dt d\tau\right\} \\&= \iint_0^T \phi_j(t) \phi_k(\tau) E\{W(t) W(\tau)\} dt d\tau = \iint_0^T \phi_j(t) \phi_k(\tau) r_W(t - \tau) dt d\tau, \\&= \underset{\substack{\uparrow \\ \text{White}}}{\frac{N_0}{2}} \iint_0^T \phi_j(t) \phi_k(\tau) \delta(t - \tau) dt d\tau = \frac{N_0}{2} \int_0^T \phi_j(t) \phi_k(t) dt \underset{\substack{\uparrow \\ \text{ON}}}{=} 0,\end{aligned}$$

Uncorrelated & jointly Gaussian $\Rightarrow$ Independent Gaussian

AWGN – Additive White Gaussian Noise

Orthogonal noise components
are statistically independent

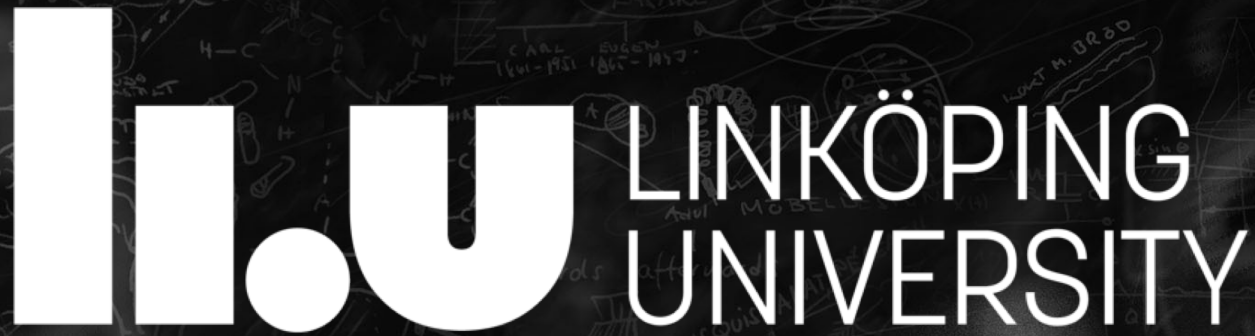


X_1 and X_2 independent

Y_1 and Y_2 independent

Variance: $\sigma_{X_i}^2 = \sigma_{Y_i}^2 = R_W(f) = N_0/2$

PSD = Variance



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