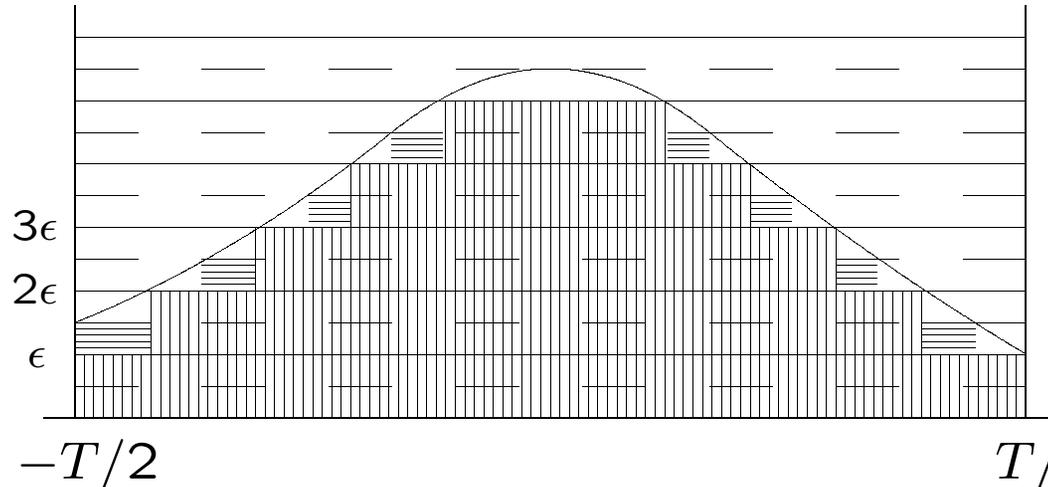


MEASURABLE FUNCTIONS

A function $\{u(t) : \mathbb{R} \rightarrow \mathbb{R}\}$ is measurable if $\{t : u(t) < b\}$ is measurable for each $b \in \mathbb{R}$.

The Lebesgue integral exists if the function is measurable and if the limit in the figure exists.



Horizontal crosshatching is what is added when $\epsilon \rightarrow \epsilon/2$. For $u(t) \geq 0$, the integral must exist (with perhaps an infinite value).

Theorem: Let $\{u(t) : [-T/2, T/2] \rightarrow \mathbb{C}\}$ be an \mathcal{L}_2 function. Then for each $k \in \mathbb{Z}$, the Lebesgue integral

$$\hat{u}_k = \frac{1}{T} \int_{-T/2}^{T/2} u(t) e^{-2\pi ikt/T} dt$$

exists and satisfies $|\hat{u}_k| \leq \frac{1}{T} \int |u(t)| dt < \infty$. Furthermore,

$$\lim_{k_0 \rightarrow \infty} \int_{-T/2}^{T/2} \left| u(t) - \sum_{k=-k_0}^{k_0} \hat{u}_k e^{2\pi ikt/T} \right|^2 dt = 0,$$

where the limit is monotonic in k_0 .

Given $\{\hat{u}_k; k \in \mathbb{Z}\}$, $\sum |\hat{u}_k|^2 < \infty$, the \mathcal{L}_2 function $u(t)$ exists

Functions not limited in time

We can segment an arbitrary \mathcal{L}_2 function into segments of any width T . The m th segment is $u_m(t) = u(t)\text{rect}(t/T - m)$. We then have

$$u(t) = \text{l.i.m.}_{m_0 \rightarrow \infty} \sum_{m=-m_0}^{m_0} u_m(t)$$

This works because $u(t)$ is \mathcal{L}_2 . The energy in $u_m(t)$ must go to 0 as $m \rightarrow \infty$.

$$u_m(t) = \text{l.i.m.} \sum_k \hat{u}_{k,m} e^{2\pi ikt/T} \text{rect}\left(\frac{t}{T} - m\right), \quad \text{where}$$

$$\hat{u}_{k,m} = \frac{1}{T} \int_{-\infty}^{\infty} u(t) e^{-2\pi ikt/T} \text{rect}\left(\frac{t}{T} - m\right) dt,$$

$$u(t) = \text{l.i.m.} \sum_{k,m} \hat{u}_{k,m} e^{2\pi ikt/T} \text{rect}\left(\frac{t}{T} - m\right)$$

Plancherel 1: There is an \mathcal{L}_2 function $\hat{u}(f)$ (the Fourier transform of $u(t)$), which satisfies the energy equation and

$$\lim_{A \rightarrow \infty} \int_{-\infty}^{\infty} |\hat{u}(f) - \hat{v}_A(f)|^2 dt = 0 \quad \text{where}$$

$$\hat{v}_A(f) = \int_{-A}^A u(t) e^{-2\pi i f t} dt.$$

We denote this function $\hat{u}(f)$ as

$$\hat{u}(f) = \text{l.i.m.} \int_{-\infty}^{\infty} u(t) e^{2\pi i f t} dt.$$

Although $\{\hat{v}_A(f)\}$ is continuous for all $A \in \mathbb{R}$, $\hat{u}(f)$ is not necessarily continuous.

Similarly, for $B > 0$, consider the finite bandwidth approximation $\hat{u}(f)\text{rect}(\frac{f}{2B})$. This is \mathcal{L}_1 as well as \mathcal{L}_2 ,

$$u_B(t) = \int_{-B}^B \hat{u}(f)e^{2\pi ift} df \quad (1)$$

exists for all $t \in \mathbb{R}$ and is continuous.

Plancherel 2: For any \mathcal{L}_2 function $u(t)$, let $\hat{u}(f)$ be the FT of Plancherel 1. Then

$$\lim_{B \rightarrow \infty} \int_{-\infty}^{\infty} |u(t) - w_B(t)|^2 dt = 0. \quad (2)$$

$$u(t) = \text{l.i.m.} \int_{-\infty}^{\infty} \hat{u}(f)e^{2\pi ift} df$$

All \mathcal{L}_2 functions have Fourier transforms in this sense.

The DTFT (Discrete-time Fourier transform) is the $t \leftrightarrow f$ dual of the Fourier series.

Theorem (DTFT) Assume $\{\hat{u}(f) : [-W, W] \rightarrow \mathbb{C}\}$ is \mathcal{L}_2 (and thus also \mathcal{L}_1). Then

$$u_k = \frac{1}{2W} \int_{-W}^W \hat{u}(f) e^{2\pi i k f / (2W)} df$$

is a finite complex number for each $k \in \mathbb{Z}$. Also

$$\lim_{k_0 \rightarrow \infty} \int_{-W}^W \left| \hat{u}(f) - \sum_{k=-k_0}^{k_0} u_k e^{-2\pi i k f / (2W)} \right|^2 df = 0,$$

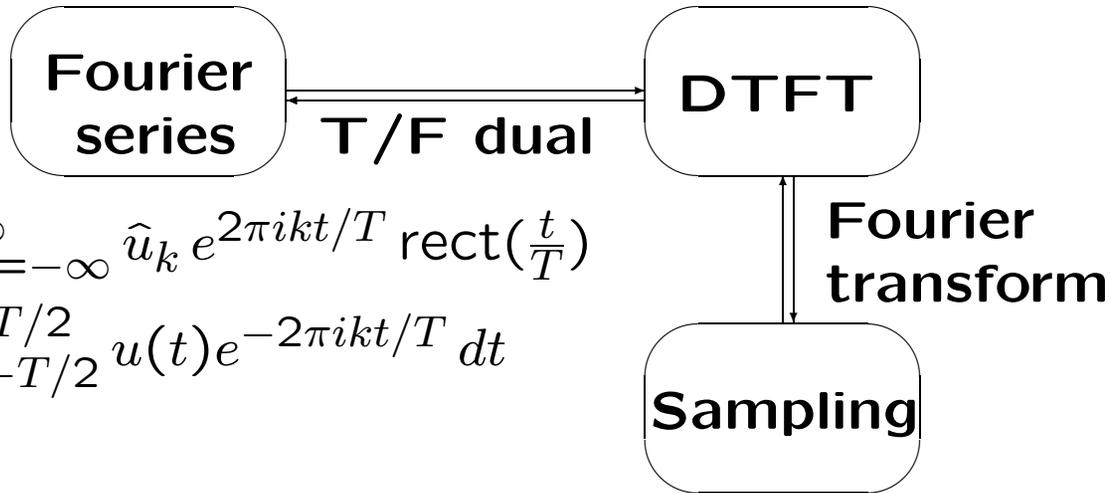
$$\hat{u}(f) = \text{l.i.m.} \sum_k u_k e^{-2\pi i k f / (2W)} \text{rect} \left(\frac{f}{2W} \right)$$

Sampling Theorem: Let $\{\hat{u}(f) : [-W W] \rightarrow \mathbb{C}\}$ be \mathcal{L}_2 (and thus also \mathcal{L}_1). For $u(t)$ in (??), let $T = 1/(2W)$. Then the inverse transform $u(t)$ is continuous, \mathcal{L}_2 , and bounded by $u(t) \leq \int_{-W}^W |\hat{u}(f)| df$. For $T = 1/(2W)$,

$$u(t) = \sum_{k=-\infty}^{\infty} u(kT) \operatorname{sinc}\left(\frac{t - kT}{T}\right).$$

$$\hat{u}(f) = \sum_k u_k e^{-2\pi i k \frac{f}{2W}} \text{rect}\left(\frac{f}{2W}\right)$$

$$u_k = \frac{1}{2W} \int_{-W}^W \hat{u}(f) e^{2\pi i k \frac{f}{2W}} df$$



$$u(t) = \sum_{k=-\infty}^{\infty} \hat{u}_k e^{2\pi i k t / T} \text{rect}\left(\frac{t}{T}\right)$$

$$\hat{u}_k = \frac{1}{T} \int_{-T/2}^{T/2} u(t) e^{-2\pi i k t / T} dt$$

$$u(t) = \sum_{k=-\infty}^{\infty} 2W u_k \text{sinc}(2Wt - k)$$

$$u_k = \frac{1}{2W} u\left(\frac{k}{2W}\right)$$

Segmenting an \mathcal{L}_2 frequency function into segments $\hat{v}_m(f) \longleftrightarrow v_m(t)$ of width $1/T$,

$$u(t) = \text{l.i.m.} \sum_{m,k} v_m(kT) \text{sinc} \left(\frac{t}{T} - k \right) e^{2\pi i m t / T}.$$

Both this and the T -spaced truncated sinusoid expansion

$$u(t) = \text{l.i.m.} \sum_{m,k} \hat{u}_{k,m} e^{2\pi i k t / T} \text{rect} \left(\frac{t}{T} - m \right)$$

break the function into increments of time duration T and frequency duration $1/T$.

ALIASING

Suppose we approximate a function $u(t)$ that is not quite baseband limited by the sampling expansion $s(t) \approx u(t)$.

$$s(t) = \sum_k u(kT) \operatorname{sinc} \left(\frac{t}{T} - k \right).$$

$$u(t) = \text{l.i.m.} \sum_{m,k} v_m(kT) \operatorname{sinc} \left(\frac{t}{T} - k \right) e^{2\pi i m t / T}$$

$$s(kT) = u(kT) = \sum_m v_m(kT) \quad (\mathbf{Aliasing})$$

$$s(t) = \sum_k \sum_m v_m(kT) \operatorname{sinc} \left(\frac{t}{T} - k \right).$$

ALIASING

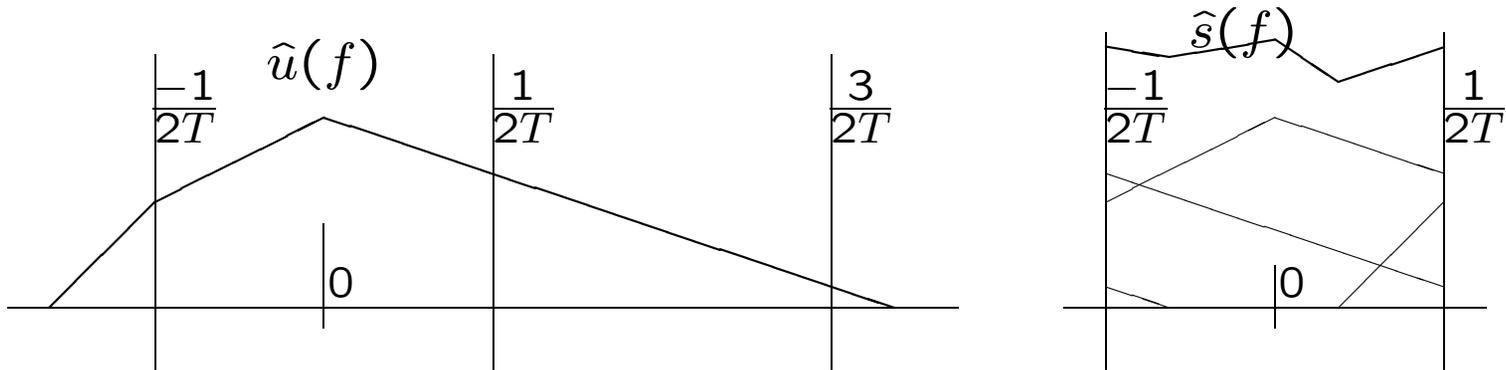
Suppose we approximate a function $u(t)$ that is not quite baseband limited by the sampling expansion $s(t) \approx u(t)$.

$$s(t) = \sum_k u(kT) \operatorname{sinc} \left(\frac{t}{T} - k \right).$$

$$u(t) = \text{l.i.m.} \sum_{m,k} v_m(kT) \operatorname{sinc} \left(\frac{t}{T} - k \right) e^{2\pi i m t / T}$$

$$s(kT) = u(kT) = \sum_m v_m(kT) \quad (\mathbf{Aliasing})$$

$$s(t) = \sum_k \sum_m v_m(kT) \operatorname{sinc} \left(\frac{t}{T} - k \right).$$



Theorem: Let $\hat{u}(f)$ be \mathcal{L}_2 , and satisfy

$$\lim_{|f| \rightarrow \infty} \hat{u}(f) |f|^{1+\varepsilon} = 0 \quad \text{for } \varepsilon > 0.$$

Then $\hat{u}(f)$ is \mathcal{L}_1 , and the inverse transform $u(t)$ is continuous and bounded. For $T > 0$, the sampling approx. $s(t) = \sum_k u(kT) \text{sinc}(\frac{t}{T} + k)$ is bounded and continuous. $\hat{s}(f)$ satisfies

$$\hat{s}(f) = \text{l.i.m.} \sum_m \hat{u}(f + \frac{m}{T}) \text{rect}[fT].$$

\mathcal{L}_2 AS A VECTOR SPACE

Orthonormal expansions represent each \mathcal{L}_2 function as sequence of numbers.

View functions as vectors in inner product space, sequence as representation in a basis.

Same as \mathbb{R}^k or \mathbb{C}^k except for need of limiting operations.

The limits always exist for \mathcal{L}_2 functions in the sense of \mathcal{L}_2 convergence.

Any two functions that are equal except on a set of measure 0 are viewed as equal (same equivalence class).

Theorem: (1D Projection) Let \mathbf{v} and $\mathbf{u} \neq 0$ be arbitrary vectors in a real or complex inner product space. Then there is a unique scalar α for which $\langle \mathbf{v} - \alpha\mathbf{u}, \mathbf{u} \rangle = 0$. That α is given by $\alpha = \langle \mathbf{v}, \mathbf{u} \rangle / \|\mathbf{u}\|^2$.

Proof: Calculate $\langle \mathbf{v} - \alpha\mathbf{u}, \mathbf{u} \rangle$ for an arbitrary scalar α and find the conditions under which it is zero:

$$\langle \mathbf{v} - \alpha\mathbf{u}, \mathbf{u} \rangle = \langle \mathbf{v}, \mathbf{u} \rangle - \alpha\langle \mathbf{u}, \mathbf{u} \rangle = \langle \mathbf{v}, \mathbf{u} \rangle - \alpha\|\mathbf{u}\|^2,$$

which is equal to zero if and only if $\alpha = \langle \mathbf{v}, \mathbf{u} \rangle / \|\mathbf{u}\|^2$.

Finite Projection: Assume that $\{\phi_1, \dots, \phi_n\}$ is an orthonormal basis for an n -dimensional subspace $\mathcal{S} \subset \mathcal{V}$. For each $\mathbf{v} \in \mathcal{V}$, there is a unique $\mathbf{v}_{|\mathcal{S}} \in \mathcal{S}$ such that $\langle \mathbf{v} - \mathbf{v}_{|\mathcal{S}}, \mathbf{s} \rangle = 0$ for all $\mathbf{s} \in \mathcal{S}$. Furthermore,

$$\mathbf{v}_{|\mathcal{S}} = \sum_j \langle \mathbf{v}, \phi_j \rangle \phi_j.$$

$$\|\mathbf{v}\|^2 = \|\mathbf{v}_{|\mathcal{S}}\|^2 + \|\mathbf{v}_{\perp\mathcal{S}}\|^2 \quad (\text{Pythagoras})$$

$$0 \leq \|\mathbf{v}_{|\mathcal{S}}\|^2 \leq \|\mathbf{v}\|^2 \quad (\text{Norm bounds})$$

$$0 \leq \sum_{j=1}^n |\langle \mathbf{v}, \phi_j \rangle|^2 \leq \|\mathbf{v}\|^2 \quad (\text{Bessel's inequality}).$$

Gram-Schmidt: Given basis $\mathbf{s}_1, \dots, \mathbf{s}_n$ for an inner product subspace, find an orthonormal basis. Let $\phi_1 = \mathbf{s}_1 / \|\mathbf{s}_1\|$. For each k ,

$$\phi_{k+1} = \frac{(\mathbf{s}_{k+1})_{\perp \mathcal{S}_k}}{\|(\mathbf{s}_{k+1})_{\perp \mathcal{S}_k}\|}$$

Infinite dimensional Projection theorem:

Let $\{\phi_m, 1 \leq m < \infty\}$ be a set of orthonormal functions, and let \mathbf{v} be any \mathcal{L}_2 vector. Then there is a unique \mathcal{L}_2 vector \mathbf{u} such that $\mathbf{v} - \mathbf{u}$ is orthogonal to each ϕ_n and

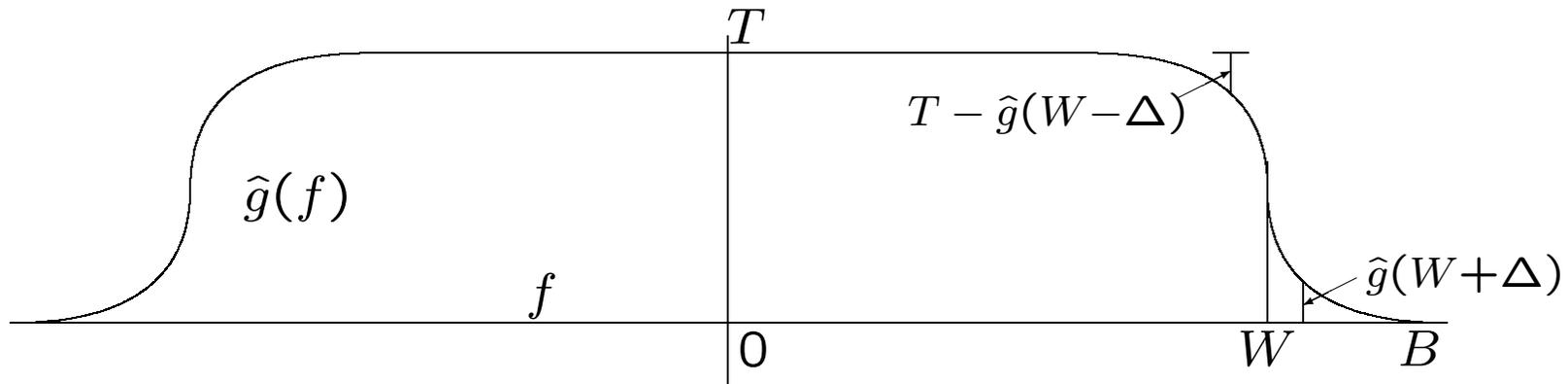
$$\lim_{n \rightarrow \infty} \left\| \mathbf{u} - \sum_{m=1}^n \langle \mathbf{v}, \phi_m \rangle \phi_m \right\| = 0.$$

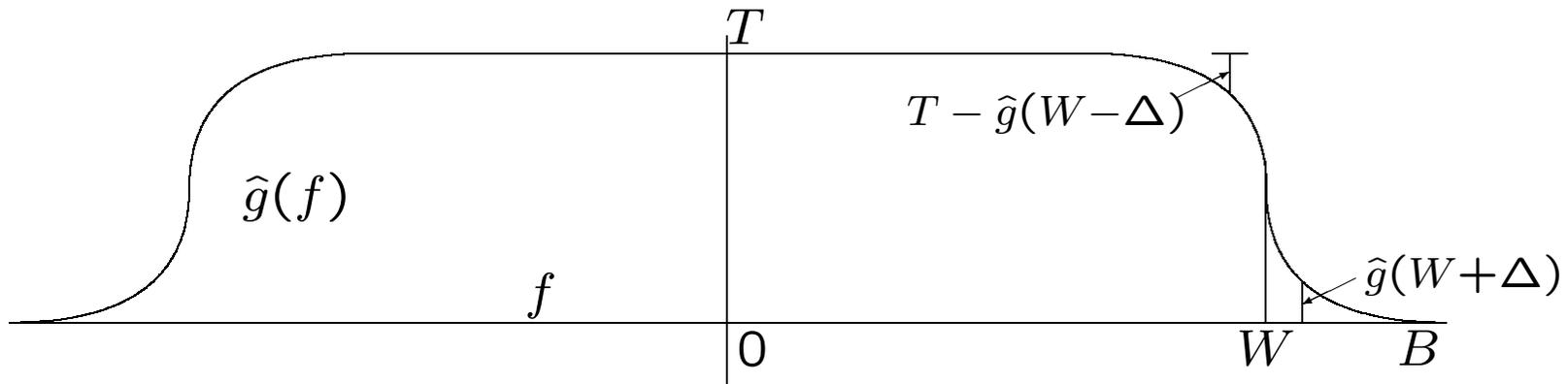
Nyquist: Convert $\{u_k\}$ into waveform $u(t) = \sum_k u_k p(t - kT)$.

At receiver, filter by $q(t)$, with combined effect $g(t) = p(t) * q(t)$.

**Want $g(t)$ to be ideal Nyquist, i.e., $g(kT) = \delta_k$.
 $g(t)$ is ideal Nyquist iff**

$$\sum_m \hat{g}(f + m/T) \text{rect}(fT) = T \text{rect}(fT)$$





**Choose $\hat{g}(f)$ so that it cuts off quickly at W ,
but $g(t)$ cuts off relatively quickly at $1/T$.**

Choose non-negative and symmetric (raised cosine for example)

Choose $q(t) = p^*(-t)$. Then $p(t)$ is orthogonal to its shifts.

A random process $\{Z(t)\}$ is a collection of rv's, one for each $t \in \mathbb{R}$.

For each epoch $t \in \mathbb{R}$, the rv $Z(t)$ is a function $Z(t, \omega)$ mapping sample points $\omega \in \Omega$ to real numbers.

For each $\omega \in \Omega$, $\{Z(t, \omega)\}$ is sample function $\{z(t)\}$.

A random process is defined by a rule establishing a joint density $f_{Z(t_1), \dots, Z(t_k)}(z_1, \dots, z_k)$ for all k, t_1, \dots, t_k and z_1, \dots, z_k .

Our favorite way to do this is $Z(t) = \sum Z_i \phi_i(t)$.

Joint densities on Z_1, Z_2, \dots define $\{Z(t)\}$.

A random vector $\mathbf{Z} = (Z_1, \dots, z_k)^\top$ of linearly independent rv's is jointly Gauss iff

1. $\mathbf{Z} = \mathbf{A}\mathbf{N}$ for normal rv \mathbf{N} ,

2. $f_{\mathbf{Z}}(\mathbf{z}) = \frac{1}{(2\pi)^{k/2} \sqrt{|\det(\mathbf{K}_{\mathbf{Z}})|}} \exp \left[-\frac{1}{2} \mathbf{z}^\top \mathbf{K}_{\mathbf{Z}}^{-1} \mathbf{z} \right].$

3. $f_{\mathbf{Z}}(\mathbf{z}) = \prod_{j=1}^k \frac{1}{\sqrt{2\pi\lambda_j}} \exp \left[\frac{-|\langle \mathbf{z}, \mathbf{q}_j \rangle|^2}{2\lambda_j} \right]$ for $\{\mathbf{q}_j\}$ orthonormal, $\{\lambda_j\}$ positive.

4. All linear combinations of \mathbf{Z} are Gaussian.

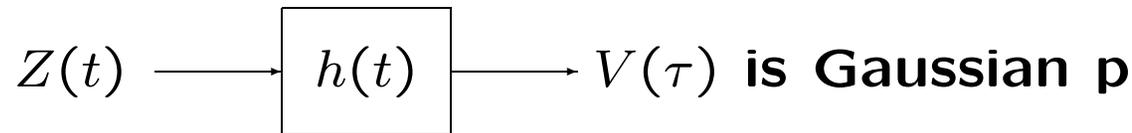
A linear functional of a rp is a rv given by

$$V = \int Z(t)g(t) dt.$$

This means that for all $\omega \in \Omega$,

$$V(\omega) = \langle Z(t, \omega), g(t) \rangle = \int_{-\infty}^{\infty} Z(t, \omega)g(t) dt.$$

If $Z(t) = \sum_j Z_j \phi_j(t)$ is Gaussian process, then $V = \sum_j Z_j \langle \phi_j, g \rangle$ is Gaussian.



$$\begin{aligned} V(\tau, \omega) &= \int_{-\infty}^{\infty} Z(t, \omega)h(\tau - t) dt \\ &= \sum_j Z_j(\omega) \int_{-\infty}^{\infty} \phi_j(t)h(\tau - t) dt. \end{aligned}$$

$\{Z(t); t \in \mathbb{R}\}$ is stationary if $Z(t_1), \dots, Z(t_k)$ and $Z(t_1 + \tau), \dots, Z(t_k + \tau)$ have same distribution for all τ , all k , and all t_1, \dots, t_k .

Stationary implies that

$$\mathbf{K}_Z(t_1, t_2) = \mathbf{K}_Z(t_1 - t_2, 0) = \tilde{\mathbf{K}}_Z(t_1 - t_2).$$

Note that $\tilde{\mathbf{K}}_Z(t)$ is real and symmetric.

A process is wide sense stationary (WSS) if $\mathbf{E}[Z(t)] = \mathbf{E}[Z(0)]$ and $\mathbf{K}_Z(t_1, t_2) = \mathbf{K}_Z(t_1 - t_2, 0)$ for all t, t_1, t_2 .

A Gaussian process is stationary if it is WSS.

An important example is $V(t) = \sum_k V_k \text{sinc}\left(\frac{t-kT}{T}\right)$.

If $\mathbf{E}[V_k V_i] = \sigma^2 \delta_{i,k}$, then

$$\mathbf{K}_{\mathbf{V}}(t, \tau) = \sigma^2 \sum_k \text{sinc}\left(\frac{t-kT}{T}\right) \text{sinc}\left(\frac{\tau-kT}{T}\right).$$

Then $\{V(t); t \in \mathbb{R}\}$ is WSS with

$$\tilde{\mathbf{K}}_{\mathbf{V}}(t - \tau) = \sigma^2 \text{sinc}\left(\frac{t - \tau}{T}\right).$$

The sample functions of a WSS non-zero process are not \mathcal{L}_2 .

The covariance $\tilde{\mathbf{K}}_{\mathbf{V}}(t)$ is \mathcal{L}_2 in cases of physical relevance. It has a Fourier transform called the spectral density.

$$S_{\mathbf{V}}(f) = \int \tilde{\mathbf{K}}_{\mathbf{V}}(t) e^{-2\pi i f t} dt$$

The spectral density is real and symmetric.

Let $V_j = \int Z(t)g_j(t) dt$. Then

$$\begin{aligned}\mathbf{E}[V_i V_j] &= \int_{t=-\infty}^{\infty} \int_{\tau=-\infty}^{\infty} g_i(t) \tilde{\mathbf{K}}_{\mathbf{Z}}(t - \tau) g_j(\tau) dt d\tau \\ &= \int \hat{g}_i(f) S_{\mathbf{Z}}(f) \hat{g}_j^*(f) df\end{aligned}$$

If $\hat{g}_i(f)$ and $\hat{g}_j(f)$ do not overlap in frequency, then $\mathbf{E}[V_i V_j] = 0$.

This means that for a WSS process, no linear functional in one frequency band is correlated with any linear functional in another band.

For a Gaussian stationary process, all linear functionals in one band are independent of all linear functionals in any other band; different frequency bands contain independent noise.

Summary of binary detection with vector observation in iid Gaussian noise.:

First remove center point from signal and its effect on observation.

Then signal is $\pm a$. and $v = \pm a + Z$.

Find $\langle v, a \rangle$ and compare with threshold (0 for ML case).

This does not depend on the vector basis - becomes trivial if a normalized is a basis vector.

Received components orthogonal to signal are irrelevant.

Review: Theorem of irrelevance

Given the signal set $\{\mathbf{a}_1, \dots, \mathbf{a}_M\}$, we transmit $X(t) = \sum_{j=1}^k a_{m,j} \phi_j(t)$ and receive $Y(t) = \sum_{j=1}^{\infty} Y_j \phi_j(t)$ where $Y_j = X_j + Z_j$ for $1 \leq j \leq k$ and $Y_j = Z_j$ for $j > k$.

Assume $\{Z_j; j \leq k\}$ are iid and $\mathcal{N}(0, N_0/2)$. Assume $\{Z_j : j > k\}$ are arbitrary rv's that are independent of $\{X_j, Z_j; j \leq k\}$.

Then the MAP detector depends only on Y_1, \dots, Y_k . The error probability depends only on $\{\mathbf{a}_1, \dots, \mathbf{a}_M\}$, and in fact, only on $\langle \mathbf{a}_j, \mathbf{a}_k \rangle$ for each $1 \leq j, k \leq M$.

All orthonormal expansions are the same; noise and signal outside of signal subspace can be ignored.

Orthogonal and simplex codes have the same error probability. The energy difference is $1 - \frac{1}{m}$.

Orthogonal and biorthogonal codes have the same energy but differ by about 2 in error probability.

For orthogonal codes, take codewords as basis and normalize by $W_j = Y_j \sqrt{2/N_0}$. Thus the input for the first codeword is $(\alpha, 0, \dots, 0)$ where $\alpha = \sqrt{2E/N_0}$. Then $W_j = \mathcal{N}(0, 1)$ for $j \neq 0$ and $W_1 = a + \mathcal{N}(0, 1)$.

$$\Pr(e) = \int_{-\infty}^{\infty} f_{W_1}(w_1) \Pr \left(\bigcup_{j=2}^M \{W_j \geq w_1\} \right) dw_1$$

Bottom line: Let $\log M = b$ and $E_b = E/b$. Then

$$\Pr(e) \leq \begin{cases} \exp \left[-b \left(\sqrt{E_b/N_0} - \sqrt{\ln 2} \right)^2 \right] & \text{for } \frac{E_b}{4N_0} \leq \ln 2 < \frac{E_b}{N_0} \\ \exp \left[-b \left(\frac{E_b}{2N_0} - \ln 2 \right) \right] & \text{for } \ln 2 < \frac{E_b}{4N_0} \end{cases}$$

This says we can get arbitrarily small error probability so long as $E_b/N_0 > \ln 2$.

This is Shannon's capacity formula for unlimited bandwidth WGN transmission.

Review of multipath model

The response to $\exp[2\pi if t]$ over J propagation paths with attenuation β_j and delay $\tau_j(t)$ is

$$\begin{aligned} y_f(t) &= \sum_{j=1}^J \beta_j \exp[2\pi if t - \tau_j(t)] \\ &= \hat{h}(f, t) \exp[2\pi if t] \end{aligned}$$

The response to $x(t) = \int_{-\infty}^{\infty} \hat{x}(f) \exp[2\pi if t] df$ is then

$$\begin{aligned} y(t) &= \int_{-\infty}^{\infty} \hat{x}(f) \hat{h}(f, t) \exp(2\pi if t) df \\ &= \int x(t - \tau) h(\tau, t) d\tau \quad \text{where} \end{aligned}$$

$$h(\tau, t) \longleftrightarrow \hat{h}(f, t); \quad h(\tau, t) = \sum_j \beta_j \delta\{\tau - \tau_j(t)\}$$

How do we define fading for a single frequency input?

$$\begin{aligned}y_f(t) &= \hat{h}(f, t) \exp[2\pi i f t] \\ &= |\hat{h}(f, t)| \exp[2\pi i f t + i \angle \hat{h}(f, t)] \\ \Re[y_f(t)] &= |\hat{h}(f, t)| \cos[2\pi f t + \angle \hat{h}(f, t)]\end{aligned}$$

The envelope of this is $|\hat{h}(f, t)|$, and this is defined as the fading.

$$\hat{h}(f, t) = \sum_j \beta_j \exp[-2\pi i f \tau_j(t)] = \sum_j \exp[2\pi i \mathcal{D}_j t - 2\pi i f \tau_j^0]$$

This contains frequencies ranging from $\min \mathcal{D}_j$ to $\max \mathcal{D}_j$. Define the Doppler spread of the channel as

$$\mathcal{D} = \max \mathcal{D}_j - \min \mathcal{D}_j$$

For any frequency Δ , $|\hat{h}(f, t)| = |e^{-2\pi i \Delta t} \hat{h}(f, t)|$

$$\hat{h}(f, t) = \sum_j \exp\{2\pi i \mathcal{D}_j t - 2\pi i f \tau_j^o\}$$

Choose $\Delta = [\max \mathcal{D}_j + \min \mathcal{D}]/2$. Then

$$\exp(-2\pi i t \Delta) \hat{h}(f, t) = \sum_{j=1}^J \beta_j \exp\{2\pi i t (\mathcal{D}_j - \Delta) - 2\pi i f \tau_j^o\}$$

This waveform is baseband limited to $\mathcal{D}/2$. Its magnitude is the fading. The fading process is the magnitude of a waveform baseband limited to $\mathcal{D}/2$. The coherence time of the channel is defined as

$$\mathcal{T}_{\text{coh}} = \frac{1}{2\mathcal{D}}$$

\mathcal{D} is linear in f ; \mathcal{T}_{coh} goes as $1/f$.

Review of time Spread

$$\hat{h}(f, t) = \sum_j \beta_j \exp[-2\pi i f \tau_j(t)]$$

For any given t , define

$$\mathcal{L} = \max \tau_j(t) - \min \tau_j(t); \quad \mathcal{F}_{\text{coh}} = \frac{1}{2\mathcal{L}}$$

The fading at f is

$$|\hat{h}(f, t)| = \left| \sum_j \exp[2\pi i (\tau_j(t) - \tau') f] \right| \quad (\text{ind. of } \tau')$$

Let $\tau' = \tau_{\text{mid}} = (\max \tau_j(t) + \min \tau_j(t))/2$. The fading is the magnitude of a function of f with transform limited to $\mathcal{L}/2$. \mathcal{F}_{coh} is a gross estimate of the frequency over which the fading changes significantly.

Baseband system functions

The baseband response to a complex baseband input $u(t)$ is

$$\begin{aligned} v(t) &= \int_{-W/2}^{W/2} \hat{u}(f) \hat{h}(f + f_c, t) e^{2\pi i(f - \Delta)t} df \\ &= \int_{-W/2}^{W/2} \hat{u}(f) \hat{g}(f, t) e^{2\pi i f t} df \end{aligned}$$

where $\hat{g}(f, t) = \hat{h}(f + f_c, t) e^{-2\pi i \Delta t}$ is the baseband system function and $\Delta = \tilde{f}_c - f_c$ is the frequency offset in demodulation.

By the same relationship between frequency and time we used for bandpass,

$$v(t) = \int_{-\infty}^{\infty} u(t - \tau) g(\tau, t) d\tau$$

$$\begin{aligned}
\hat{h}(f, t) &= \sum_j \beta_j \exp\{-2\pi i f \tau_j(t)\} \\
\hat{g}(f, t) &= \sum_j \beta_j \exp\{-2\pi i (f + f_c) \tau_j(t) - 2\pi i \Delta t\} \\
\hat{g}(f, t) &= \sum_j \gamma_j(t) \exp\{-2\pi i f \tau_j(t)\} \quad \text{where} \\
\gamma_j(t) &= \beta_j \exp\{-2\pi i f_c \tau_j(t) - 2\pi i \Delta t\} \\
&= \beta_j \exp\{2\pi i [\mathcal{D}_j - \Delta] t - 2\pi i f_c \tau_j^0\} \\
g(\tau, t) &= \sum_j \gamma_j(t) \delta(\tau - \tau_j(t)) \\
v(t) &= \sum_j \gamma_j(t) u(t - \tau_j(t))
\end{aligned}$$

Flat fading

Flat fading is defined as fading where the bandwidth $W/2$ of $u(t)$ is much smaller than \mathcal{F}_{coh} .

For $|f| < W/2 \ll \mathcal{F}_{\text{coh}}$,

$$\hat{g}(f, t) = \sum_j \gamma_j(t) \exp\{-2\pi i f \tau_j(t)\} \approx \hat{g}(0, t) = \sum_j \gamma_j(t)$$

$$v(t) = \int_{-W/2}^{W/2} \hat{u}(f) \hat{g}(f, t) e^{2\pi i f t} df \approx u(t) \sum_j \gamma_j(t)$$

Equivalently, $u(t)$ is approximately constant over intervals much less than \mathcal{L} .

$$v(t) = \sum_j \gamma_j(t) u(t - \tau_j(t)) = u(t) \sum_j \gamma_j(t)$$

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6.450 Principles of Digital Communication I
Fall 2009

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