Frequency-Domain Analysis Fourier Series

Consider a continuous complex signal

 $x(t) \in [-T/2, T/2].$

Represent x(t) using an arbitrary orthonormal basis $\varphi_n(t)$:

$$x(t) = \sum_{n=-\infty}^{\infty} \alpha_n \varphi_n(t)$$

Orthonormality condition:

$$\frac{1}{T} \int_{-T/2}^{T/2} \varphi_n(t) \varphi_k^*(t) dt = \delta(n-k).$$

Multiplying the above expansion with $\varphi_k^*(t)$ and integrating over the interval, we obtain

$$\frac{1}{T} \int_{-T/2}^{T/2} x(t) \varphi_k^*(t) dt = \frac{1}{T} \int_{-T/2}^{T/2} \sum_{n=-\infty}^{\infty} \alpha_n \varphi_n(t) \varphi_k^*(t) dt$$
$$= \sum_{n=-\infty}^{\infty} \alpha_n \left(\frac{1}{T} \int_{-T/2}^{T/2} \varphi_n(t) \varphi_k^*(t) dt \right)$$
$$= \sum_{n=-\infty}^{\infty} \alpha_n \delta(n-k) = \alpha_k.$$

Thus, the coefficients of expansion are given by

$$\alpha_k = \frac{1}{T} \int_{-T/2}^{T/2} x(t) \varphi_k^*(t) dt.$$

Proposition. The functions $\varphi_n(t) = \exp(j2\pi nt/T)$ are orthonormal at the interval [-T/2, T/2].

Proof.

$$\frac{1}{T} \int_{-T/2}^{T/2} \varphi_n(t) \varphi_k^*(t) dt = \frac{1}{T} \int_{-T/2}^{T/2} e^{j \frac{2\pi(n-k)}{T} t} dt$$
$$= \frac{\sin[\pi(n-k)]}{\pi(n-k)} = \delta(n-k).$$

Thus, we can take exponential functions $\varphi_n(t) = \exp(j2\pi nt/T)$ as orthonormal basis \implies we obtain Fourier series.

Fourier series for a periodic signal x(t) = x(t+T):

$$x(t) = \sum_{n=-\infty}^{\infty} X_n e^{j\frac{2\pi n}{T}t}$$
$$X_n = \frac{1}{T} \int_{-T/2}^{T/2} x(t) e^{-j\frac{2\pi n}{T}t} dt.$$

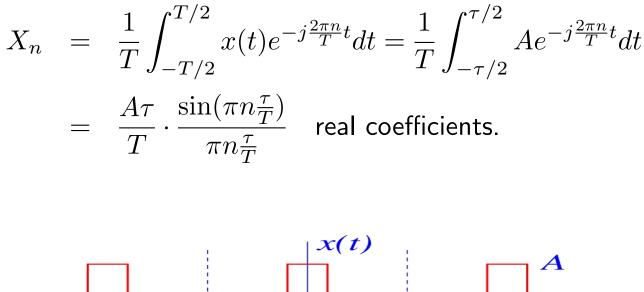
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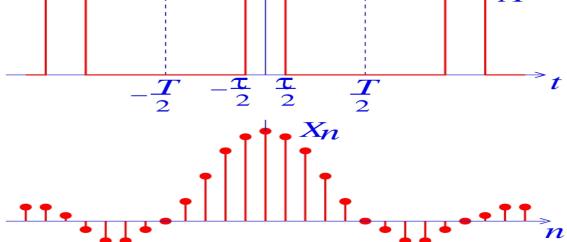
Fourier coefficients can be viewed as a signal spectrum:

$$X_n \sim X(\Omega_n), \quad \text{where} \quad \Omega_n = \frac{2\pi n}{T} \quad \Rightarrow$$

Fourier series can be applied to analyze signal spectrum! Also, this interpretation implies that periodic signals have discrete spectrum.

Example: Periodic sequence of rectangles:





Remarks:

- In general, Fourier coefficients are complex-valued,
- For real signals, $X_{-n} = X_n^*$.
- Alternative expressions exist for trigonometric Fourier series, exploiting summation of sine and cosine functions.

Convergence of Fourier Series

Dirichlet conditions:

Condition 1. x(t) is absolutely integrable over one period, i. e. $\int_{T} |x(t)| dt < \infty$ And **Condition 2.** In a finite time interval, x(t) has a *finite* number of maxima and minima. An example that violates Ex. Condition 2. $x(t) = \sin\left(\frac{2\pi}{t}\right) \quad 0 < t \le 1$ And **Condition 3.** In a finite time interval, x(t) has only a *finite* number of discontinuities. Ex. An example that violates Condition 3.

Dirichlet conditions are met for most of the signals encountered in the real world.

Still, convergence has some interesting characteristics:

$$x_N(t) = \sum_{n=-N}^N X_n e^{j\frac{2\pi n}{T}t}.$$

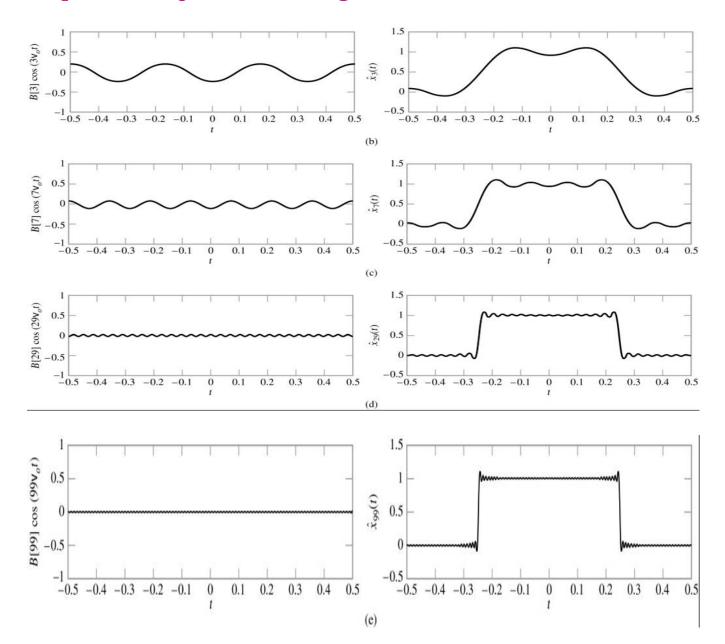
As $N \to \infty$, $x_N(t)$ exhibits Gibbs' phenomenon at points of discontinuity. Under the Dirichlet conditions:

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- The Fourier series = x(t) at points where x(t) is continuous,
- The Fourier series = "midpoint" at points of discontinuity.

Demo: Fourier series for continuous-time square wave (Gibbs' phenomenon).

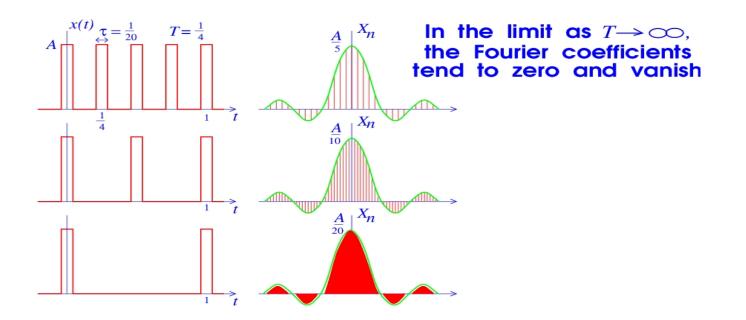
http://www.jhu.edu/~signals/fourier2/index.html.



Review of Continuous-time Fourier Transform

What about Fourier representations of nonperiodic continuoustime signals?

Assuming a finite-energy signal and $T \to \infty$ in the Fouries series, we get $\lim_{T\to\infty} X_n = 0$.



Trick: To preserve the Fourier coefficients from disappearing as $T \to \infty$, introduce

$$\widetilde{X}_n = TX_n = \int_{-T/2}^{T/2} x(t) e^{-j\frac{2\pi n}{T}t} dt.$$

Transition to Fourier transform:

$$\begin{aligned} X(\Omega) &= \lim_{T \to \infty} \widetilde{X}_n \\ &= \lim_{T \to \infty} \int_{-T/2}^{T/2} x(t) e^{-j\frac{2\pi n}{T}t} dt \\ &= \int_{-\infty}^{\infty} x(t) e^{-j\Omega t} dt, \end{aligned}$$

where the "discrete" frequency $2\pi n/T$ becomes the continuous frequency Ω .

Transition to inverse Fourier transform:

$$\begin{aligned} x(t) &= \lim_{T \to \infty} \sum_{n = -\infty}^{\infty} X_n e^{j\frac{2\pi n}{T}t} = \lim_{T \to \infty} \sum_{n = -\infty}^{\infty} \frac{\widetilde{X}_n}{T} e^{j\frac{2\pi n}{T}t} \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\Omega) e^{j\Omega t} d\Omega \iff d\Omega = \frac{2\pi}{T}, \ \Omega = \frac{2\pi n}{T}. \end{aligned}$$

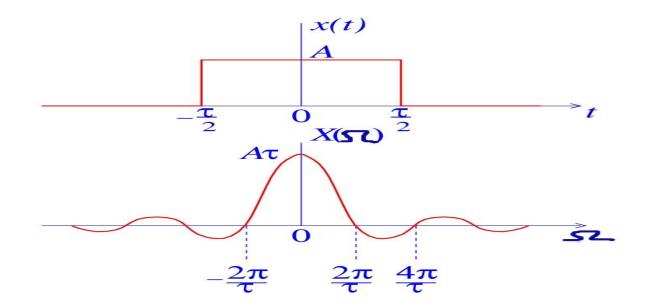
Continuous-time Fourier transform (CTFT):

$$\begin{aligned} X(\Omega) &= \int_{-\infty}^{\infty} x(t) e^{-j\Omega t} dt, \\ x(t) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\Omega) e^{j\Omega t} d\Omega. \end{aligned}$$

Example: Finite-energy rectangular signal:

$$\begin{split} X(\Omega) &= \int_{-\infty}^{\infty} x(t) e^{-j\Omega t} dt \\ &= \int_{-\tau/2}^{\tau/2} A e^{-j\Omega t} dt \\ &= A \tau \frac{\sin(\Omega \tau/2)}{\Omega \tau/2} \quad \text{real spectrum.} \end{split}$$

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Remarks:

- In general, Fourier spectrum is complex-valued,
- For real signals, $X(-\Omega) = X^*(\Omega)$.

Dirac Delta Function

Definition:

$$\delta(t) = \begin{cases} \infty, & t = 0, \\ 0, & t \neq 0 \end{cases}, \quad \int_{-\infty}^{\infty} \delta(t) dt = 1.$$

Do not confuse continuous-time $\delta(t)$ with discrete-time $\delta(n)$!

Sifting property:

$$\int_{-\infty}^{\infty} f(t)\delta(t-\tau)dt = f(\tau).$$

The spectrum of $\delta(t-t_0)$:

$$X(\Omega) = \int_{-\infty}^{\infty} x(t)e^{-j\Omega t}dt$$
$$= \int_{-\infty}^{\infty} \delta(t-t_0)e^{-j\Omega t}dt$$
$$= e^{-j\Omega t_0}.$$

Delta function in time domain:

$$\delta(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{j\Omega t} d\Omega.$$

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Delta function in frequency domain:

$$\delta(\Omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-j\Omega t} dt = \begin{cases} \infty, & \Omega = 0, \\ 0, & \Omega \neq 0 \end{cases}$$

For signal

$$x(t) = A e^{j \Omega_0 t}$$

we have

$$X(\Omega) = \int_{-\infty}^{\infty} x(t)e^{-j\Omega t}dt$$
$$= A \int_{-\infty}^{\infty} e^{-j(\Omega - \Omega_0)t}dt$$
$$= A 2\pi \,\delta(\Omega - \Omega_0).$$

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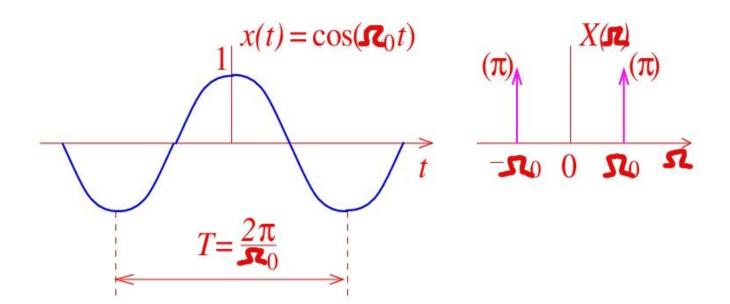
Harmonic Fourier Pairs

Delta function in frequency domain:

$$e^{j\Omega_0 t} \leftrightarrow 2\pi \,\delta(\Omega - \Omega_0),$$

$$\cos(\Omega_0 t) \leftrightarrow \pi \left[\delta(\Omega - \Omega_0) + \delta(\Omega + \Omega_0)\right],$$

$$\sin(\Omega_0 t) \leftrightarrow \frac{\pi}{j} \left[\delta(\Omega - \Omega_0) - \delta(\Omega + \Omega_0)\right].$$



Parseval's Theorem for CTFT

$$\int_{-\infty}^{\infty} |x(t)|^2 dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} |X(\Omega)|^2 d\Omega$$

$$\begin{split} &\frac{1}{2\pi} \int_{-\infty}^{\infty} |X(\Omega)|^2 d\Omega \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x(t) x^*(\tau) e^{-j\Omega(t-\tau)} dt d\tau \right\} d\Omega \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x(t) x^*(\tau) \underbrace{\left\{ \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{j\Omega(\tau-t)} d\Omega \right\}}_{\delta(\tau-t)} dt d\tau \\ &= \int_{-\infty}^{\infty} |x(t)|^2 dt. \end{split}$$

Discrete-time Fourier Transform (DTFT)

Represent continuous signal x(t) via discrete sequence x(n):

$$x(t) = \sum_{n=-\infty}^{\infty} x(n)\delta(t - nT).$$

Substituting this equation into the CTFT formula, we obtain:

$$X(\Omega) = \int_{-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x(n)\delta(t-nT)e^{-j\Omega t}dt$$
$$= \sum_{n=-\infty}^{\infty} x(n) \int_{-\infty}^{\infty} \delta(t-nT)e^{-j\Omega t}dt$$
$$= \sum_{n=-\infty}^{\infty} x(n)e^{-j\Omega nT}.$$

Switch to the discrete-time frequency, i.e. use $\omega = \Omega T$:

$$X(\omega) = \sum_{n = -\infty}^{\infty} x(n) e^{-j\omega n}.$$

 $X(\omega)$ is periodic with period 2π :

$$X(\omega) = \sum_{n=-\infty}^{\infty} x(n) e^{-j\omega n} \underbrace{e^{-j2\pi n}}_{1}$$

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$$= \sum_{n=-\infty}^{\infty} x(n)e^{-j(\omega+2\pi)n} = X(\omega+2\pi).$$

Trick: in computing inverse DTFT, use only one period of $X(\omega)$:

$$\begin{array}{lll} X(\omega) &=& \displaystyle\sum_{n=-\infty}^{\infty} x(n) e^{-j\omega n} \quad {\rm DTFT}, \\ x(n) &=& \displaystyle\frac{1}{2\pi} \displaystyle\int_{-\pi}^{\pi} X(\omega) e^{j\omega n} d\omega \quad {\rm Inverse \ DTFT}. \end{array}$$

Inverse DTFT: Proof.

$$\begin{aligned} x(n) &= \frac{1}{2\pi} \int_{-\pi}^{\pi} X(\omega) e^{j\omega n} d\omega \\ &= \frac{1}{2\pi} \int_{-\pi}^{\pi} \sum_{m=-\infty}^{\infty} x(m) e^{j\omega(n-m)} d\omega \\ &= \sum_{m=-\infty}^{\infty} x(m) \underbrace{\frac{1}{2\pi} \int_{-\pi}^{\pi} e^{j\omega(n-m)} d\omega}_{\delta(n-m)} = x(n). \end{aligned}$$

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Fourier Series vs. DTFT

$$x(t) = \sum_{n=-\infty}^{\infty} X_n e^{j\frac{2\pi n}{T}t}, \quad X_n = \frac{1}{T} \int_{-T/2}^{T/2} x(t) e^{-j\frac{2\pi n}{T}t} dt \quad \mathsf{FS}$$
$$X(\omega) = \sum_{n=-\infty}^{\infty} x(n) e^{-j\omega n}, \quad x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(\omega) e^{j\omega n} d\omega \quad \mathsf{DTFT}$$

Observation: Replacing, in Fourier Series

$$\begin{array}{rccc} x(t) & \to & X(\omega), \\ X_n & \to & x(n), \\ t & \to & -\omega, \\ T & \to & 2\pi, \end{array}$$

we obtain DTFT!

An important conclusion: DTFT is equivalent to Fourier series but applied to the "opposite" domain. In Fourier series, a periodic continuous signal is represented as a sum of exponentials weighted by discrete Fourier (spectral) coefficients. In DTFT, a periodic continuous spectrum is represented as a sum of exponentials, weighted by discrete signal values.

Remarks:

- DTFT can be derived directly from the Fourier series,
- All Fourier series results can be applied to DTFT
- Duality between time and frequency domains.

Parseval's Theorem for DTFT

$$\sum_{n=-\infty}^{\infty} |x(n)|^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} |X(\omega)|^2 d\omega$$
$$\frac{1}{2\pi} \int_{-\pi}^{\pi} |X(\omega)|^2 d\omega$$
$$= \frac{1}{2\pi} \int_{-\pi}^{\pi} \sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} x(n) x^*(m) e^{-j\omega(n-m)} d\omega$$
$$\sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} x(n) x^*(m) \underbrace{\frac{1}{2\pi} \int_{-\pi}^{\pi} e^{-j\omega(n-m)} d\omega}_{\delta(n-m)}$$
$$= \sum_{n=-\infty}^{\infty} |x(n)|^2.$$

 $n = -\infty$

Sufficient condition:

$$\sum_{n=-\infty}^{\infty} |x(n)| < \infty.$$

$$|X(\omega)| = \left| \sum_{n=-\infty}^{\infty} x(n) e^{-j\omega n} \right|$$

$$\leq \sum_{n=-\infty}^{\infty} |x(n)| \underbrace{|e^{-j\omega n}|}_{1}$$

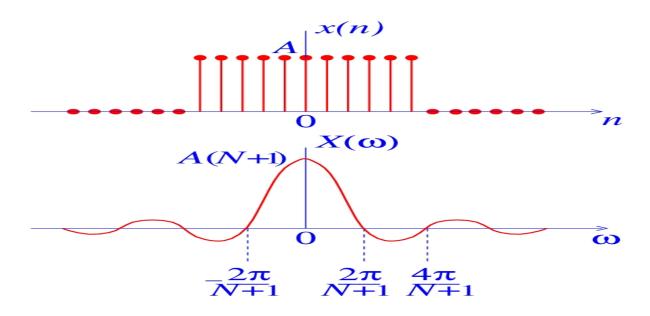
$$= \sum_{n=-\infty}^{\infty} |x(n)| < \infty.$$

Example: Finite-energy rectangular signal:

$$|X(\omega)| = \sum_{n=-N/2}^{N/2} Ae^{-j\omega n} = A \sum_{n=-N/2}^{N/2} e^{-j\omega n}$$
$$= A(N+1) \frac{\sin(\frac{N+1}{2}\omega)}{(N+1)\sin(\frac{\omega}{2})}$$

$$\approx A(N+1) \qquad \underbrace{\frac{\sin(\frac{N+1}{2}\omega)}{(N+1)\frac{\omega}{2}}}_{\text{well-known function}} \qquad \text{for } \omega \ll \pi$$

Both functions look very similar in their "mainlobe" domain.



DTFT — Convolution Theorem

If $X(\omega) = \mathcal{F}\{x(n)\}$ and $H(\omega) = \mathcal{F}\{h(n)\}$ and

$$y(n) = \sum_{k=-\infty}^{\infty} x(k)h(n-k) = \{x(n)\} \star \{h(n)\}$$

then $Y(\omega) = \mathcal{F}\{y(n)\} = X(\omega)H(\omega)$.

$$Y(\omega) = \mathcal{F}\{y(n)\} = \sum_{n=-\infty}^{\infty} \left\{ \sum_{k=-\infty}^{\infty} x(k)h(\underline{n-k}) \right\} e^{-j\omega n}$$
$$= \sum_{m=-\infty}^{\infty} \left\{ \sum_{k=-\infty}^{\infty} x(k)h(m)e^{-j\omega(m+k)} \right\}$$
$$= \left\{ \sum_{k=-\infty}^{\infty} x(k)e^{-j\omega k} \right\} \left\{ \sum_{m=-\infty}^{\infty} h(m)e^{-j\omega m} \right\}$$
$$= X(\omega)H(\omega).$$

Windowing theorem: If $X(\omega)=\mathcal{F}\{x(n)\},\ W(\omega)=\mathcal{F}\{w(n)\},$ and y(n)=x(n)w(n), then

$$Y(\omega) = \mathcal{F}\{y(n)\} = \frac{1}{2\pi} \int_{-\pi}^{\pi} X_1(\lambda) X_2(\omega - \lambda) d\lambda.$$

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Frequency-Domain Characteristics of LTI Systems

Recall impulse response h(n) of an LTI system:

$$y(n) = \sum_{k=-\infty}^{\infty} h(k)x(n-k).$$

Consider input sequence $x(n) = e^{j\omega n}$, $-\infty < n < \infty$.

$$y(n) = \sum_{k=-\infty}^{\infty} h(k)e^{j\omega(n-k)} = e^{j\omega n} \underbrace{\sum_{k=-\infty}^{\infty} h(k)e^{-j\omega k}}_{H(\omega)} = e^{j\omega n}H(\omega).$$

The complex function

$$\sum_{k=-\infty}^{\infty} h(k) e^{-j\omega k}$$

is called the *frequency response* or the *transfer function* of the system.

• Impulse response and transfer function represent a DTFT pair $\implies H(\omega)$ is a *periodic* function.

- Transfer function shows how different input frequency components are changed (e.g. attenuated) at system output.
- $Y(\omega) = X(\omega)H(\omega)$ implies that an LTI system cannot generate any new frequencies, i.e. it can only amplify or reduce/remove frequency components of the input. Conversely, if a system generates new frequencies, then it is not LTI!
- Systems that are not LTI do not have a meaningful frequency response.

Elements of Sampling Theory Preliminaries

How are CTFT and Fourier series related for periodic signals? Consider a continuous-time signal $x_c(t)$ with CTFT

$$X(\Omega) = 2\pi\delta(\Omega - \Omega_0).$$

Then

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} 2\pi \delta(\Omega - \Omega_0) e^{j\Omega t} dt = e^{j\Omega_0 t}.$$

We know: periodic signal has line equispaced spectrum. Let $X(\Omega)$ be a linear combination of impulses equally spaced in frequency:

$$X(\Omega) = \sum_{n=-\infty}^{\infty} 2\pi X_n \delta(\Omega - n\Omega_0).$$
 (1)

Using inverse CTFT, i.e. applying it to each term in the sum, we obtain:

$$\begin{aligned} x(t) &= \sum_{n=-\infty}^{\infty} \frac{1}{2\pi} \int_{-\infty}^{\infty} 2\pi X_n \delta(\Omega - n\Omega_0) e^{j\Omega t} d\Omega \\ &= \sum_{n=-\infty}^{\infty} X_n e^{jn\Omega_0 t} \quad \text{Fourier series!} \end{aligned}$$

CTFT of a periodic signal with Fourier-series coefficients $\{X_n\}$ can be interpreted as a train of impulses occurring at the harmonically-related frequencies with the weights $\{2\pi X_n\}$.

How about the following signal (periodic impulse train), defined as

$$s(t) = \sum_{n = -\infty}^{\infty} \delta(t - nT)?$$

Note: The above periodic impulse train does not satisfy the Dirichlet conditions. Hence, its CTFT is introduced and understood in a limiting sense.

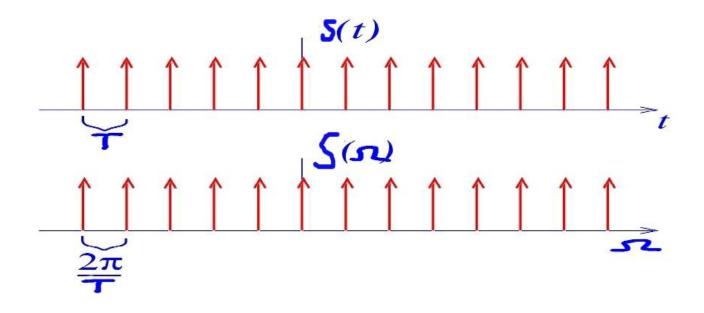
Here are couple of useful expressions for the periodic impulse train:

$$\sum_{k=-\infty}^{\infty} \delta(t-kT) = \frac{1}{T} \sum_{n=-\infty}^{\infty} e^{jn(2\pi/T)t},$$
$$\frac{2\pi}{T} \sum_{n=-\infty}^{\infty} \delta\left(\Omega - \frac{2\pi n}{T}\right) = \sum_{k=-\infty}^{\infty} e^{-j\Omega kT}.$$

Also, the Fourier transform of a periodic impulse train is a periodic impulse train:

$$\sum_{k=-\infty}^{\infty} \delta(t-kT) \quad \leftrightarrow \quad \frac{2\pi}{T} \sum_{n=-\infty}^{\infty} \delta\left(\Omega - \frac{2\pi n}{T}\right).$$

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Proof.

The impulse train $s(t) = \sum_{k=-\infty}^{\infty} \delta(t - kT)$ is a periodic signal with period $T \implies$ we can apply Fourier series and find the Fourier coefficients:

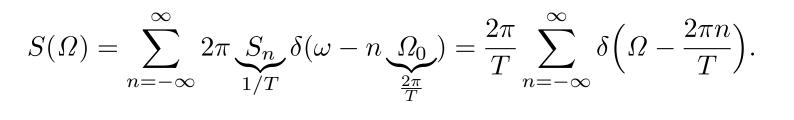
$$S_n = \frac{1}{T} \int_{-T/2}^{T/2} \delta(t) e^{-j\frac{2\pi n}{T}t} dt = \frac{1}{T}.$$

Hence

$$s(t) = \frac{1}{T} \sum_{n = -\infty}^{\infty} e^{jn(2\pi/T)t}.$$

$$S(\Omega) = \int_{-\infty}^{\infty} s(t)e^{-j\Omega t}dt = \sum_{k=-\infty}^{\infty} e^{-j\Omega kT}.$$

From (1), we obtain



The Sampling Theorem

Introduce the "modulated" signal

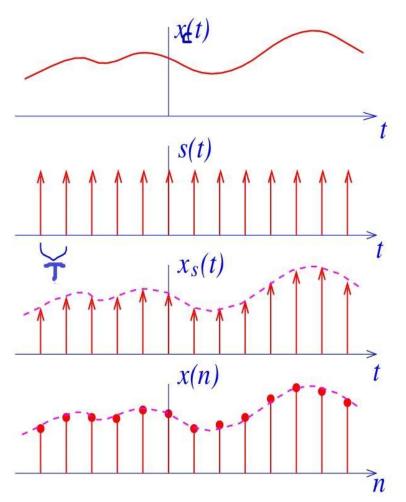
$$x_{\rm s}(t) = x_{\rm c}(t)s(t) = x_{\rm c}(t)\sum_{n=-\infty}^{\infty}\delta(t-nT).$$

Since
$$x_{c}(t) \,\delta(t-t_{0}) = x_{c}(t_{0}) \,\delta(t-t_{0})$$
, we obtain

$$x_{s}(t) = \sum_{n=-\infty}^{\infty} x(nT) \,\delta(t-nT) = \sum_{n=-\infty}^{\infty} x(n) \,\delta(t-nT).$$

Using this "modulated" signal, we describe the sampling operation.

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from analog to digital signal using impulse train

$$x_{s}(t) = x_{c}(t) s(t) = x_{c}(t) \cdot \frac{1}{T} \sum_{n=-\infty}^{\infty} e^{jn(2\pi/T)t}$$
$$= \frac{1}{T} \sum_{n=-\infty}^{\infty} x_{c}(t) e^{jn(2\pi/T)t}.$$

It turns out that the problem is much easier to understand in the frequency domain. Hence, we compute the Fourier transform of $x_s(t)$. Looking at each term of the summation, we have from the frequency-shift theorem:

$$x_{\rm c}(t) e^{jn(2\pi/T)t} \leftrightarrow X_{\rm c} \left(\Omega - n \frac{2\pi}{T} \right).$$

Hence, the Fourier transform of the sum is

$$X_{\rm s}(\Omega) = \frac{1}{T} \sum_{n=-\infty}^{\infty} X_{\rm c} \left(\Omega - \frac{2\pi n}{T} \right).$$

Recall that:

$$x_{\rm s}(t) = \sum_{n=-\infty}^{\infty} x(nT)\,\delta(t-nT) = \sum_{n=-\infty}^{\infty} x(n)\,\delta(t-nT).$$

Taking the FT of the above expression, we obtain another expression for $X_{\rm s}(\Omega)$:

$$X_{s}(\Omega) = \sum_{n=-\infty}^{\infty} x(n) \int_{-\infty}^{\infty} \delta(t-nT) e^{-j\Omega t} dt$$
$$= \sum_{n=-\infty}^{\infty} x(n) e^{-j\Omega NT} = \underbrace{X(\omega)}_{\text{DTFT}\{x(n)\}} \Big|_{\omega=\Omega T}.$$

By sampling, we throw out a lot of information: all values of x(t) between the sampling points are lost.

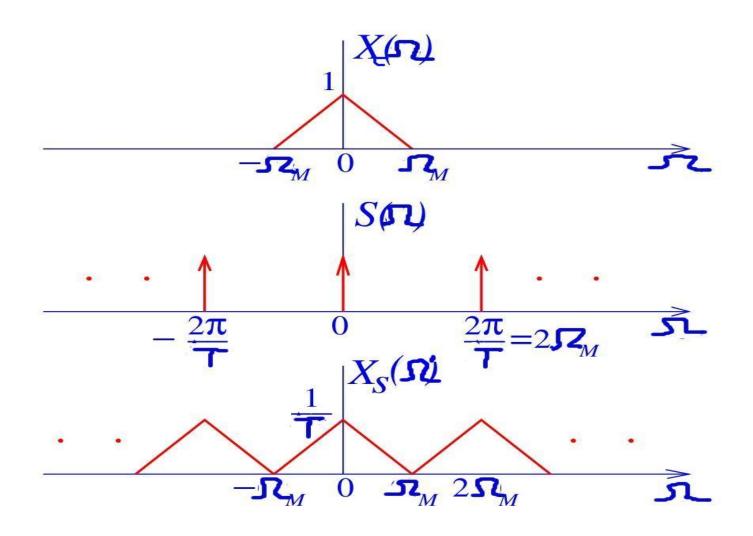
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Question: Under which conditions can we reconstruct the original continuous-time signal x(t) from the sampled signal $x_{\rm s}(t)$?

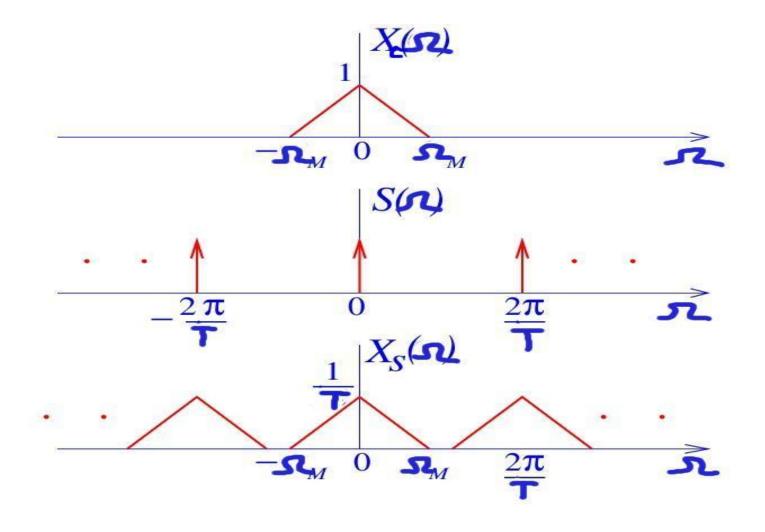
Theorem. Suppose x(t) is bandlimited, so that $X(\Omega) = 0$ for $|\Omega| > \Omega_M$. Then x(t) is uniquely determined by its samples $\{x(nT)\} = \{x(n)\}$ if

$$\Omega_{
m s}=rac{2\pi}{T}>2\Omega_{
m M}\equiv$$
 the Nyquist rate.

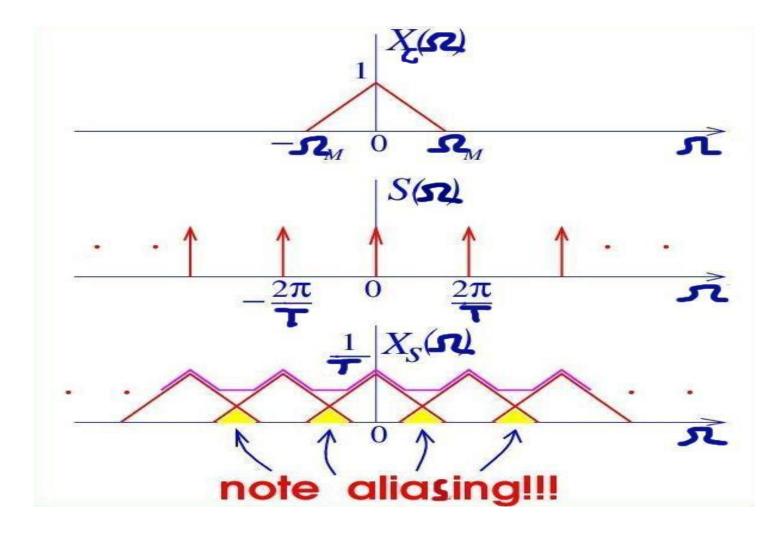
Frequency-Domain Effect for Nyquist Sampling $(2\pi/T = 2\Omega_{\rm M})$



Frequency-domain Effect for Sampling Faster than Nyquist ($2\pi/T > 2\Omega_{\rm M}$)



Frequency-domain Effect for Sampling Slower than Nyquist ($2\pi/T < 2\Omega_{\rm M}$)



Elements of Sampling Theory (cont.)

Introduce a lowpass filtering operation. The spectrum of the filtered signal:

$$X_{\rm f}(\Omega) = H_{\rm LP}(\Omega) X_{\rm s}(\Omega)$$

where $H_{\rm LP}(\Omega) \equiv$ ideal lowpass filter:

$$H_{\mathrm{LP}}(\varOmega) = \left\{ egin{array}{cc} T, & -\varOmega_{\mathrm{c}} \leq \varOmega \leq \varOmega_{\mathrm{c}}, \\ 0, & ext{otherwise} \end{array}
ight.$$

,

with the cut-off frequency Ω_c . How to reconstruct a bandlimited signal from its samples in the time domain?

Having a signal sampled at a rate higher than the Nyquist rate and infinite number of its discrete values, the signal can be exactly recovered as

$$x_{\rm f}(t) = \sum_{n=-\infty}^{\infty} x(n) \frac{\sin[\pi(t-nT)/T]}{\pi(t-nT)/T} \text{ ideal interpolation formula.}$$

Proof. Start from: $X_{\rm f}(\Omega) = X_{\rm s}(\Omega)H_{\rm LP}(\Omega)$. In time domain

$$x_{\rm f}(t) = \{x_{\rm s}(t)\} \star \{h_{\rm LP}(t)\}$$
$$= \left\{\sum_{n=-\infty}^{\infty} x_{\rm c}(nT)\delta(t-nT)\right\} \star \{h_{\rm LP}(t)\}$$

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$$= \int_{-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x_{c}(nT)\delta(\tau - nT)h_{LP}(t - \tau)d\tau$$
$$= \sum_{n=-\infty}^{\infty} x(n)h_{LP}(t - nT).$$

Ideal transfer function:

$$H_{\mathrm{LP}}(\varOmega) = \left\{ egin{array}{cc} T, & -rac{\pi}{T} \leq \varOmega \leq rac{\pi}{T}, \\ 0, & ext{otherwise} \end{array}
ight.$$

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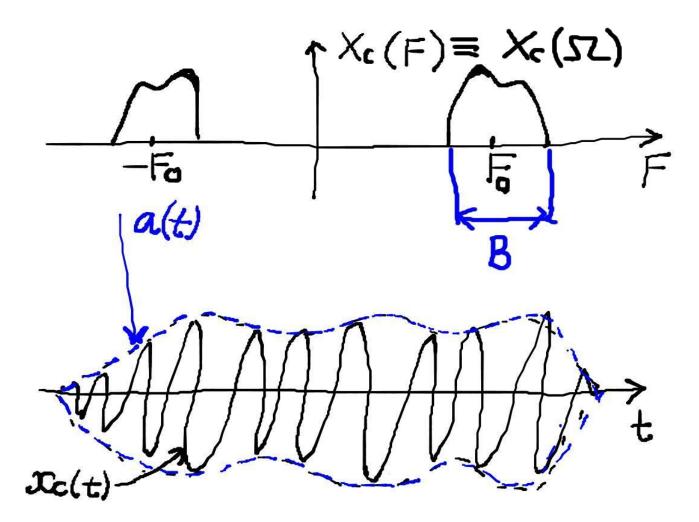
Ideal impulse response:

$$h_{\rm LP}(t) = \frac{\sin(\pi t/T)}{\pi t/T}.$$

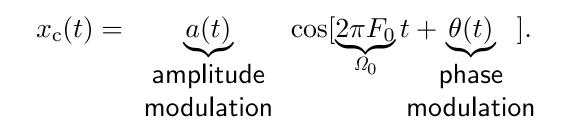
Now, insert $h_{\rm LP}(t)$ into the equation for $x_{\rm f}(t)$. \Box

Representations of Narrowband Signals

Narrowband signals have small bandwidth compared to the band center (carrier) frequency.



 $B \ll F_0.$



The above representation can be used to describe any signal, but it makes sense only if a(t) and $\theta(t)$ vary slowly compared with $\cos(2\pi F_0 t)$, or, equivalently, $B \ll F_0$.

- Complex-envelope and
- Quadrature-component

representations of narrowband signals.

Complex-envelope representation:

$$x_{c}(t) = \operatorname{Re}\{a(t)\exp(j[\Omega_{0}t + \theta(t)])\}$$
$$= \operatorname{Re}\{\underline{a(t)}\exp[j\theta(t)]}\exp(j\Omega_{0}t)\}.$$
$$\widetilde{x}_{c}(t)$$

The complex-valued signal $\tilde{x}_{c}(t)$ contains both the amplitude and phase variations of $x_{c}(t)$, and is hence referred to as the complex envelope of the narrowband signal $x_{c}(t)$.

Quadrature-component representation:

$$x_{c}(t) = \underbrace{a(t)\cos\theta(t)}_{x_{cI}(t)}\cos(\Omega_{0}t) - \underbrace{a(t)\sin\theta(t)}_{x_{cQ}(t)}\sin(\Omega_{0}t).$$

 $x_{cI}(t)$ and $x_{cQ}(t)$ are termed the *in-phase* and *quadrature* components of narrowband signal $x_{c}(t)$, respectively.

Note that

$$\widetilde{x}_{c}(t) = x_{cI}(t) + jx_{cQ}(t).$$

If we "blindly" apply the Nyquist theorem, we would choose

$$F_{\mathrm{N}} = 2(F_0 + \frac{B}{2}) \approx 2F_0 \quad \text{for } B \ll F_0.$$

However, since the effective bandwidth of $x_c(t)$ [and $\tilde{x}_c(t)$] is B/2, the optimal rate should be B!

Recall

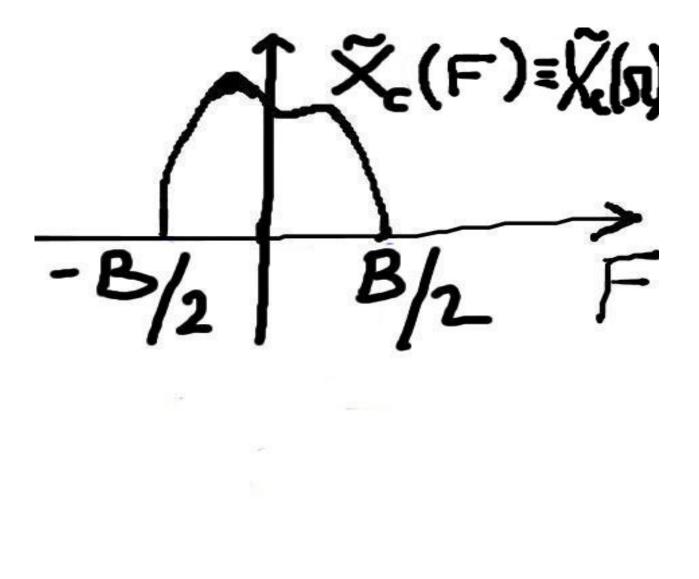
$$\begin{aligned} x_{c}(t) &= a(t)\cos[2\pi F_{0}t + \theta(t)] \\ &= a(t) \cdot \frac{\exp\{j[\Omega_{0}t + \theta(t)]\} + \exp\{-j[\Omega_{0}t + \theta(t)]\}}{2} \\ &= \underbrace{\frac{a(t)\exp[j\theta(t)]}{2}}_{\frac{1}{2}\widetilde{x}_{c}(t)} \exp(j\Omega_{0}t) + \underbrace{\frac{a(t)\exp[-j\theta(t)]}{2}}_{\frac{1}{2}\widetilde{x}_{c}^{*}(t)} \exp(-j\Omega_{0}t) \end{aligned}$$

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and hence

$$X_{\rm c}(\Omega) = \frac{1}{2} [\widetilde{X}_{\rm c}(\Omega - \Omega_0) + \widetilde{X}_{\rm c}^*(-\Omega - \Omega_0)],$$

implying that \tilde{x}_{c} is a *baseband* complex-valued signal (occupying the band [-B/2, B/2]):



$$\widetilde{x}_{c}(t) = \sum_{n=-\infty}^{\infty} \widetilde{x}_{c} \left(\frac{n}{B}\right) \frac{\sin[\pi B(t-n/B)]}{\pi B(t-n/B)}$$

Now,

$$\begin{aligned} x_{c}(t) &= \operatorname{Re}\left\{\widetilde{x}_{c}(t)\exp(j2\pi F_{0}t)\right\} \\ &= \operatorname{Re}\left\{\sum_{n=-\infty}^{\infty}\widetilde{x}_{c}\left(\frac{n}{B}\right)\frac{\sin[\pi B(t-n/B)]}{\pi B(t-n/B)}\exp(j2\pi F_{0}t)\right\} \\ &= \operatorname{Re}\left\{\sum_{n=-\infty}^{\infty}a\left(\frac{n}{B}\right)\exp\{j[\theta(n/B)+2\pi F_{0}t]\}\frac{\sin[\pi B(t-n/B)]}{\pi B(t-n/B)}\right\} \\ &= \sum_{n=-\infty}^{\infty}a\left(\frac{n}{B}\right)\cos[2\pi F_{0}t+\theta(n/B)]\frac{\sin[\pi B(t-n/B)]}{\pi B(t-n/B)} \\ &= \sum_{n=-\infty}^{\infty}\left[x_{cI}\left(\frac{n}{B}\right)\cos(2\pi F_{0}t)-x_{cQ}\left(\frac{n}{B}\right)\sin(2\pi F_{0}t)\right] \\ &\quad \cdot \frac{\sin[\pi B(t-n/B)]}{\pi B(t-n/B)}. \end{aligned}$$

Z Transform

$$X(z) = \mathcal{Z}\{x(n)\} = \sum_{n=-\infty}^{\infty} x(n)z^{-n}.$$

Relationship between the z transform and DTFT: substitute $z=re^{j\omega}$,

$$\begin{aligned} X(z)|_{z=re^{j\omega}} &= \sum_{n=-\infty}^{\infty} x(n)(re^{j\omega})^{-n} \\ &= \sum_{n=-\infty}^{\infty} \{x(n)r^{-n}\}e^{-j\omega n} \\ &= \mathcal{F}\{x(n)r^{-n}\} \implies \end{aligned}$$

The z transform of an arbitrary sequence x(n) is equivalent to DTFT of the exponentially weighted sequence $x(n)r^{-n}$.

If r = 1 then

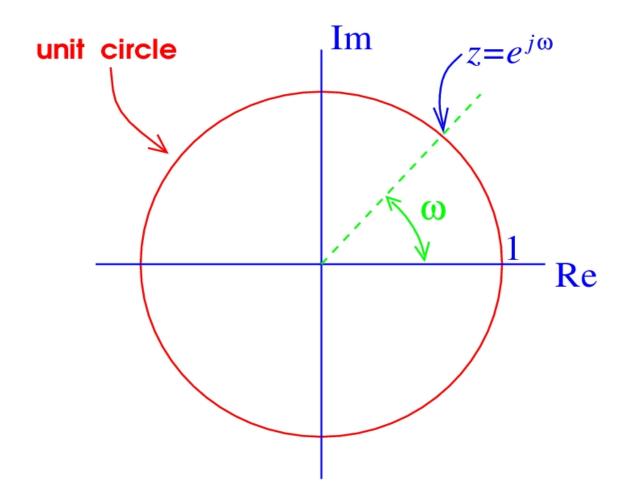
$$X(z)|_{z=e^{j\omega}} = X(\omega) = \mathcal{F}\{x(n)\} \quad \Longrightarrow \quad$$

DTFT corresponds to z transform with |z| = 1.

Notation: Observe that $X(e^{j\omega}) \equiv X(\omega)$.

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The z transform reduces to the DTFT for values of z on the unit circle:



Question: When does the *z* transform converge?

Region of convergence (ROC) \equiv range of values of z for which $|X(z)| < \infty$.

Example: The z transform of the signal $x(n) = a^n u(n)$ is

$$X(z) = \sum_{n = -\infty}^{\infty} a^n u(n) z^{-n} = \sum_{n = 0}^{\infty} (az^{-1})^n.$$

For convergence, we require that

$$\sum_{n=0}^{\infty} |az^{-1}|^n < \infty,$$

which holds if $|az^{-1}| < 1$ or, equivalently, |z| > |a|. Note:

$$X(z) = \frac{1}{1 - az^{-1}}$$

Example: The z transform of the signal

$$x(n) = -a^{n}u(-n-1) = \begin{cases} 0, & n \ge 0, \\ -a^{n}, & n \le -1 \end{cases}$$

is

$$\begin{aligned} X(z) &= -\sum_{n=-\infty}^{-1} a^n z^{-n} = -\sum_{n=1}^{\infty} a^{-n} z^n = -\sum_{n=1}^{\infty} (a^{-1} z)^n \\ &= -\frac{a^{-1} z}{1 - a^{-1} z} = \frac{1}{1 - a z^{-1}} \equiv \text{ same as previous ex.} \end{aligned}$$

But, ROC is now |z| < |a|.

Remark: a discrete-time signal x(n) is uniquely determined by its z transform X(z) and its ROC.

ROC Properties

- The ROC of X(z) consists of a ring in the z plane centered about the origin,
- The ROC does not contain any poles,
- If x(n) is of finite duration, then the ROC is the entire z plane, except possibly z = 0 and/or $z = \infty$,
- If x(n) is a right-sided sequence, and if the circle $|z| = r_0$ is in the ROC, then all finite values of z for which $|z| > r_0$ will also be in the ROC (need to check $z = \infty$),
- If x(n) is a left-sided sequence, and if the circle $|z| = r_0$ is in the ROC, then all finite values of z for which $0 < |z| < r_0$ will also be in the ROC (need to check z = 0),
- If x(n) is a two-sided sequence, and if the circle $|z| = r_0$ is in the ROC, then the ROC will be a ring in the z plane that includes the circle $|z| = r_0$ (we can represent this sequence as right-sided sequence + left-sided sequence).

Z Transform (cont.)

Inverse Z transform:

Recall that

Applying the inverse DTFT, we get

$$\begin{split} x[n] &= r^{n} \mathcal{F}^{-1} \{ X(re^{j\omega}) \} \\ &= r^{n} \cdot \frac{1}{2\pi} \int_{-\pi}^{\pi} X(re^{j\omega}) e^{j\omega n} d\omega \\ &= \frac{1}{2\pi} \int_{-\pi}^{\pi} X(\underbrace{re^{j\omega}}_{z}) (\underbrace{re^{j\omega}}_{z})^{n} d\omega \\ &= \frac{1}{2\pi j} \oint X(z) z^{n-1} dz \quad \longleftarrow dz = j r e^{j\omega} d\omega. \end{split}$$

Comments:

- $\oint \cdots dz$ denotes integration around a closed circular contour centered at the origin and having radius r,
- r must be chosen so that the contour of integration |z| = r belongs to the ROC,
- contour integration in complex plane may be a complicated task; simpler alternative procedures exist for obtaining a sequence from a Z transform.

LTI system analysis:

$$y(n) = \{h(n)\} \star \{x(n)\} \quad \leftrightarrow \quad Y(z) = H(z)X(z)$$

Results:

- A discrete-time LTI system is causal if and only if the ROC of its transfer function is the exterior of a circle including infinity.
- A discrete-time LTI system is stable if and only if the ROC of its transfer function includes the unit circle |z| = 1.

Rational Z transforms

Recall LCCD equations of ARMA processes

$$\sum_{k=0}^{N} a_k y(n-k) = \sum_{k=0}^{M} b_k x(n-k).$$

Taking z-transforms of both sides, we get

$$\sum_{k=0}^{N} \mathcal{Z}\{a_k y(n-k)\} = \sum_{k=0}^{M} b_k \mathcal{Z}\{x(n-k)\},\$$

yielding

$$Y(z)\sum_{k=0}^{N} a_k z^{-k} = X(z)\sum_{k=0}^{M} b_k z^{-k}.$$

Hence, the transfer function of an ARMA process is

$$H(z) = \frac{Y(z)}{X(z)} = \frac{\sum_{k=0}^{M} b_k z^{-k}}{\sum_{k=0}^{N} a_k z^{-k}}$$