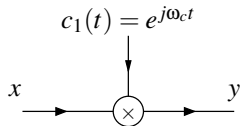
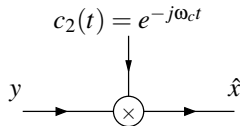


Trivial Amplitude Modulation (AM) System



Transmitter



Receiver

- The transmitter is characterized by

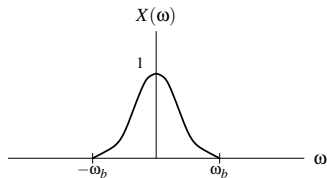
$$y(t) = e^{j\omega_c t} x(t) \iff Y(\omega) = X(\omega - \omega_c).$$

- The receiver is characterized by

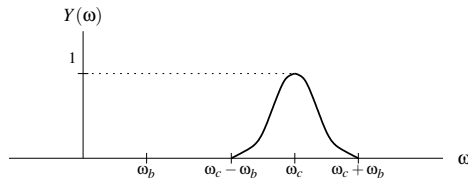
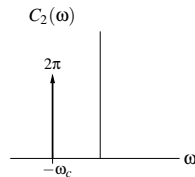
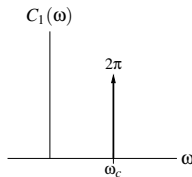
$$\hat{x}(t) = e^{-j\omega_c t} y(t) \iff \hat{X}(\omega) = Y(\omega + \omega_c).$$

- Clearly, $\hat{x}(t) = e^{j\omega_c t} e^{-j\omega_c t} x(t) = x(t)$.

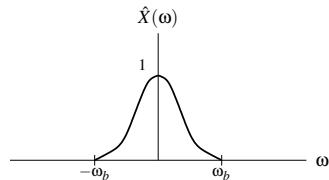
Trivial Amplitude Modulation (AM) System: Example



Transmitter Input

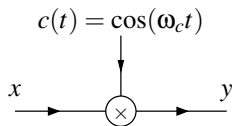


Transmitter Output

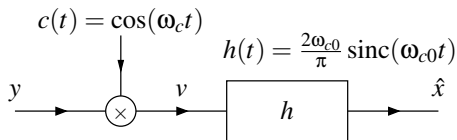


Receiver Output

Double-Sideband Suppressed-Carrier (DSB-SC) AM



Transmitter



Receiver

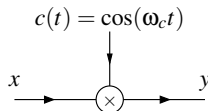
- Let $X = \mathcal{F}x$, $Y = \mathcal{F}y$, and $\hat{X} = \mathcal{F}\hat{x}$.
- Suppose that $X(\omega) = 0$ for all $\omega \notin [-\omega_b, \omega_b]$.
- The transmitter is characterized by

$$Y(\omega) = \frac{1}{2} [X(\omega + \omega_c) + X(\omega - \omega_c)].$$

- The receiver is characterized by

$$\hat{X}(\omega) = [Y(\omega + \omega_c) + Y(\omega - \omega_c)] \text{rect}\left(\frac{\omega}{2\omega_{c0}}\right).$$

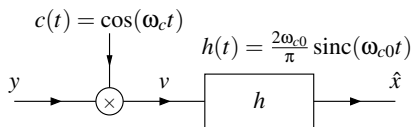
- If $\omega_b < \omega_{c0} < 2\omega_c - \omega_b$, we have $\hat{X}(\omega) = X(\omega)$ (implying $\hat{x}(t) = x(t)$).



$$y(t) = \cos(\omega_c t)x(t)$$

$$X = \mathcal{F}x, \quad Y = \mathcal{F}y$$

$$\begin{aligned} Y(\omega) &= \mathcal{F}\{\cos(\omega_c t)x(t)\}(\omega) \\ &= \mathcal{F}\left\{\frac{1}{2}(e^{j\omega_c t} + e^{-j\omega_c t})x(t)\right\}(\omega) \\ &= \frac{1}{2}[\mathcal{F}\{e^{j\omega_c t}x(t)\}(\omega) + \mathcal{F}\{e^{-j\omega_c t}x(t)\}(\omega)] \\ &= \frac{1}{2}[X(\omega - \omega_c) + X(\omega + \omega_c)] \end{aligned}$$



$$v(t) = \cos(\omega_c t)y(t), \quad h(t) = \frac{2\omega_{c0}}{\pi} \text{sinc}(\omega_{c0}t), \quad \hat{x}(t) = v * h(t)$$

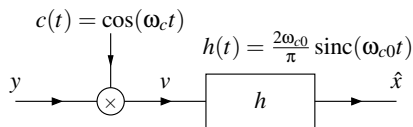
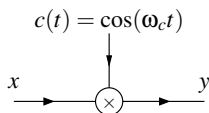
$$Y = \mathcal{F}y, \quad V = \mathcal{F}v, \quad H = \mathcal{F}h, \quad \hat{X} = \mathcal{F}\hat{x}$$

$$\begin{aligned} V(\omega) &= \mathcal{F}\{\cos(\omega_c t)y(t)\}(\omega) \\ &= \mathcal{F}\left\{\frac{1}{2}(e^{j\omega_c t} + e^{-j\omega_c t})y(t)\right\}(\omega) \\ &= \frac{1}{2}[\mathcal{F}\{e^{j\omega_c t}y(t)\}(\omega) + \mathcal{F}\{e^{-j\omega_c t}y(t)\}(\omega)] \\ &= \frac{1}{2}[Y(\omega - \omega_c) + Y(\omega + \omega_c)] \end{aligned}$$

$$\begin{aligned} H(\omega) &= \mathcal{F}\left\{\frac{2\omega_{c0}}{\pi} \text{sinc}(\omega_{c0}t)\right\}(\omega) \\ &= 2 \text{rect}\left(\frac{\omega}{2\omega_{c0}}\right) \end{aligned}$$

$$\hat{X}(\omega) = H(\omega)V(\omega)$$

DSB-SC AM: Complete System

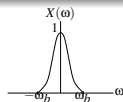


$$Y(\omega) = \frac{1}{2} [X(\omega - \omega_c) + X(\omega + \omega_c)]$$

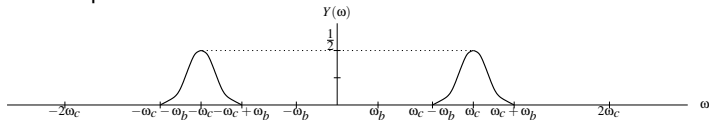
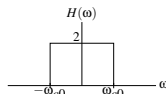
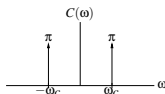
$$\begin{aligned} V(\omega) &= \frac{1}{2} [Y(\omega - \omega_c) + Y(\omega + \omega_c)] \\ &= \frac{1}{2} \left[\frac{1}{2} [X([\omega - \omega_c] - \omega_c) + X([\omega - \omega_c] + \omega_c)] + \right. \\ &\quad \left. \frac{1}{2} [X([\omega + \omega_c] - \omega_c) + X([\omega + \omega_c] + \omega_c)] \right] \\ &= \frac{1}{2} X(\omega) + \frac{1}{4} X(\omega - 2\omega_c) + \frac{1}{4} X(\omega + 2\omega_c) \end{aligned}$$

$$\begin{aligned} \hat{X}(\omega) &= H(\omega) V(\omega) \\ &= H(\omega) \left[\frac{1}{2} X(\omega) + \frac{1}{4} X(\omega - 2\omega_c) + \frac{1}{4} X(\omega + 2\omega_c) \right] \\ &= \frac{1}{2} H(\omega) X(\omega) + \frac{1}{4} H(\omega) X(\omega - 2\omega_c) + \frac{1}{4} H(\omega) X(\omega + 2\omega_c) \\ &= \frac{1}{2} [2X(\omega)] + \frac{1}{4}(0) + \frac{1}{4}(0) \\ &= X(\omega) \end{aligned}$$

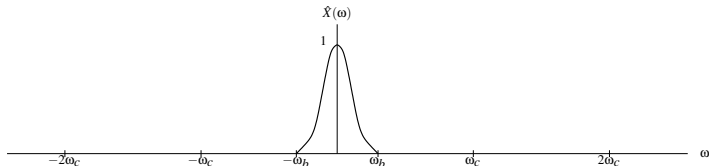
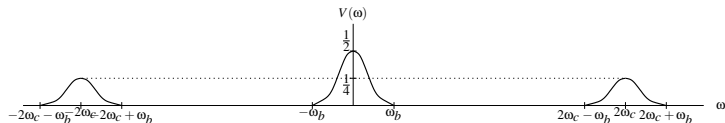
DSB-SC AM: Example



Transmitter Input

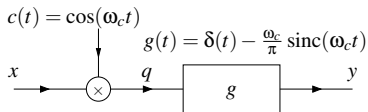


Transmitter Output

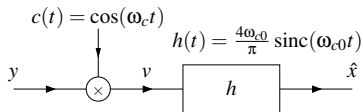


Receiver Output

Single-Sideband Suppressed-Carrier (SSB-SC) AM



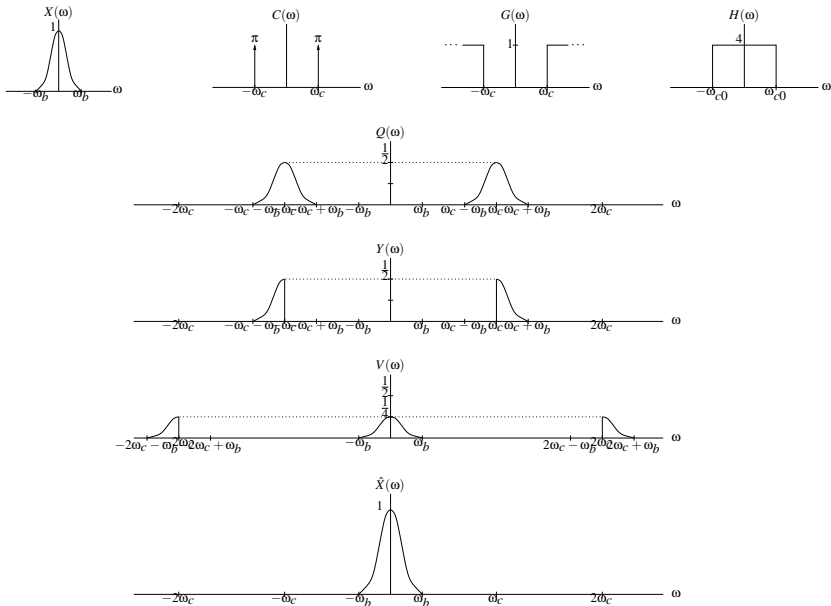
Transmitter



Receiver

- The basic analysis of the SSB-SC AM system is similar to the DSB-SC AM system.
- SSB-SC AM requires half as much bandwidth for the transmitted signal as DSB-SC AM.

SSB-SC AM: Example

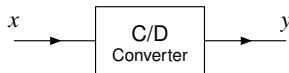


Section 6.11

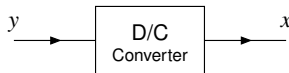
Application: Sampling and Interpolation

Sampling and Interpolation

- Often, we want to be able to transform a continuous-time signal (i.e., a function) into a discrete-time signal (i.e., a sequence) and vice versa.
- This is accomplished through processes known as *sampling* and *interpolation*.
- **Sampling**, which is performed by a **continuous-time to discrete-time (C/D) converter** shown below, transforms a function x to a sequence y .



- **Interpolation**, which is performed by a **discrete-time to continuous-time (D/C) converter** shown below, transforms a sequence y to a function x .



- Note that, unless very special conditions are met, the sampling process loses information (i.e., is *not invertible*).

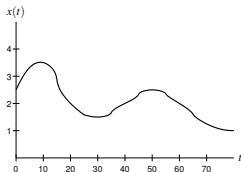
Periodic Sampling

- Although sampling can be performed in many different ways, the most commonly used scheme is **periodic sampling**.
- With this scheme, a sequence y of samples is obtained from a function x according to the relation

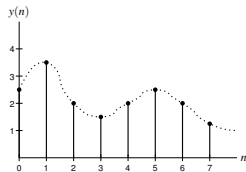
$$y(n) = x(Tn) \quad \text{for all integer } n,$$

where T is a (strictly) positive real constant.

- As a matter of terminology, we refer to T as the **sampling period**, and $\omega_s = \frac{2\pi}{T}$ as the (angular) **sampling frequency**.
- An example of periodic sampling is shown below, where the function x has been sampled with **sampling period $T = 10$** , yielding the sequence y .



Function to Be Sampled



Sequence Produced by Sampling

Invertibility of Sampling

- Unless constraints are placed on the functions being sampled, the sampling process is *not invertible*.
- In other words, in the absence of any constraints, a function cannot be uniquely determined from a sequence of its equally-spaced samples.
- Consider, for example, the functions x_1 and x_2 given by

$$x_1(t) = 0 \quad \text{and} \quad x_2(t) = \sin(2\pi t).$$

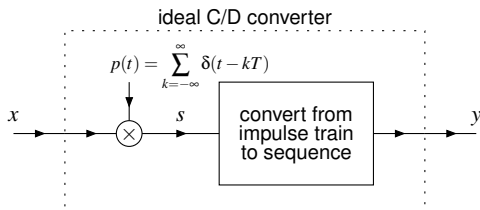
- Sampling x_1 and x_2 with the sampling period $T = 1$ yields the respective sequences

$$y_1(n) = x_1(Tn) = x_1(n) = 0 \quad \text{and} \\ y_2(n) = x_2(Tn) = \sin(2\pi n) = 0.$$

- So, although x_1 and x_2 are *distinct*, y_1 and y_2 are *identical*.
- Given the sequence y where $y = y_1 = y_2$, it is impossible to determine which function was sampled to produce y .
- Only by imposing a carefully chosen set of constraints on the functions being sampled can we ensure that a function can be exactly recovered from only its samples.

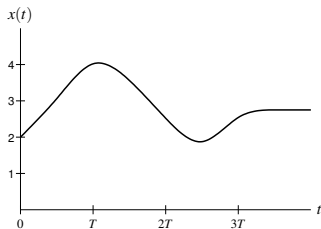
Model of Sampling

- An **impulse train** is a function of the form $v(t) = \sum_{k=-\infty}^{\infty} c_k \delta(t - kT)$, where c_k and T are real constants.
- For the purposes of analysis, sampling with sampling period T and frequency $\omega_s = \frac{2\pi}{T}$ can be modelled as shown below.

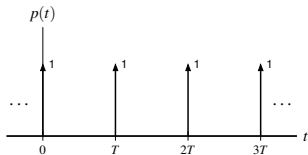


- The sampling of a function x to produce a sequence y consists of the following two steps (in order):
 - 1 Multiply the function x to be sampled by a periodic impulse train p , yielding the impulse train $s(t) = \sum_{n=-\infty}^{\infty} x(nT) \delta(t - nT)$.
 - 2 Convert the impulse train s to a sequence y by forming y from the weights of successive impulses in s so that $y(n) = x(nT)$.

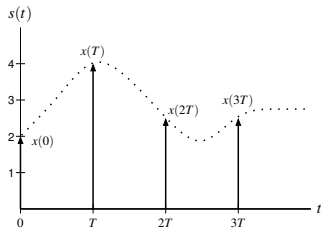
Model of Sampling: Various Signals



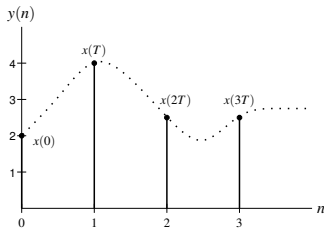
Input Function



Periodic Impulse Train

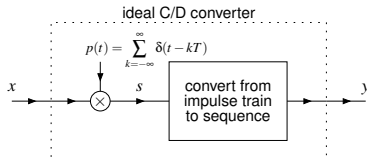


Impulse-Sampled Function
(Continuous-Time)



Output Sequence (Discrete-Time)

Model of Sampling: Invertibility of Sampling Revisited



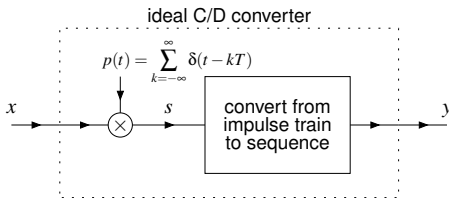
- Since sampling is not invertible and our model of sampling consists of only two steps, at least one of these two steps must not be invertible.
- Recall the two steps in our model of sampling are as follows (in order):

1 $x \longrightarrow s(t) = x(t)p(t) = \sum_{n=-\infty}^{\infty} x(nT)\delta(t - nT)$; and

2 $s(t) = \sum_{n=-\infty}^{\infty} x(nT)\delta(t - nT) \longrightarrow y(n) = x(nT)$.

- Step 1 cannot be undone (unless we somehow restrict which functions x can be sampled).
- Step 2 is always invertible.
- Therefore, the fact that sampling is not invertible is entirely due to step 1.

Model of Sampling: Characterization



- In the time domain, the impulse-sampled function s is given by

$$s(t) = x(t)p(t) \quad \text{where} \quad p(t) = \sum_{k=-\infty}^{\infty} \delta(t - kT).$$

- In the Fourier domain, the preceding equation becomes

$$S(\omega) = \frac{\omega_s}{2\pi} \sum_{k=-\infty}^{\infty} X(\omega - k\omega_s) \quad (\text{where } \omega_s = \frac{2\pi}{T}).$$

- Thus, the spectrum of the impulse-sampled function s is a scaled sum of an infinite number of *shifted copies* of the spectrum of the original function x .

Sampling: Fourier Series for a Periodic Impulse Train

$$p(t) = \sum_{k=-\infty}^{\infty} \delta(t - kT), \quad \omega_s = \frac{2\pi}{T}$$

$$p(t) = \sum_{k=-\infty}^{\infty} c_k e^{jk\omega_s t}$$

$$c_k = \frac{1}{T} \int_{-T/2}^{T/2} p(t) e^{-jk\omega_s t} dt$$

$$= \frac{1}{T} \int_{-T/2}^{T/2} \delta(t) e^{-jk\omega_s t} dt$$

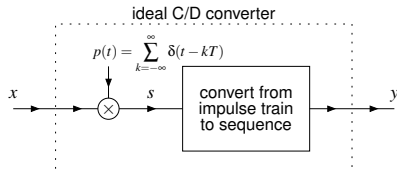
$$= \frac{1}{T} \int_{-\infty}^{\infty} \delta(t) e^{-jk\omega_s t} dt$$

$$= \frac{1}{T}$$

$$= \frac{\omega_s}{2\pi}$$

$$p(t) = \frac{\omega_s}{2\pi} \sum_{k=-\infty}^{\infty} e^{jk\omega_s t}$$

Sampling: Multiplication by a Periodic Impulse Train



$$s(t) = p(t)x(t), \quad p(t) = \sum_{k=-\infty}^{\infty} \delta(t - kT), \quad \omega_s = \frac{2\pi}{T}$$

$$p(t) = \frac{\omega_s}{2\pi} \sum_{k=-\infty}^{\infty} e^{jk\omega_s t}$$

$$s(t) = \frac{\omega_s}{2\pi} \sum_{k=-\infty}^{\infty} e^{jk\omega_s t} x(t)$$

$$X = \mathcal{F}x, \quad S = \mathcal{F}s$$

$$S(\omega) = \frac{\omega_s}{2\pi} \sum_{k=-\infty}^{\infty} X(\omega - k\omega_s)$$

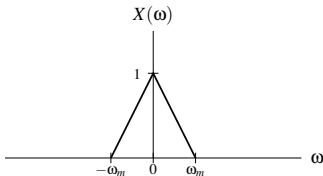
Model of Sampling: Aliasing

- Consider frequency spectrum S of the impulse-sampled function s given by

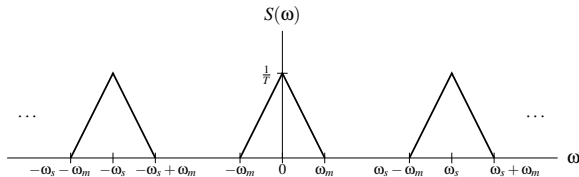
$$S(\omega) = \frac{\omega_s}{2\pi} \sum_{k=-\infty}^{\infty} X(\omega - k\omega_s).$$

- The function S is a scaled sum of an infinite number of *shifted copies* of X .
- Two distinct behaviors can result in this summation, depending on ω_s and the bandwidth of x .
- In particular, the nonzero portions of the different shifted copies of X can either:
 - 1 overlap; or
 - 2 not overlap.
- In the case where overlap occurs, the various shifted copies of X add together in such a way that the original shape of X is lost. This phenomenon is known as **aliasing**.
- When aliasing occurs, the original function x cannot be recovered from its samples in y .

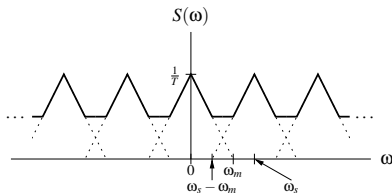
Model of Sampling: Aliasing (Continued)



Spectrum of Input
Function
(Bandwidth ω_m)



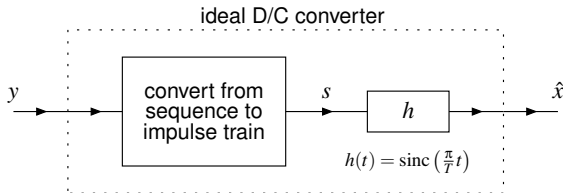
Spectrum of Impulse-
Sampled Function:
No Aliasing Case
($\omega_s > 2\omega_m$)



Spectrum of Impulse-
Sampled Function:
Aliasing Case
($\omega_s \leq 2\omega_m$)

Model of Interpolation

- For the purposes of analysis, interpolation can be modelled as shown below.



- The reconstruction of a function x from its sequence y of samples (i.e., bandlimited interpolation) consists of the following two steps (in order):
 - Convert the sequence y to the impulse train s by using the samples in y as the weights of successive impulses in s so that $s(t) = \sum_{n=-\infty}^{\infty} y(n)\delta(t - Tn)$.
 - Apply the lowpass filter with impulse response h to s to produce \hat{x} so that $\hat{x}(t) = s * h(t) = \sum_{n=-\infty}^{\infty} y(n) \text{sinc}[\frac{\pi}{T}(t - Tn)]$.
- The lowpass filter is used to eliminate the extra copies of the originally-sampled function's spectrum present in the spectrum of s .

Sampling Theorem

- **Sampling Theorem.** Let x be a function with Fourier transform X , and suppose that $|X(\omega)| = 0$ for all ω satisfying $|\omega| > \omega_M$ (i.e., x is bandlimited to frequencies $[-\omega_M, \omega_M]$). Then, x is uniquely determined by its samples $y(n) = x(Tn)$ for all integer n , if

$$\omega_s > 2\omega_M,$$

where $\omega_s = \frac{2\pi}{T}$. The preceding inequality is known as the **Nyquist condition**. If this condition is satisfied, we have that

$$x(t) = \sum_{n=-\infty}^{\infty} y(n) \operatorname{sinc} \left[\frac{\pi}{T} (t - Tn) \right],$$

or equivalently (i.e., rewritten in terms of ω_s instead of T),

$$x(t) = \sum_{n=-\infty}^{\infty} y(n) \operatorname{sinc} \left(\frac{\omega_s}{2} t - \pi n \right).$$

- We call $\frac{\omega_s}{2}$ the **Nyquist frequency** and $2\omega_M$ the **Nyquist rate**.

Part 7

Laplace Transform (LT)

Motivation Behind the Laplace Transform

- Another important mathematical tool in the study of signals and systems is known as the Laplace transform.
- The Laplace transform can be viewed as a *generalization of the Fourier transform*.
- Due to its more general nature, the Laplace transform has a number of *advantages* over the Fourier transform.
- First, the Laplace transform representation *exists for some functions that do not have a Fourier transform representation*. So, we can handle some functions with the Laplace transform that cannot be handled with the Fourier transform.
- Second, since the Laplace transform is a more general tool, it can provide *additional insights* beyond those facilitated by the Fourier transform.