

# ECE4634 Digital Communications Fall 2007

Instructor: R. Michael Buehrer  
Lecture #9: Digital Pulse  
Modulation: Line Codes



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## Lecture Objectives



- The objectives of this lecture are
  - to introduce ways of mapping data bits (1's and 0's) to waveforms which is termed a *line code*
  - to derive the Power Spectral Density of common line codes
  - to present properties of common line codes

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## Overview



- Digital communication systems transmit a finite number of messages (typically a train of pulses) from a transmitter to the receiver.
- These waveforms represent the bit stream.
- The bits can either represent an analog signal (after analog-to-digital conversion) or can be binary data.
- The data bits are mapped to waveforms (i.e., the messages) for transmission.
- Previously we assumed that bits were mapped to rectangular pulses
- Today we will study several different potential waveforms (sometimes termed "line codes") and their properties.
- What to read – Section 5.9

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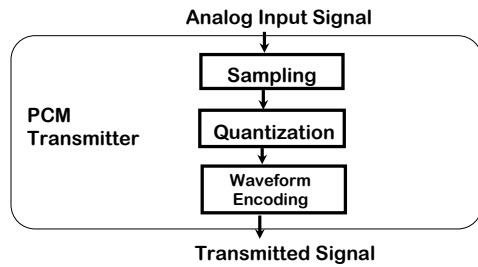
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## Structure of Digital Communications Transmitter



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## Digital Signaling and Line Codes



- We learned that PCM converts an analog signal into a serial stream of 1's and 0's to encode pulses (or waveforms) for transmission.
- We have not yet discussed the properties of these pulses.
- The mapping of the bits to waveforms or pulses is the essence of digital signaling.
- Today we look at several different mappings from  $\{0, 1\}$  to signaling formats called *line codes*.

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## Binary Signaling



- The simplest method of digital signaling is *binary signaling*
- For binary data,  $b_k = \{0, 1\}$

Note  $b_k = \{-1, +1\}$  is also possible

$$w(t) = \sum_{k=-\infty}^{\infty} b_k p(t - kT)$$

- where  $p(t)$  is a pulse and  $T$  is the pulse duration.
- One simple pulse is a square pulse:

$$p(t) = \begin{cases} \frac{1}{\sqrt{T}} & T/2 < t < T/2 \\ 0 & \text{else} \end{cases}$$

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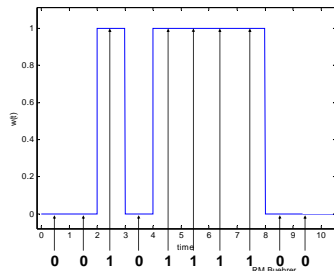
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## Example: Square Pulses



Data = [0,0,1,0,1,1,1,1,0,0]



- Data controls pulse amplitude.
- Pulses are non-overlapping
- Receiver determines data by examining a sample within the pulse width (note that with square pulse the exact sampling time is irrelevant)

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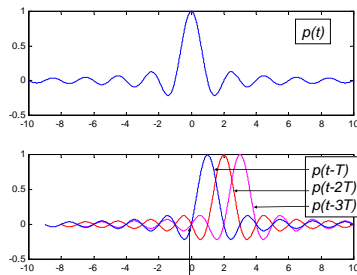
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## Example: Sinc Pulses



- Sinc pulses are a second possibility.
- They require less bandwidth than square pulses
- Unfortunately they are non-causal

$$p(t) = \frac{\sin\left(\frac{\pi}{T}t\right)}{\frac{\pi}{T}t}$$

Note: Pulses go to zero every  $T$  seconds

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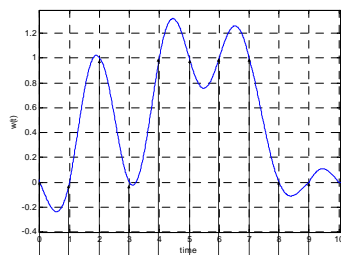
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## Example: Sinc Pulses



Data = [0,0,1,0,1,1,1,1,0,0]



- Data controls pulse amplitude.
- Pulses overlap, but go to zero every symbol period
- Receiver determines data by examining the sample at specific sampling time (note that with sinc pulses the exact sampling time is important to avoid interference between pulses)

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## Multi-level Signaling



- With binary signaling each pulse is modulated by a single bit. Thus, the symbol rate is equal to the bit rate.
- One method of reducing bandwidth is to map more than one bit to each pulse.
- This can be accomplished by allowing the amplitude to take on  $L > 2$  values where  $L$  is a power of 2
  - Groups of  $n$  bits are mapped into one of  $L=2^n$  levels.
  - Ex: 4-ary signaling, 8-ary signaling

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## Multi-level Signaling (cont.)



$$w(t) = \sum_{k=-\infty}^{\infty} w_k p(t - kT)$$

- Ex: 4-ary signaling  $\rightarrow w_k = \{0, 1, 2, 3\}$ 
  - 00  $\rightarrow$  0
  - 01  $\rightarrow$  1
  - 10  $\rightarrow$  2
  - 11  $\rightarrow$  3

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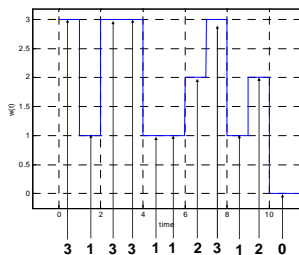
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## Example: Square pulses



- Data controls pulse amplitude.
- Pulses are non-overlapping
- Receiver determines data by examining a sample within the pulse width (note that with square pulse the exact sampling time is irrelevant)

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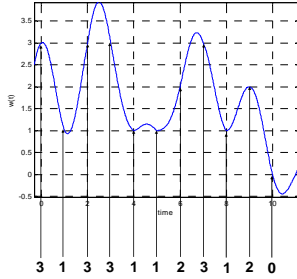
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## Example: Sinc pulses



- Data controls pulse amplitude.
- Pulses overlap, but go to zero every symbol period
- Receiver determines data by examining the sample at specific sampling time (note that with sinc pulse the exact sampling time is important to avoid interference between pulses)

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13

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## Binary Line Codes



- When binary signaling is used, there are various ways to create waveforms with a square pulse shape (so far we have assumed *unipolar NRZ signaling*).
- These various signaling formats are called *line codes*.
- There are two major categories of line codes
  - Return to zero codes (RZ)
    - The signal returns to zero for  $\frac{1}{2}$  (or other fraction) of the pulse
  - Non-return to zero codes (NRZ)
- Codes have different
  - Spectral properties
  - Synchronization capabilities
  - Error performance

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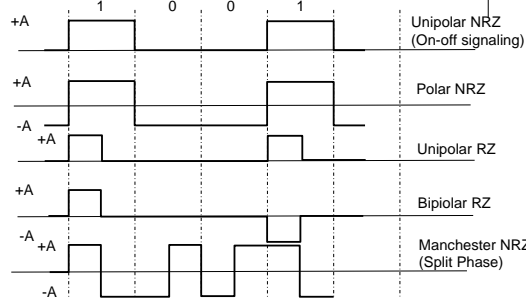
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## Binary Line Codes



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## Power Spectral Densities (Deterministic)



- Deterministic and Periodic Power Signals

$$x(t) = \sum_{n=-\infty}^{\infty} c_n e^{j2\pi n f_0 t}$$

- where  $c_n$  are the Fourier Series Coefficients

- Deterministic power signals have Power Spectral Density (PSD):

$$S_x(f) = \sum_{n=-\infty}^{\infty} |c_n|^2 \delta(f - n f_0)$$

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## Power Spectral Densities (Random)



- It is easiest to talk about random signals that extend for all time (i.e., power signals). Hence almost every sample function (or realization of a stochastic process) is a power signal with a power spectral density. In fact any *stationary* random process will have infinite energy. The PSD of the random process is just the ensemble average of all sample power spectral densities.

$$S_x(f) = E \left[ \lim_{T \rightarrow \infty} \frac{|X_T(f)|^2}{T} \right] = \lim_{T \rightarrow \infty} \frac{E[|X_T(f)|^2]}{T}$$

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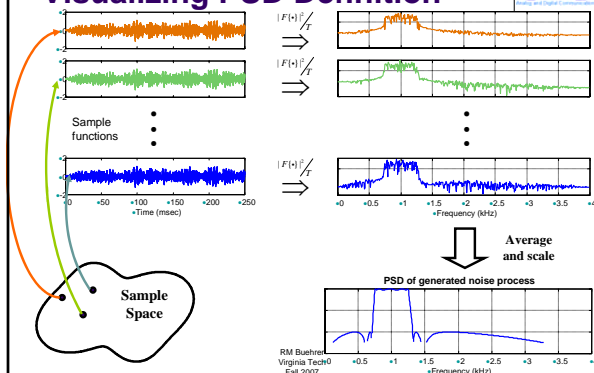
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## Visualizing PSD Definition




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## Power Spectral Density



- $S_x(f)$  (PSD) tells us how much power is at each frequency
- For deterministic signals, the function description  $x(t)$  tells us how the value changes with time, thus its Fourier transform  $X(f)$  gives us the spectral properties. However, random processes have a random function description

- Wiener-Khinchine Theorem

- For a WSS process

$$S_x(f) = F\{R_x(\tau)\} \\ = \int_{-\infty}^{\infty} R_x(\tau) e^{-j2\pi f\tau} d\tau$$

- The autocorrelation function  $R_x(\tau) = \int_{-\infty}^{\infty} x(t)x(t+\tau)dt$  tells us how the value is *expected* to change with time rather than the exact change.
- Power spectral density and autocorrelation are a Fourier Transform pair

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## Power Spectral Density for Digital Modulated Pulse Train



- Consider a digitally modulated pulse train:

$$x(t) = \sum_n a_n f(t - nT_s)$$

where  $f(t)$  is the pulse shape and  $a_n$  are the digital values.

- We can show (see Appendix) that the PSD of this signal is:

$$S_x(f) = \underbrace{\frac{\sigma_a^2}{T_s} |F(f)|^2}_{\text{continuous}} + \underbrace{\frac{m_a^2}{T_s^2} \sum_{n=-\infty}^{\infty} \left| F\left(\frac{n}{T_s}\right) \right|^2}_{\text{discrete}} \delta\left(f - \frac{n}{T_s}\right)$$

- PSD has continuous portion which is dependent on the pulse shape  $f(t)$  and a discrete portion which is also dependent on the data mean value and variance.
- This will become very important when we examine the bandwidth requirements of digitally modulated signals

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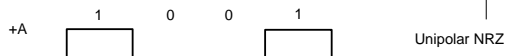
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## Unipolar NRZ Signaling



$$m_x = \frac{A}{2}$$

$$\sigma_x^2 = \frac{A^2}{4}$$

$$F(f) = T_b \frac{\sin(\pi f T_b)}{\pi f T_b}$$

$$P(f) = \frac{A^2 T_b}{4} \left[ \underbrace{\left( \frac{\sin(\pi f T_b)}{\pi f T_b} \right)^2}_{\text{due to pulse shape}} \right] \left[ 1 + \underbrace{\frac{1}{T_b} \delta(f)}_{\text{due to DC component}} \right]$$

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21

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## Polar NRZ Signaling

Polar NRZ

$m_a = 0$   
 $\sigma_a^2 = A^2$

$F(f) = T_b \frac{\sin(\pi f T_b)}{\pi f T_b}$

$$P(f) = A^2 T_b \left( \frac{\sin(\pi f T_b)}{\pi f T_b} \right)^2$$

Same as Polar RZ except that DC component is eliminated.

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## Unipolar RZ

Unipolar RZ

$m_a = \frac{A}{2}$   
 $\sigma_a^2 = \frac{A^2}{4}$

$F(f) = \frac{T_b}{2} \frac{\sin(\pi f T_b / 2)}{\pi f T_b / 2}$

$$P(f) = \frac{A^2 T_b}{16} \left( \frac{\sin(\pi f T_b / 2)}{\pi f T_b / 2} \right)^2 \left[ 1 + \frac{1}{T_b} \sum_{n=-\infty}^{\infty} \delta\left(f - \frac{n}{T_b}\right) \right]$$

due to pulse shape
discrete terms due to correlation in data

Note: Discrete terms occur at multiples of  $1/T_b$ . However, the pulse shape forces the spectrum to zero at multiples of  $2/T_b$ .

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23

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## Bipolar RZ Signaling

Bipolar RZ

$m_a = 0$   
 $\sigma_a^2 = \frac{A^2}{4}$

$F(f) = \frac{T_b}{2} \frac{\sin(\pi f T_b / 2)}{\pi f T_b / 2}$

$$P(f) = \frac{A^2 T_b}{4} \left( \frac{\sin(\pi f T_b / 2)}{\pi f T_b / 2} \right)^2 \sin^2(\pi f T_b)$$

Note: Discrete terms eliminated by removing correlation in data (including DC component).  $\sin^2(x)$  term forces spectrum to zero at DC.

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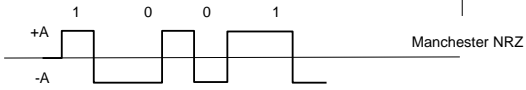
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## Manchester NRZ Signaling



$$m_s = 0$$

$$\sigma_s^2 = A^2$$

$$F(f) = jT_b \frac{\sin(\pi f T_b / 2)}{\pi f T_b / 2} \sin\left(\frac{2\pi f T_b}{4}\right)$$

$\sin^2(x)$  term forces spectrum to zero at DC. First null BW twice that of bipolar RZ

$$P(f) = A^2 T_b \left( \frac{\sin(\pi f T_b / 2)}{\pi f T_b / 2} \right)^2 \sin^2(\pi f T_b / 2)$$

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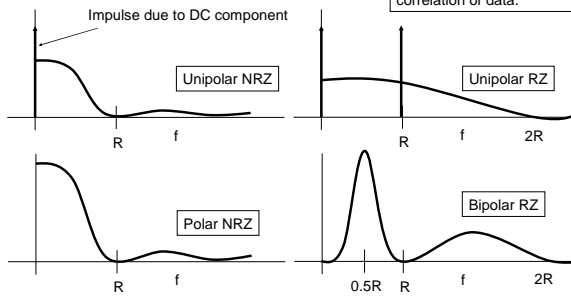
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## Spectra of Line Codes



Note: Spectra are dependent on pulse shape and auto-correlation of data.



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## Properties of Line Codes



- Self-synchronization
  - Timing information is built into the code to allow clock recovery.
  - Strings of 1's and 0's do not cause timing problems
- Spectrum
  - The spectrum must be appropriate for the channel being used.
  - Bandwidth should be as small as possible
- Error-probability
  - The code should provide low probability of bit error
  - Code should allow easy implementation of error corrections coding/decoding

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## Properties of Line Codes



- Unipolar codes
  - Have the advantage of requiring only a single positive voltage power supply.
  - Have the disadvantage of having a DC value which is less power efficient and requires channels that have DC response.
- Bipolar Codes
  - Have zero DC level provided 0's and 1's occur at the same frequency and there are not long strings of 0's or 1's.
- Manchester Codes
  - Have no DC value regardless of the number of consecutive 1's or 0's.
  - Twice the bandwidth of NRZ codes
- RZ codes
  - Have self-synchronization properties due to spectral lines (or ability to produce spectral lines) at  $f = R$ .
  - Have twice the bandwidth of NRZ signals

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28

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## Summary



- PCM is a common method of converting an analog signal to a digital waveform
- Sampling and quantization converts analog waveforms into a series of bits
- There are several methods of mapping the bits to digital waveforms
  - Binary vs. multi-level signaling
  - Various pulse shapes
  - Various line codes
- Next class we will look more closely at the effect of pulse shape

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## Appendix

Derivation of the PSD for a digitally modulated pulse train



Analogy and Digital Communications

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## Power Spectral Density for Digitally Modulated Pulse Train



Let us define a general digitally modulated pulse train as  $x(t) = \sum_{n=-\infty}^{\infty} a_n f(t - nT_s)$

where  $a_n$  is the sequence of data values,  $f(t)$  is the pulse shape used and  $T_s$  is the symbol duration. This is sometimes called a modulated pulse train.

Now the Power Spectral Density can be found as  $P_x(f) = \lim_{T \rightarrow \infty} \frac{|X_T(f)|^2}{T}$

Where  $X_T(f) = \int_{-T/2}^{T/2} x(t) e^{-j2\pi ft} dt$  and  $\overline{X(f)} = E[X(f)] =$  ensemble average

From our signal definition we have  $X_T(f) = \int_{-T/2}^{T/2} \sum_{n=-N}^N a_n f(t - nT_s) e^{-j2\pi ft} dt$   
 $= \sum_{n=-N}^N a_n \int_{-T/2}^{T/2} f(t - nT_s) e^{-j2\pi ft} dt$   $T = (2N+1)T_s$

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31

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## Power Spectral Density for Digital Signals (cont.)



Continuing from the previous slide  $X_T(f) = \sum_{n=-N}^N a_n \int_{-T/2}^{T/2} f(t - nT_s) e^{-j2\pi ft} dt$

$$= \sum_{n=-N}^N a_n F(f) e^{-j2\pi f n T_s}$$

$$= F(f) \sum_{n=-N}^N a_n e^{-j2\pi f n T_s}$$

Returning to our definition for PSD  $P_x(f) = \lim_{T \rightarrow \infty} \frac{|X_T(f)|^2}{T}$

$$= \lim_{T \rightarrow \infty} \frac{|F(f) \sum_{n=-N}^N a_n e^{-j2\pi f n T_s}|^2}{T}$$

$$= |F(f)|^2 \lim_{T \rightarrow \infty} \left( \frac{1}{(2N+1)T_s} \sum_{n=-N}^N \sum_{m=-N}^N \overline{a_n a_m} e^{-j2\pi f(n-m)T_s} \right)$$

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## Power Spectral Density for Digital Signals (cont.)



Defining  $R(k) = \overline{a_n a_{n+k}}$  and  $m = n+k$

$$P_x(f) = |F(f)|^2 \lim_{N \rightarrow \infty} \left( \frac{1}{(2N+1)T_s} \sum_{n=-N}^N \sum_{m=-N}^N \overline{a_n a_m} e^{-j2\pi f(n-m)T_s} \right)$$

$$= |F(f)|^2 \lim_{N \rightarrow \infty} \left( \frac{1}{(2N+1)T_s} \sum_{n=-N}^N \sum_{k=-N-n}^{N-n} R(k) e^{-j2\pi f k T_s} \right)$$

$$= \frac{|F(f)|^2}{T_s} \lim_{N \rightarrow \infty} \left( \frac{(2N+1)}{(2N+1)} \sum_{k=-N}^N R(k) e^{-j2\pi f k T_s} \right)$$

$$= \frac{|F(f)|^2}{T_s} \sum_{k=-\infty}^{\infty} R(k) e^{-j2\pi f k T_s}$$

$$= \frac{|F(f)|^2}{T_s^2} \sum_{k=-\infty}^{\infty} R(k) \delta\left(f - \frac{k}{T_s}\right)$$

$$\sum_{k=-\infty}^{\infty} e^{-j2\pi f k T_s} = \frac{1}{T_s} \sum_{k=-\infty}^{\infty} \delta\left(f - \frac{k}{T_s}\right)$$

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33

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## Power Spectral Density for Digital Signals (cont.)



For uncorrelated\* data

$$R(k) = \begin{cases} \overline{a_n^2} & k = 0 \\ a_n a_{n+k} & k \neq 0 \end{cases} = \begin{cases} \sigma_a^2 + m_a^2 & k = 0 \\ m_a^2 & k \neq 0 \end{cases}$$

Thus,

$$\begin{aligned} P_x(f) &= \frac{|F(f)|^2}{T_s} \sum_{k=-\infty}^{\infty} R(k) e^{j2\pi k T_s f} \\ &= \frac{|F(f)|^2}{T_s} \left( \sigma_a^2 + m_a^2 \sum_{n=-\infty}^{\infty} e^{j2\pi n T_s f} \right) \\ &= \frac{\sigma_a^2}{T_s} |F(f)|^2 + \frac{m_a^2}{T_s} |F(f)|^2 \sum_{n=-\infty}^{\infty} \delta\left(f - \frac{n}{T_s}\right) \\ &= \underbrace{\frac{\sigma_a^2}{T_s} |F(f)|^2}_{\text{continuous}} + \underbrace{\frac{m_a^2}{T_s} \sum_{n=-\infty}^{\infty} \left|F\left(\frac{n}{T_s}\right)\right|^2}_{\text{discrete}} \delta\left(f - \frac{n}{T_s}\right) \end{aligned}$$

\* For uncorrelated data,  $E\{XY\} = E\{X\}E\{Y\}$

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## Power Spectral Density for Digital Signals (cont.)



$$P_x(f) = \underbrace{\frac{\sigma_a^2}{T_s} |F(f)|^2}_{\text{continuous}} + \underbrace{\frac{m_a^2}{T_s} \sum_{n=-\infty}^{\infty} \left|F\left(\frac{n}{T_s}\right)\right|^2}_{\text{discrete}} \delta\left(f - \frac{n}{T_s}\right)$$

- PSD has continuous portion which is dependent on the pulse shape  $f(t)$  and a discrete portion which is also dependent on the data mean value and variance.
- This will become very important when we examine the bandwidth requirements of digitally modulated signals

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