Discrete Time Signals and Systems Time-frequency Analysis

Gloria Menegaz

Time-frequency Analysis

- Fourier transform (1D and 2D)
- Reference textbook:

Discrete time signal processing, A.W. Oppenheim and R.W. Shafer

- Chapter 1: Introduction
- Chapter 2: Discrete time Signals and Systems
- Chapter 3: Sampling of Continuos Time Signals
- (Chapter 4: The z-Transform)

Signal Classification

• Continuous time signals x(t) are functions of a continuous independent variable t

 $x = x(t), t \in \mathcal{R}$

- Discrete time signals are functions of a discrete variable $x = \{x[n]\}, n \in \mathbb{Z}, -\infty < n < +\infty$
 - Are defined at discrete time intervals
 - Are represented as *sequences of numbers*
- *Digital signals* both the independent variable **and** the amplitude are discrete

Digital systems: both the input and the output are digital signals \Rightarrow Digital Signal Processing: processing of signals that are discrete in both time and amplitude

3

Periodic Sampling

The sequences are obtained by sampling the analog signal at equi-spaced points:

 $x[n] = x(nT), n \in I$

T: *sampling period*, interval between samples

 $f = \frac{1}{T}$: sampling frequency



Basic Sequences

- Products and sums among sequences: element by element operations
- Delayed or shifted sequence: y[n] = x[n-k]
- Unit sample sequence $\delta[n]$ (Dirac function, impulse):

$$\delta[n] = \begin{cases} 0, & n \neq 0 \\ 1, & n = 0 \end{cases}$$
(1)

• Unit step sequence:

$$u[n] = \begin{cases} 0, & n < 0 \\ 1, & n \ge 0 \end{cases}$$
(2)

Basic Sequences

ightarrow relation between the two functions:

$$u[n] = \sum_{k=0}^{\infty} \delta[n-k]$$
(3)

$$\delta[n] = u[n] - u[n-1] \tag{4}$$

• Sinusoidal sequence:

$$x[n] = Acos(\omega_0 n + \Phi), \forall n$$

Basic Sequences

• Complex exponential

$$x[n] = Ae^{(\alpha + j(\omega_0 n + \phi))}$$

- $|\alpha| < 1$: exponentially decaying envelop
- $|\alpha| > 1$: exponentially growing envelop
- $|\alpha| = 1$: complex exponential sequence:

$$x[n] = |A|\cos(\omega_0 n + \phi) + j|A|\sin(\omega_0 n + \phi)$$

The real and imaginary parts oscillate sinusoidally with *n*. The fact that *n* is an integer leads to important differences with respect to the corresponding functions in the continuous domain. By analogy, ω_0 and Φ are called *frequency* and *phase*.

Graphically



Discrete vs. continuous

1. Complex exponentials and sinusoids are 2π -periodic

$$x[n] = A \exp^{j(\omega_0 + 2\pi)n} = A \exp^{j\omega_0 n} \exp^{j2\pi n} = A \exp^{j\omega_0 n}$$
(5)

 \Rightarrow Complex exponentials with frequencies $(\omega_0 + 2\pi r)$ are *indistinguishable* from one another \Rightarrow only frequencies in an interval of length 2π need to be considered

2. Complex exponentials in general are not periodic Periodicity condition: $x[n] = x[n+N], \forall n, N \in I$. For this condition to be true, the following relation must hold true:

$$\omega_0 N = 2\pi k, \ k \in I \tag{6}$$

 \Rightarrow Complex exponentials and sinusoidal sequences are *not* necessarily periodic with period $T_0 = 2\pi/\omega_0$ as in the continuous domain and, depending on the value of ω_0 , might not be periodic at all.

Discrete vs. continuous

Hint: relation (??) can be written as:

$$T_0 = \frac{2\pi}{\omega_0} = \frac{N}{k} \tag{7}$$

where T_0 is the period. If one thinks of the discrete time signal as to the sampled version of a continuous time signal of period T_0 with unitary sampling interval ($T_s = 1$), then relation (??) can be naturally interpreted as follows: in order to obtain a discrete time *periodic* signal of period N by sampling a continuous time signal of period T_0 , the period T_0 must be an integer factor of N, or, viceversa, N must be a multiple of T_0 . This can be easily generalized to the case $T_s \neq 1$ (not necessarily integer) as follows:

$$\omega_0 N T_s = 2\pi k \quad T_0 = \frac{N}{k} T_s \tag{8}$$

namely, $N = kT_0/T_s$ must be an integer multiple of the ratio between the period and the sampling step.

Examples

1. Example 1

$$x(t) = A \sin(\omega_0 t)$$

$$x[n] = A \sin(\omega_0 n)$$

$$\omega_0 = \frac{3}{4}\pi$$

$$\rightarrow \frac{3}{4}\pi N = 2\pi k \rightarrow 3N = 8k \rightarrow$$

the first two integers satisfying the condition are N = 8, k = 3, thus the signal x[n] obtained by sampling a continuous sinusoid x(t) with frequency $\omega_0 = \frac{3}{4}\pi$ is periodic with period N = 8; each period of x[n]corresponds to three (k = 3) periods of the original signal.

2. Example 2

$$\omega_0 = 1 \rightarrow \text{no solutions!}$$

Gloria Menegaz

Discrete Time Signals and SystemsTime-frequency Analysis

Summary

$$\begin{split} \omega_0 &\leftrightarrow & \omega_0 + 2\pi r, \quad r \in I \\ \omega_0 &= & \frac{2k\pi}{N}, \quad k, N \in I \text{ condition for periodicity} \end{split}$$
 (9) (10)

Let's assume that, given N, ω_0 satisfies relation (??) for a certain k. Relation (??) implies that only N distinguishable frequencies satisfy relation (??). Proof: let $\omega_k = \frac{2k\pi}{N}$, k = 0, 1, ..., N - 1

$$\begin{split} \omega_{d} &= 0 \quad \text{degenerate case} \\ \omega_{1} &= \frac{2\pi}{N} \\ \omega_{2} &= \frac{2 \times 2\pi}{N} \\ \cdots \\ \omega_{N-1} &= \frac{(N-1) \times 2\pi}{N} \\ \omega_{N} &= \frac{N \times 2\pi}{N} = 2\pi \\ \cdots \\ \omega_{N+i} &= \frac{(N+i) \times 2\pi}{N} = 2\pi + \frac{2\pi i}{N} \leftrightarrow \omega_{i} \end{split}$$

Gloria Menegaz

Discrete Time Signals and SystemsTime-frequency Analysis

Examples



Figure 4.16: DT sinusoids of various frequencies: (a) lowest rate $\Omega = 0$ to (d) highest rate $\Omega = \pi$.

Gloria Menegaz

Discrete vs Continuous

Conclusion: for a sinusoidal signal $x[n] = A \sin(\omega_0 n)$, as ω_0 increases from $\omega_0 = 0$ to $\omega_0 = \pi$, x[n] oscillates more and more rapidly. Conversely, from $\omega_0 = \pi$ to $\omega_0 = 2\pi$ the oscillations become slower. In fact, because of the periodicity in ω_0 of complex exponentials and sinusoidal sequences, $\omega_0 = 0$ is indistinguishable from $\omega_0 = 2\pi$ and, more in general, frequencies around $\omega_0 = 2\pi$ are indistinguishable from frequencies around $\omega_0 = 0$. As a consequence, values of ω_0 in the vicinity of $\omega_0 = 2k\pi$ are referred to as *low frequencies*, whereas frequencies in the vicinity of $\omega_0 = (2k+1)\pi$ are referred to as *high frequencies*. This is a fundamental difference from the continuous case, where the speed of the oscillations increases monotonically with the frequency ω_0 .

Operations and Properties

• Periodicity: a sequence is periodic with *period* N *iif*: $x[n+N] = x[n], \forall n$

• Energy:
$$E = \sum_{n=-\infty}^{+\infty} |x[n]|^2$$

- Sample-wise operations:
 - Product: $x \cdot y = \{x[n]y[n]\}$
 - Sum: $x + y = \{x[n] + y[n]\}$
 - Scaling: $\alpha x = {\alpha x[n]}$
 - Delay: $y[n] = x[n-n_0], n, n_0 \in I$

Operations and Properties

Any sequence can be represented as a sum of *scaled* and *delayed* unit samples:



Discrete Time Signals and SystemsTime-frequency Analysis

Discrete Time Fourier Transform

$$X(e^{j\omega}) = \sum_{n=-\infty}^{+\infty} x[n]e^{-j\omega n}$$
(13)

$$x[n] = \int_{-\pi}^{\pi} X(e^{j\omega}) e^{j\omega n} d\omega$$
 (14)

- x[n] is a *discrete time* signal
- The DTFT $X(e^{j\omega})$ is a complex *continuos function* of the independent variable ω . As such, can be put in the equivalent forms:

$$X(e^{j\omega}) = X_R(e^{j\omega}) + X_I(e^{j\omega})$$
(15)

$$X(e^{j\omega}) = |X(e^{j\omega})|e^{\angle X(e^{j\omega})}$$
(16)

 $|X(e^{j\omega})|$ is the *magnitude* or Fourier spectrum of the signal and $e^{\angle X(e^{j\omega})}$ is the phase spectrum of the transformed signal.

- x[n] and $X(e^{j\omega})$ form the *Fourier representation* for the sequence.
- Eq. (??): analysis formula. It *projects* the signal to the frequency domain.
- Eq. (??): synthesis or reconstruction formula. It is used to recover the signal from its frequency domain representation.

DTFT: Interpretation

The DTFT represents the sequence x[n] as a linear superposition of infinitesimally small complex sinusoids of the form

$$\frac{1}{2\pi}X(e^{j\omega n})d\omega \tag{17}$$

with $-\pi \leq \omega \leq \pi$ and $X(e^{j\omega n})$ representing the relative amount of each complex sinusoidal component.

By comparing (??) with relation (??) it is easy to realize that the frequency response of a LTIS is the Fourier transform of its impulse response

$$H(e^{j\omega}) = \sum_{n=-\infty}^{+\infty} h[n]e^{-j\omega n} \quad \leftrightarrow \quad h[n] = \frac{1}{2\pi} \int_{-\pi}^{\pi} H(e^{j\omega})e^{j\omega n}$$

DTFT

Symmetry properties of the DTFT: see Table 2.1, page 53 of the reference textbook

The DTFT is a *periodic* function of ω with period 2π .

$$X(e^{j(\omega+2\pi)}) = \sum_{n=-\infty}^{+\infty} x[n]e^{-j(\omega+2\pi)n}$$
(18)
$$= e^{-j2\pi n} \sum_{n=-\infty}^{+\infty} x[n]e^{-j\omega n} = X(e^{j\omega})$$
(19)

More in general:

$$X(e^{j(\omega+2r\pi)}) = X(e^{j\omega}), \forall r \in I$$
(20)

The Fourier spectrum of a discrete (sampled) signal is periodic

Eulero's formula

$$e^{jx} = \cos x + j\sin x \rightarrow e^{-j\omega 2n\pi} = e^{-j\omega n}e^{-j2\pi n} = e^{-j\omega n}, \forall n \in \mathbb{Z}^{21}$$

Reminder:

$$\sin x = \frac{e^{jx} - e^{-jx}}{2j}$$
 $\cos x = \frac{e^{jx} + e^{-jx}}{2}$

Example: rect() function



The rect () function is important because it represents the impulse response of the ideal band-pass filter in the frequency domain. Its Fourier transform is a sinc() function which spreads over $(\infty, +\infty)$.

Ideal low pass filter

$$H(e^{j\omega n}) = H(\omega) = \begin{cases} 1 & |\omega| \le \omega_c \\ 0 & \omega_c < |\omega| \le \pi \end{cases}$$
(22)

$$h[n] = \frac{1}{2\pi} \int_{-\infty}^{+\infty} H(e^{i\omega}) e^{j\omega n} d\omega = \frac{1}{2\pi} \int_{-\omega_c}^{\omega_c} e^{j\omega n} d\omega =$$
$$= \frac{1}{2\pi} \frac{1}{jn} \left[e^{j\omega n} \right]_{-\omega_c}^{\omega_c} = \frac{\omega_c}{\pi} \frac{\sin(\omega_c n)}{\omega_c n} = \frac{\omega_c}{\pi} \operatorname{sinc}(\omega_c n)$$

$$h[n] = \frac{\omega_c}{\pi} \operatorname{sinc}(\omega_c n) \tag{23}$$

 ω_c : cutting frequency of the filter \leftrightarrow bandwidth Let ω_s be the sampling frequency. If we let $\omega_c = \frac{\omega_s}{2}$ then

$$h[n] = \frac{1}{T_s} \operatorname{sinc}\left(\frac{n\pi}{T_s}\right) \tag{24}$$

To keep in mind

Sequence	Fourier transform
$\delta[n]$	1
$\delta[n-n_0]$	$e^{-j\omega n_0}$
1	$\sum_{k} 2\pi \delta(\omega + 2k\pi)$
$\frac{\sin(\omega_c n)}{n}$	$X(\boldsymbol{\omega}) = \begin{cases} 1 & \boldsymbol{\omega} \leq \boldsymbol{\omega}_{\mathcal{C}} \\ 0 & \boldsymbol{\omega}_{\mathcal{C}} < \boldsymbol{\omega} \leq \pi \end{cases}$
$x[n] = \operatorname{rect}_T[n]$	$2T \operatorname{sinc}(\omega T)$
$e^{j\omega_0 n}$	$\sum_{k} 2\pi \delta(\omega - \omega_0 + 2k\pi)$
$\cos(\omega_0 n + \Phi)$	$\pi \sum_{k} \left[e^{j\Phi} \delta(\omega - \omega_0 + 2k\pi + e^{-j\Phi} \delta(\omega + \omega_0 + 2k\pi) \right]$

Table 2.3, page 61, reference textbook

Discrete Time Systems

A DTS is an operator that maps a discrete sequence x[n] at its input to a discrete sequence y[n] at its output: $y[n] = T\{x[n]\}$



• Linearity:

$$T\{x_{1}[n] + x_{2}[n]\} = T\{x_{1}[n]\} + T\{x_{2}[n]\}, additivity$$
(25)
$$T\{ax[n]\} = aT\{x[n]\}, scaling or homogeneity$$
(26)

 \Rightarrow Principle of superposition:

 $T\{a_1x_1[n] + a_2x_2[n]\} = a_1T\{x_1[n]\} + a_2T\{x_2[n]\}$ (27)

Discrete Time Signals and SystemsTime-frequency Analysis

Discrete Time Systems

• Time-invariance: a delayed input sequence maps to a delayed output sequence:

$$x[n] \rightarrow y[n]$$
 (28)

$$x[n-n_0] \rightarrow y[n-n_0] \tag{29}$$

• Causality: the output value y[n] for $n = n_0$ only depends on *previous* input samples $x[n] : n < n_0$

In images causality doesn't matter!

• Stability: a bounded input generates a bounded output

Linear Time Invariant Systems

Linear systems:

$$y[n] = T\left\{\sum_{k=-\infty}^{\infty} x[k]\delta[n-k]\right\}$$
(30)

Principle of superposition:

$$y[n] = \sum_{k=-\infty}^{\infty} x[k]T \{\delta[n-k]\} =$$
(31)
$$= \sum_{k=-\infty}^{\infty} x[k]h_k[n]$$
(32)

Time invariance:

$$y[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k] \leftrightarrow \text{Convolution sum}$$
 (33)

 \rightarrow The system is *completely* characterized by the *impulse response* h[k]

Discrete Time Signals and SystemsTime-frequency Analysis

Convolution operator

$$x[n] \star y[n] = \sum_{k=-\infty}^{+\infty} x[k] \cdot y[n-k]$$
(34)
$$= \sum_{k=-\infty}^{+\infty} x[n-k] \cdot y[k]$$
(35)

Recipe for the convolution (refer to(**??**)):

- 1. Reflect y[k] about the origin to get y[-k]
- 2. Shift the reflected sequence of *n* steps
- 3. Multiply (point wise) the resulting sequence by x[n]
- 4. Sum over the samples of the resulting signal to get the value of the convolution at position n
- 5. Increment *n* and ge back to point 2.

Properties of LTIS

• Commutativity (see(**??**))

A LTIS with input x[n] and impulse response h[n] has the same output of a system with input h[n] and impulse response x[n]

 \rightarrow The cascade of LTIS systems has an impulse response that is the convolution of the IRs of the individual systems

• Distributivity:

$$x[n] \star (h_1[n] + h_2[n]) = x[n] \star h_1[n] + x[n] \star h_2[n]$$

 \rightarrow The *parallel connection* of LTIS systems has an impulse response that is the sum of the IRs of the single systems

Properties of LTIS



Difference Equation

The transfer function is a N-th order linear constant coefficient difference equation:

$$\sum_{k=0}^{N-1} a_k y[n-k] = \sum_{k=0}^{M} b_k x[n-k] \rightarrow$$

$$y[n] = \frac{1}{a_0} \left\{ \sum_{k=1}^{N-1} a_k y[n-k] + \sum_{k=0}^{M} b_k x[n-k] \right\}$$
(36)
(37)

 \rightarrow The output value y[n] is the linear combination of the N-1 last values of the output and the M last values of the input x[n]. System classification:

- Finite Impulse Response (FIR): the impulse response involves a *finite* number of samples
- Infinite Impulse Response (IIR): the impulse response involves a *infinite* number of samples

Frequency domain

- Complex exponential sequences are eigenfunctions of LTIS
- The response to a complex sinusoid x[n] = e^{jωn}, -∞ < n < +∞ is a sinusoid with *same* frequency and *amplitude* and *phase* determined by the system (i.e. by the impulse response)

$$y[n] = \sum_{k=-\infty}^{+\infty} h[k]e^{j\omega(n-k)} = e^{j\omega n} \left(\sum_{k=-\infty}^{+\infty} h[k]e^{-j\omega k}\right)$$
(38)

Let:

$$H(e^{j\omega}) = \sum_{k=-\infty}^{+\infty} h[k]e^{-j\omega k}$$
(39)

Then:

$$y[n] = H(e^{j\omega})e^{j\omega n}$$
(40)

Gloria Menegaz

Discrete Time Signals and SystemsTime-frequency Analysis

Frequency domain

 $H(e^{j\omega})$ frequency response of the system

$$H(e^{j\omega}) = H_R(e^{j\omega}) + H_I(e^{j\omega})$$
(41)

$$= |H(e^{j\omega})|e^{\angle H(e^{j\omega})}$$
(42)

 \rightarrow If we manage to put the input signal in the form of a sum of complex exponentials then the output can be obtained as the sum of the responses to such *signal components*:

$$x[n] = \sum_{k=-\infty}^{+\infty} \alpha_k e^{j\omega_k n} \text{ Fourier representation} \rightarrow$$
(43)
$$y[n] = \sum_{k=-\infty}^{+\infty} \alpha_k H(e^{j\omega_k}) e^{j\omega_k} \text{ output of the LTIS}$$
(44)

Gloria Menegaz

Frequency response of a LTIS

 $H(e^{j\omega})$ is *always* a periodic function of ω with period 2π

$$H(e^{j(\omega+2r\pi)}) = \sum_{n=-\infty}^{+\infty} h[n]e^{-j(\omega+2r\pi)n} = \sum_{n=-\infty}^{+\infty} h[n]e^{-j\omega n} = H(e^{j\omega})$$
(45)

Due to this property as well as to the fact that frequencies differing for multiples of 2π are indistinguishable, $H(e^{j\omega})$ only needs to be specified over an interval of length 2π . The inherent periodicity defines the frequency response on the entire frequency axis. It is common use to specify H over the interval $-\pi \leq \omega \leq \pi$. Then, the frequencies around even multiples of π are referred to as *low frequencies*, while those around odd multiples of π are *high frequencies*.