Digital Signal Processing

Chapter IV: The Fourier Transform and its applications

IV.1 Vector spaces of signals (crash course)

Vector spaces

- **Vector space** $=$ a set $V\{v_i\}$ with the following two properties:
  - one element $+$ another element $=$ still an element of the same space
  - a scalar constant $\times$ an element $=$ still an element of the same space
- You **can't escape** a vector space by summing or scaling
- The elements of a vector space are called **vectors**

Examples of vector spaces

- Geometric spaces are great intuitive examples:
  - a line, or the set $\mathbb{R}$ (one-dimensional)
  - a plane, or the set $\mathbb{C}$ (two-dimensional)
  - 3D space (three-dimensional)
  - 4D space (four-dimensional, like the spatio-temporal universe)
  - arrays with N numbers (N-dimensional)
  - space of continuous signals (∞-dimensional)
- The **dimension** of the space = "how many numbers you need in order to specify one element" (informal)
- A "vector" like in maths = a sequence of N numbers = a "vector" like in programming
  - e.g. a point in a plane has two coordinates = a vector of size $N = 2$
  - e.g. a point in a 3D-space has three coordinates = a vector of size $N = 3$

Inner product

- Many vector spaces have a fundamental operation: **the (Euclidean) inner product**
  - for **discrete** signals:
$$\langle \mathbf{x}, \mathbf{y} \rangle = \sum_i x_i y_i^*$$
  - for **continuous** signals:
$$\langle \mathbf{x}, \mathbf{y} \rangle = \int x(t) y^*(t)$$
- * represents **complex conjugate** (has no effect for real signals)
- The result is one number (real or complex)
- Also known as **dot product** or **scalar product** (“produs scalar”)

Inner product

- Each entry in $\mathbf{x}$ times the complex conjugate of the one in $\mathbf{y}$, all summed
- For discrete signals, it can be understood as a row $\times$ column multiplication
- Discrete vs continuous: just change sum/integral depending on signal type

Inner product properties

- Inner product is **linear** in both terms:

$$\langle \mathbf{x_1} + \mathbf{x_2}, \mathbf{y} \rangle = \langle \mathbf{x_1}, \mathbf{y} \rangle + \langle \mathbf{x_2}, \mathbf{y} \rangle$$

$$\langle c \cdot \mathbf{x}, \mathbf{y} \rangle = c \cdot \langle \mathbf{x_1}, \mathbf{y} \rangle$$

$$\langle \mathbf{x}, \mathbf{y_1} + \mathbf{y_2} \rangle = \langle \mathbf{x}, \mathbf{y_1} \rangle + \langle \mathbf{x}, \mathbf{y_2} \rangle$$

$$\langle \mathbf{x}, c \cdot \mathbf{y} \rangle = c^* \cdot \langle \mathbf{x_1}, \mathbf{y} \rangle$$

The distance between two vectors

- An inner product induces a **norm** and a **distance** function
- **The (Euclidean) distance** between two vectors =

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + ... + (x_N - y_N)^2}$$

- This distance is the **usual geometric distance** you know from geometry
- It has the exact same intuition like in **normal geometry**:
  - if two vectors have small distance, they are close, they are similar
  - two vectors with large distance are far away, not similar
  - two identical vectors have zero distance

The norm of a vector

- An inner product induces a **norm** and a **distance** function
- The **norm** (length) of a vector = sqrt(inner product with itself)

$$\|\mathbf{x}\| = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle} = \sqrt{x_1^2 + x_2^2 + ... + x_N^2}$$

- The **norm** of a vector is the distance from $\mathbf{x}$ to point $\mathbf{0}$.
- It has the exact same intuition like in **normal geometry**:
    - vector has large norm = has big values, is far from $\mathbf{0}$
    - vector has small norm = has small values, is close to $\mathbf{0}$
    - vector has zero norm = it is the vector $\mathbf{0}$
- Norm of a vector = sqrt(the signal **energy**)

Norm and distance

- The norm and distance are related
- The distance between **a** and **b** = norm (length) of their difference

$$d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\| = \sqrt{x_1^2 + x_2^2 + ... + x_N^2}$$

- Just like in geometry: distance = length of the difference vector

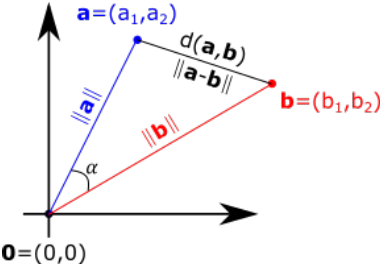

Figure 1: Norm and distance in vector spaces

Angle between vectors

- The **angle** between two vectors is:

$$\cos(\alpha) = \frac{\langle x, y \rangle}{||x|| \cdot ||y||}$$

  - is a value between -1 and 1

- **Otrhogonal vectors** $=$ two vectors with $\langle x, y \rangle = 0$
  - their angle $= 90\,\text{deg}$
  - in geometric language, the two vectors are **perpendicular**

Why vector space

- Why are all these useful?
- They are a very general **framework** for different kinds of signals
- We can have **generic** algorithms expressed in terms of distances, norms, angles, and they will work the same in all vector spaces
  - Example in DEDP class: ML decision with 1, 2, N samples

Vector spaces in DSP class

We deal mainly with the following vector spaces:

- The vector space of all infinitely-long real signals $x[n]$
- The vector space of all infinitely-long periodic signals $x[n]$ with period N
  - for each N we have a different vector space
- The vector space of all finite-length signals $x[n]$ with only N samples
  - for each N we have a different vector space

Bases

- A **basis** = a set of N linear independent elements from a vector space

$$B = \{\mathbf{b}^1, \mathbf{b}^2 ... \mathbf{b}^N\}$$

- Any vector in a vector space is expressed as a **linear combination** of the basis elements:

$$\mathbf{x} = \alpha_1 \mathbf{b}^1 + \alpha_2 \mathbf{b}^2 + ... + \alpha_N \mathbf{b}^N$$

- The vector is defined by these coefficients:

$$\mathbf{x} = (\alpha_1, \alpha_2, ... \alpha_N)$$

Bases and coordinate systems

- Bases are just like **coordinate systems** in a geometric space
  - any point is expressed w.r.t. a coordinate system

$$\mathbf{x} = x_1 \mathbf{i} + x_2 \mathbf{j}$$

  - any vector is expressed w.r.t. a basis

$$\mathbf{x} = \alpha_1 \mathbf{b}^1 + \alpha_2 \mathbf{b}^2 + \cdots + \alpha_N \mathbf{b}^N$$

- N = The number of basis elements = The dimension of the space
- Example: any color = RGB values (monitor) or Cyan-Yellow-Magenta values (printer)

Bases and coordinate systems

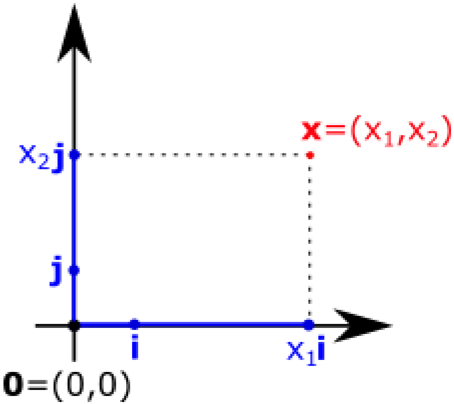

Figure 2: Basis expansion of a vector x

Choice of bases

- There is typically an infinite choice of bases
- The **canonical basis** = all basis vectors are full of zeros, just with one 1
- You used it already in an exercise:
  - any signal $x[n]$ can be expressed of a sum of $\delta[n-k]$

$$\{\dots, 3, 6, 2, \dots\} = \dots + 3\delta[n] + 6\delta[n-1] + 2\delta[n-2] + \dots$$

  - the canonical basis is $B = \{..., \delta[n], \delta[n-1], \delta[n-2], \dots\}$

Orthonormal bases

- An **orthonormal basis** a basis where all elements $\mathbf{b}^i$ are:
  - orthogonal to each other:
$$\langle \mathbf{b}^i, \mathbf{b}^j \rangle = 0, \forall i \neq j$$
  - **normalized** (their norm $= 1$):
$$||\mathbf{b}^i|| = \sqrt{\langle \mathbf{b}^i, \mathbf{b}^i \rangle} = 1, \forall i$$
- Example: the canonical basis $\{\delta[n-k]\}$ is orthonormal:
  - $\langle \delta[n-k], \delta[n-l] \rangle = 0, \forall k \neq l$
  - $\langle \delta[n-k], \delta[n-k] \rangle = 1, \forall k$

Orthonormal bases

- Orthonormal basis = like a coordinate system with orthogonal vectors, of length 1

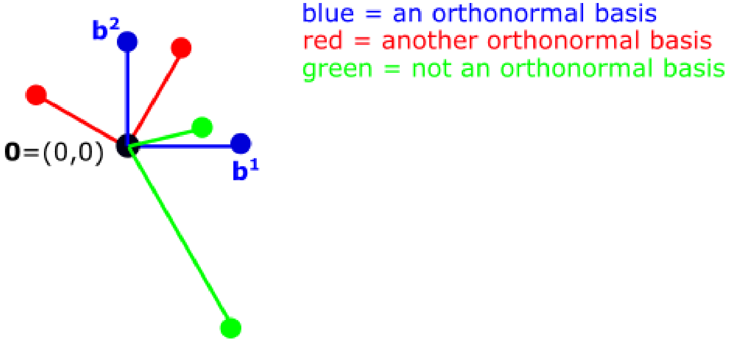

Figure 3: Sample bases in a 2D space

Basis expansion of a vector

- Suppose we have an **orthonormal basis** $B = \{\mathbf{b}^i\}$
- Suppose we have a vector $\mathbf{x}$
- We can write (expand) $\mathbf{x}$ as:

$$\mathbf{x} = \alpha_1 \mathbf{b}^1 + \alpha_2 \mathbf{b}^2 + \cdots + \alpha_N \mathbf{b}^N$$

- Question: how to **find** the coefficients α_i?

Basis expansion of a vector

- If the basis is **orthonormal**, we have:

$$
\begin{aligned}
\langle \mathbf{x}, \mathbf{b}^i \rangle =& \langle \alpha_1 \mathbf{b}^1 + \alpha_2 \mathbf{b}^2 + \cdots + \alpha_N \mathbf{b}^N, \mathbf{b}^i \rangle \\
&= \langle \alpha_1 \mathbf{b}^1, \mathbf{b}^i \rangle + \langle \alpha_2 \mathbf{b}^2, \mathbf{b}^i \rangle + \cdots + \langle \alpha_N \mathbf{b}^N, \mathbf{b}^i \rangle \\
&= \alpha_1 \langle \mathbf{b}^1, \mathbf{b}^i \rangle + \alpha_2 \langle \mathbf{b}^2, \mathbf{b}^i \rangle + \cdots + \alpha_N \langle \mathbf{b}^N, \mathbf{b}^i \rangle \\
&= \alpha_i
\end{aligned}
$$

Basis expansion of a vector

- Any vector $\mathbf{x}$ can be written as:

$$\mathbf{x} = \alpha_1 \mathbf{b}^1 + \alpha_2 \mathbf{b}^2 + \cdots + \alpha_N \mathbf{b}^N$$

- For orthonormal basis: the coefficients α_i are found by inner product with the corresponding basis vector:

$$\alpha_i = \langle, \mathbf{x}, \mathbf{b}^i \rangle$$

Why bases

- How does all this talk about bases help us?
- To better understand the Fourier transform
- The signals $\{e^{j\omega n}\}$ form an **orthonormal basis**
- The Fourier Transform of a signal x = finding the coefficients of $\mathbf{x}$ in this basis
- The Inverse Fourier Transform = expanding $\mathbf{x}$ with the elements of this basis
- Same **generic** thing every time, only the type of signals differ

IV.2 Introducing the Fourier Transforms

Reminder

- Reminder:

$$e^{jx} = \cos(x) + j\sin(x)$$

$$\cos(x) = \frac{e^{jx} + e^{-jx}}{2}$$

$$\sin(x) = \frac{e^{jx} - e^{-jx}}{2j}$$

$$\sin(x) = \cos(x - \frac{\pi}{2})$$

$$\cos(x) = \sin(x + \frac{\pi}{2})$$

Why sinusoidal signals

- Why are sinusoidal signals sin() and cos() **so prevalent** in signal processing?
- Answer: because they are combinations of an e^{jx} and an e^{-jx}
- Why are these e^{jx} so special?
- Answer: because they are **eigen-functions** of linear and time-invariant (LTI) systems

Response of LTI systems to harmonic signals

- Consider an LTI system with $h[n]$
- Input signal = complex harmonic (exponential) signal $x[n] = Ae^{j\omega_0 n}$
- Output signal = convolution

$$
\begin{aligned}
y[n] &= \sum_{k=-\infty}^{\infty} h[k]x[n-k] \\
&= \sum_{k=-\infty}^{\infty} h[k]e^{-j\omega_0 k} Ae^{j\omega_0 n} \\
&= H(\omega_0) \cdot x[n]
\end{aligned}
$$

- Output signal = input signal $\times$ a (complex) constant $(H(\omega_0))$

Eigen-function

- **Eigen-function** of a system ("funcție proprie") = a function f which, if input in a system, produces an output proportional to it

$$H\{f\} = \lambda \cdot f, \lambda \in \mathbb{C}$$

  - just like **eigen-vectors** of a matrix (remember algebra): $A\underset{\approx}{x} = \lambda\underset{\approx}{x}$
  - we call the "functions" to allow for continuous signals as well

- Complex exponential signals $e^{j\omega t}$ (or $e^{j\omega n}$) are **eigen-functions** of Linear and Time Invariant (LTI) systems:

  - output signal = input signal $\times$ a (complex) constant

Representation with respect to eigen-functions (-vectors)

- We can understand the effect of a LTI system very easily if we **decompose all signals** $x[n]$ **as a combination of** $\{e^{j\omega n}\}$
- Example: RGB color filter
  - suppose we have some photographic filters (lenses):
    - one reduces red to 50%
    - one reduces green to 25%
    - one reduces blue to 80%
    - RGB are eigen-functions of the system: input = 200 Blue, output = 0.8 * 200 Blue
    - what is the output color if input is “pink”?
    - Answer is easy if we represent all colors in RGB

Representation with respect to eigen-functions (-vectors)

- We can understand the effect of a LTI system **very easily** if we decompose all signals as a combination of $\{e^{j\omega n}\}$
- All vector space theory becomes useful now:
  - $\{e^{j\omega n}\}$ is an **orthonormal basis**
  - decomposing signals = finding coefficients α_i
  - we know how to do this, just like for any orthonormal basis

$$x[n] = \sum \alpha_\omega \cdot e^{j\omega n}$$

$$\alpha_\omega = \langle x, e^{j\omega n} \rangle$$

Discrete-Time Fourier Transform (DTFT)

- Consider the vector space of **non-periodic infinitely-long signals**
- This vector space is **infinite-dimensional**
- The signals $\{e^{j2\pi fn}\}, \forall f \in [-\frac{1}{2}, \frac{1}{2}]$ form an **orthonormal basis**
- We can expand (almost) any $\mathbf{x}$ in this basis:

$$x[n] = \int_{f=-1/2}^{1/2} \underbrace{X(f)}_{\alpha_\omega} e^{j2\pi fn} df$$

- The coefficient of every $e^{j2\pi fn}$ is found by inner product:

$$\alpha_\omega = X(f) = \langle x[n], e^{j2\pi fn} \rangle = \sum_n x[n] e^{-j2\pi fn}$$

Discrete-Time Fourier Transform (DTFT)

Inverse Discrete-Time Fourier Transform (DTFT)

$$x[n] = \int_{f=-1/2}^{1/2} X(f) e^{j2\pi fn} df$$

- A signal $x[n]$ can be written as a linear combination of $\{e^{j2\pi fn}\}, \forall f \in [-\frac{1}{2}, \frac{1}{2}]$, with some coefficients $X(f)$

Discrete-Time Fourier Transform (DTFT)

$$X(f) = \langle x[n], e^{j2\pi fn} \rangle = \sum_{n=\infty}^{\infty} x[n] e^{-j2\pi fn}$$

- The coefficient $X(f)$ of every $\{e^{j2\pi fn}\}$ is found using the inner product $\langle \mathbf{x}, e^{j2\pi fn} \rangle$

Discrete-Time Fourier Transform (DTFT)

- Alternative form with ω
- We can replace $2\pi f = \omega$, and $df = \frac{1}{2\pi} d\omega$

$$x[n] = \frac{1}{2\pi} \int_{\omega=-\pi}^{\pi} X(\omega) e^{j\omega n} d\omega$$

$$X(\omega) = \langle x[n], e^{j\omega n} \rangle = \sum_{n} x[n] e^{-j\omega n}$$

Discrete-Time Fourier Transform (DTFT)

- A non-periodic signal $x[n]$ has a **continuous spectrum** $X(\omega)$, with $f \in [-\frac{1}{2}, \frac{1}{2}]$
  - e.g. $\omega \in [-\frac{1}{2}, \frac{1}{2}]$

Discrete Fourier Transform (DFT)

- Consider the vector space of **periodic** signals with **period N**
  - for some fixed $N = 2$, 3 or ... etc
- This is a vector space of **dimension N**
  - we need N numbers to identify a signal (specify its period)
- We can consider $x[n]$ only for **one period**, i.e. $n = 0, \dots N - 1$
- The signals $\{e^{j2\pi fn}\}, \forall f \in \{0, \frac{1}{N}, \dots \frac{N-1}{N}\}$ form an **orthonormal basis** with N elements
- It is a **discrete** set of frequencies: $f = \frac{k}{N}, \forall k \in \{0, 1, \dots N - 1\}$

Discrete Fourier Transform (DFT)

Inverse Discrete Fourier Transform

$$x[n] = \sum_{k=0}^{N-1} X_k e^{j2\pi kn/N}$$

- A periodic signal $x[n]$ can be written as a linear combination of k signals $\{e^{j2\pi kn/N}\}$, with some coefficients X_k

Discrete Fourier Transform

$$X_k = \frac{1}{N}\langle x[n], e^{j2\pi fn}\rangle = \sum_{n=0}^{N-1} x[n]e^{-j2\pi kn/N}$$

- The coefficient $X(f)$ of every $\{e^{j2\pi fn}\}$ is found using the inner product $\langle \mathbf{x}, e^{j2\pi fn}\rangle$

Discrete Fourier Transform (DFT)

- A periodic signal $x[n]$ with period N has a **discrete spectrum** $X(\omega)$ composed of only N frequencies $\{0, \frac{1}{N} \dots \frac{N-1}{N}\}$
- Each frequency $\frac{k}{N}$ has a **coefficient** X_k
  - also written as c_k
  - The N coefficients X_k are the equivalent of $X(\omega)$
- It is also known as the "Fourier Series for Discrete Signals"

IV.3 The Discrete-Time Fourier Transform (DTFT)

Definition

Definitions (again):

Inverse Discrete-Time Fourier Transform (DTFT)

$$x[n] = \int_{f=-1/2}^{1/2} X(f) e^{j2\pi fn} df = \frac{1}{2\pi} \int_{\omega=-\pi}^{\pi} X(\omega) e^{j\omega n} d\omega$$

Discrete-Time Fourier Transform (DTFT)

$$X(f) = \langle x[n], e^{j2\pi fn} \rangle = \sum_{n=\infty}^{\infty} x[n] e^{-j2\pi fn}$$

Basic properties of DTFT

- $X(\omega)$ is defined only for $\omega \in [-\pi, \pi]$
  - or $f \in [-\frac{1}{2}, \frac{1}{2}]$
- $X(\omega)$ is complex (has $|X(\omega)|$, $\angle X(\omega)$)
- If the signal $x[n]$ is real, $X(\omega)$ is **even**

$$x[n] \in \mathbb{R} \to X(-\omega) = X^*(\omega)$$

  - This means:
    - modulus is even: $|X(\omega)| = |X(-\omega)|$
    - phase is odd: $X(\omega) = -X(-\omega)$

Expressing as sum of sinusoids

- Grouping terms with $e^{j\omega n}$ and $e^{j(-\omega)n}$ we get:

$$
\begin{aligned}
x[n] &= \frac{1}{2\pi}\int_{-\pi}^{0} X(\omega)e^{j\omega n} + \frac{1}{2\pi}\int_{0}^{\pi} X(\omega)e^{j\omega n}d\omega \\
&= \frac{1}{2\pi}\int_{0}^{\pi} (X(\omega)e^{j\omega n} + X(-\omega)e^{j(-\omega)n})d\omega \\
&= \frac{1}{2\pi}\int_{0}^{\pi} 2|X(\omega)|(e^{j\omega n+\angle X(\omega)} + e^{-j\omega n-\angle X(\omega)})d\omega \\
&= \frac{1}{2\pi}\int_{0}^{\pi} 2|X(\omega)|\cos(\omega n + \angle X(\omega))d\omega
\end{aligned}
$$

- Any signal $x[n]$ is **a sum of sinusoids with all frequencies** $f \in [0, \frac{1}{2}]$, or $\omega \in [0, \pi]$

Expressing as sum of sinusoids

- Any signal $x[n]$ is **a sum of sinusoids with all frequencies** $f \in [0, \frac{1}{2}]$, or $\omega \in [0, \pi]$
  - this is the fundamental practical interpretation of the Fourier transform
- The **modulus** $|X(\omega)|$ is the **amplitude** of the sinusoids ($\times$ 2)
  - for $\omega = 0$, $|X(\omega = 0)|$ = the DC component
- The **phase** $\angle X(\omega)$ gives the initial phase

Properties of DTFT

1. Linearity

$$a \cdot x_1[n] + b \cdot x_2[n] \leftrightarrow a \cdot X_1(\omega) + b \cdot X_2(\omega)$$

Proof: via definition

Properties of DTFT

2. Shifting in time

$$x[n - n_0] \leftrightarrow e^{-j\omega n_0} X(\omega)$$

Proof: via definition

- The amplitudes $|X(\omega)|$ is not affected, shifting in time affects only the phase

Properties of DTFT

3. Modulation in time

$$e^{j\omega_0 n}x[n] \leftrightarrow X(\omega - \omega_0)$$

4. Complex conjugation

$$x^*[n] \leftrightarrow X^*(-\omega)$$

Properties of DTFT

5. Convolution

$$x_1[n] * x_2[n] \leftrightarrow X_1(\omega) \cdot X_2(\omega)$$

- Not circular convolution, this is the normal convolution

Properties of DTFT

6. Product in time

Product in time $\leftrightarrow$ convolution of Fourier transforms

$$x_1[n] \cdot x_2[n] \leftrightarrow \frac{1}{2\pi} \int_{-\pi}^{\pi} X_1(\lambda) X_2(\omega - \lambda) d\lambda$$

Properties of DTFT

Correlation theorem

$$r_{x_1x_2}[l] \leftrightarrow X_1(\omega)X_2(-\omega)$$

Wiener Khinchin theorem

Autocorrelation of a signal $\leftrightarrow$ Power spectral density

$$r_{xx}[l] \leftrightarrow S_{xx}(\omega) = |X(\omega)|^2$$

Parseval theorem

- **Parseval theorem**: energy of the signal is the same in time and frequency domains

$$E = \sum_{-\infty}^{\infty} |x[n]|^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} |X(\omega)|^2$$

- Is true for all orthonormal bases

IV.4 The Discrete Fourier Transform (DFT)

Definitions

Definitions (again)

Inverse Discrete Fourier Transform (DFT)

$$x[n] = \sum_{k=0}^{N-1} X_k e^{j2\pi kn/N}$$

Discrete Fourier Transform (DFT)

$$X_k = \frac{1}{N} \langle x[n], e^{j2\pi fn} \rangle = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/N}$$

Periodicity and notation

- In discrete domain, $f = \frac{N-k}{N} = \frac{-k}{N}$ (aliasing, we can subtract 1 from f)
- We can consider X_{N-k} as X_{-k}, due to periodicity
- Example: a signal with period $N = 6$ has 6 DFT coefficients
  - we can call them X_0, X_1, X_2, X_3, X_4, X_5
  - we have $X_5 = X_{-1}$, $X_4 = X_{-2}$
  - we can also call them X_{-2}, X_{-1}, X_0, X_1, X_2, X_3

Basic Properties of the DFT

- X_k is complex (has $|X_k|$, $\angle X_k$)
- If the signal $x[n]$ is real, the coefficients are **even**

$$x[n] \in \mathbb{R} \rightarrow X_{-k} = X_k^*$$

  - This means:
    - modulus is even: $|X_k| = |X_{-k}|$
    - phase is odd: $\angle X_{-k} = -\angle X_k$

Expressing as sum of sinusoids

- Grouping terms with k and $-k$:
- If N is odd, we have X_0 and pairs (X_k, X_{-k}):

$$
\begin{aligned}
x[n] &= X_0 e^{j0n} + \frac{1}{N}\sum_{k=-(N-1)/2}^{0} X_k e^{j2\pi kn/N} + \frac{1}{N}\sum_{k=0}^{(N-1)/2} X_k e^{j2\pi kn/N} \\
&= X(0) + \frac{1}{N}\sum_{k=0}^{(N-1)/2} \left(X_k e^{j2\pi kn/N} + X_{-k} e^{-j2\pi kn/N}\right) \\
&= X(0) + \frac{1}{N}\sum_{k=0}^{(N-1)/2} 2|X_k|\left(e^{j2\pi kn/N + \angle X(k)} + e^{-j2\pi kn/N - \angle X(\omega)}\right) \\
&= X(0) + \frac{1}{N}\sum_{k=0}^{(N-1)/2} 2|X_k| \cos(2\pi k/Nn + \angle X_k)
\end{aligned}
$$

Expressing as sum of sinusoids

- If N is even, we have X_0 and pairs $(X_k,\ X_{-k})$, with an extra term $X_{N/2}$ which has no pair
  - e.g. N = 6: $X_{-2}, X_{-1}, X_0, X_1, X_2, X_3$
- $X_{N/2}$ must be a real number
- The extra term will be $\frac{1}{N}X_{N/2}e^{j2\pi N/2n/N} = X_{N/2}\cos(n\pi)$
- Overall:

$$x[n] = X(0) + \frac{1}{N}\sum_{k=0}^{(N-2)/2} 2|X_k|\cos(2\pi k/Nn + \angle X_k) + \frac{1}{N}X_{N/2}\cos(n\pi)$$

- Any signal $x[n]$ is **a sum of sinusoids with frequencies** $f = 0$, 1/N, 2/N, ... (N-1)/2 or N/2

Expressing as sum of sinusoids

- Any periodic signal $x[n]$ with period N is **a sum of N sinusoids with frequencies** $f = 0$, 1/N, 2/N, ... (N-1)/2 or N/2
- The **modulus** $|X_k|$ gives the **amplitude** of the sinusoids (sometimes $\times$ 2)
  - for $\omega = 0$, $|X_0| =$ the DC component
  - when modulus $= 0$, that frequency has amplitude 0
- The **phase** $\angle X_k$ gives the initial phase

Properties of the DFT

1. Linearity

If the signal $x_1[n]$ has the DFT coefficients $\{X_k^{(1)}\}$, and $x_2[n]$ has $\{X_k^{(2)}\}$, then their sum has
$a \cdot x_1[n] + b \cdot x_2[n] \leftrightarrow \{a \cdot X_k^{(1)} + b \cdot X_k^{(2)}\}$
Proof: via definition

Properties of Fourier series

2. Shifting in time

If $x[n] \leftrightarrow \{X_k\}$, then

$$x[n - n_0] \leftrightarrow \{e^{(-j2\pi k n_0/N)} X_k\}$$

Proof: via definition

- The amplitudes $|X_k|$ are not affected, shifting in time **affects only the phase**

Properties of Fourier series

3. Modulation in time

$$e^{j2\pi k_0 n/N} \leftrightarrow \{X_{k-k_0}\}$$

4. Complex conjugation

$$x^*[n] \leftrightarrow \{X^*_{-k}\}$$

Properties of Fourier series

5. Circular convolution

Circular convolution of two signals $\leftrightarrow$ product of coefficients

$$x_1[n] \otimes x_2[n] \leftrightarrow \{N \cdot X_k^{(1)} \cdot X_k^{(2)}\}$$

Circular convolution definition:

$$x_1[n] \otimes x_2[n] = \sum_{k=0}^{N-1} x_1[k] x_2[(n-k)_N]$$

- takes two periodic signals of period N, result is also periodic with period N
- Example at the whiteboard: how it is computed

Circular convolution

- We are in the vector space of **periodic signals** with period N
- Linear (e.g. normal) convolution produces a result which is longer periodic with period N
- Circular convolution takes two sequences of length N and produces another sequence of length N
  - each sequence is a period of a periodic signal
  - circular convolution $=$ like a convolution of periodic signals

Properties of Fourier series

6. Product in time

Product in time $\leftrightarrow$ circular convolution of Fourier series coefficients

$$x_1[n] \cdot x_2[n] \leftrightarrow \sum_{m=0}^{N-1} X_m^{(1)} X_{(k-m)_N}^{(2)} = X_k^{(1)} \otimes X_k^{(2)}$$

Properties of Fourier series

- **Parseval theorem**: energy of the signal is the same in time and frequency domains

$$E = \sum_{0}^{N-1} |x[n]|^2 = \frac{1}{2\pi} \sum |X_k|^2$$

- Is true for all orthonormal bases

Relationship between DTFT and DFT

- How are DTFT and DFT related?
- Discrete Time Fourier Transform:
  - for non-periodical signals
  - spectrum is continuous
- Discrete Fourier Transform
  - for periodical signals
  - spectrum is discrete
- Duality: periodic in time $\leftrightarrow$ discrete in frequency

Relationship between DTFT and DFT

- Consider a non-periodic signal $x[n]$
- It has a continuous spectrum $X(\omega)$
- If we **periodize** it by repeating with period N:

$$x_N[n] = \sum_{k=-\infty}^{\infty} x[n - kN]$$

- then the Fourier transform is **discrete** (made of Diracs):

$$X_N(\omega) = 2\pi X_k \delta(\omega - k\frac{2\pi}{N})$$

- The coefficients of the Diracs = the DFT coefficients

$$X_k = X(2\pi k/Nn)$$

Relationship between DTFT and DFT

- Example: consider a sequence of 7 values

$$x = [6, 3, -4, 2, 0, 1, 2]$$

- If we consider a non-periodic $x[n]$ with infinitely long zeros on either side, we have a continuous spectrum $X(\omega)$ (DTFT)
- If we consider that x is just a period of a periodic signal, we have a discrete spectrum X_k (DFT)
- Moreover, the discrete X_k are just **samples from** $X(\omega)$:

$$X_k = X(2\pi k/Nn)$$

Relation between DTFT and Z transform

- Z transform:

$$X(z) = \sum_n x[n] z^{-n}$$

- DTFT:

$$X(\omega) = \sum_n x[n] e^{-j\omega n}$$

- DTFT can be obtained from Z transform with

$$z = e^{j\omega}$$

- These $z = e^{j\omega}$ are **points on the unit circle**
  - $|z| = |e^{j\omega}| = 1(modulus)$
  - $\angle z = \angle e^{j\omega} = \omega(phase)$

Relation between DTFT and Z transform

- Fourier transform = Z transform evaluated **on the unit circle**
  - if the unit circle is in the convergence region of Z transform
  - otherwise, equivalence does not hold
- This is true for most usual signals we work with
  - some details and discussions are skipped

Geometric interpretation of Fourier transform

$$X(z) = C \cdot \frac{(z - z_1)\cdots(z - z_M)}{(z - p_1)\cdots(z - p_N)}$$

$$X(\omega) = C \cdot \frac{(e^{j\omega} - z_1)\cdots(e^{j\omega} - z_M)}{(e^{j\omega} - p_1)\cdots(e^{j\omega} - p_N)}$$

- Modulus:

$$|X(\omega)| = |C| \cdot \frac{|e^{j\omega} - z_1|\cdots|e^{j\omega} - z_M|}{|e^{j\omega} - p_1|\cdots|e^{j\omega} - p_N|}$$

- Phase:

$$\angle X = \angle C + \angle(e^{j\omega} - z_1) + \cdots + \angle(e^{j\omega} - z_M) - \angle(e^{j\omega} - p_1) - \cdots - \angle(e^{j\omega} - p_N)$$

Geometric interpretation of Fourier transform

- For complex numbers:
  - modulus of $|a - b|$ = the length of the segment between a and b
  - phase of $|a - b|$ = the angle of the segment from b to a (direction is important)
- So, for a point on the unit circle $z = e^{j\omega}$
  - modulus $|X(\omega)|$ is **given by the distances to the zeros and to the poles**
  - phase $\angle X(\omega)$ is **given by the angles from the zeros and poles to z**

Geometric interpretation of Fourier transform

- Consequences:
  - when a **pole** is very close to unit circle –> Fourier transform is **large** at this point
  - when a **zero** is very close to unit circle –> Fourier transform is **small** at this point
- Examples: ...

Geometric interpretation of Fourier transform

- Simple interpretation for modulus $|X(\omega)|$:
  - Z transform $X(z)$ is like **a landscape**
    - **poles = mountains** of infinite height
    - **zeros = valleys** of zero height
  - Fourier transform $X(\omega) =$ "*Walking over this landscape along the unit circle*"
  - The height profile of the walk gives the amplitude of the Fourier transform
  - When close to a mountain –> road is high –> Fourier transform has large amplitude
  - When close to a valley –> road is low –> Fourier transform has small amplitude

Geometric interpretation of Fourier transform

- Note: $X(z)$ might also have a constant C in front!
  - It does not appear in pole-zero plot
  - The value of $|C|$ and $\angle C$ must be determined separately
- This "geometric method" can be applied for phase as well

Time-frequency duality

- **Duality** properties related to Fourier transform/series
- Discrete $\leftrightarrow$ Periodic
  - **discrete** in time –> **periodic** in frequency
  - **periodic** in time –> **discrete** in frequency
- Continuous $\leftrightarrow$ Non-periodic
  - **continous** in time –> **non-periodic** in frequency
  - **non-periodic** in time –> **continuous** in frequency

Terminology

- Based on frequency content:
  - **low-frequency** signals
  - **mid-frequency** signals (band-pass)
  - **high-frequency** signals
- **Band-limited** signals: spectrum is 0 beyond some frequency f_{max}
- **Bandwitdh** B: frequency interval $[F_1, F_2]$ which contains 95% of energy
  - $B = F_2 - F_1$
- Based on bandwidth B:
  - **Narrow-band** signals: $B << \text{central frequency } \frac{F_1+F_2}{2}$
  - **Wide-band** signals: not narrow-band