

# 3F1, Signals and Systems

PART V.1

Discrete Fourier Transform

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Goal of the lecture:

The DFT tool in digital filtering



#### From $\mathcal{Z}$ to DTFT

#### z-transform:

Signal: 
$$x_k \Rightarrow X(z) := \mathcal{Z}(x) = \sum_{k=0}^{\infty} x_k z^{-k}$$

#### Discrete time Fourier transform:

Fourier transform of a sampled signal, sampling time T

$$\bar{x}_{\omega} := \text{DTFT}(x) = \sum_{k=-\infty}^{\infty} x_k e^{-j\omega Tk}$$

#### Relation between Z and DTFT:

if  $x_k = 0$  for k < 0 then

$$\bar{x}_{\omega} = X(z)_{|z=e^{j\omega}} \tau$$

#### From DTFT to DFT

Digital signal: 
$$\{x_k\}$$
  $x_k = 0$  for  $k < 0$ 

#### Discrete time Fourier transform:

Fourier transform of a sampled signal, sampling time T

$$\bar{x}_{\omega} := \text{DTFT}(x) = \sum_{k=0}^{\infty} x_k e^{-j\omega Tk}$$

- $\blacktriangleright$   $\omega$  is continuous, how to represent it in a computer?
- infinite sum, how to compute it?

$$\Rightarrow$$

- ▶ Sampling a finite number of frequencies  $\omega$  (small sampling  $\rightarrow$  good approximation).
- Truncation, use a finite number of data points.

#### From DTFT to DFT

Digital signal: 
$$\{x_k\}$$
  $x_k = 0$  for  $k < 0$ 

#### Discrete time Fourier transform:

$$\bar{x}_{\omega} := \mathrm{DTFT}(x) = \sum_{k=0}^{\infty} x_k e^{-j\omega Tk}$$

## **Discrete Fourier transform:**

$$\bar{x}_p := \sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}pk}$$

- Finite sampling:  $\omega = \frac{2\pi}{NT}$
- ▶ Finite computation: finite data points  $0 \le k \le N$
- ▶ Finite representation:  $0 \le p \le N 1$

periodicity 
$$ar{x}_p = ar{x}_{p+N}$$
 since  $e^{-jrac{2\pi}{N}(p+N)} = e^{-jrac{2\pi}{N}p}$ 

#### DFT and $\mathcal{Z}$

Digital signal: 
$$\{x_k\}$$
  $x_k = 0$  for  $k < 0$ 

#### Discrete Fourier transform:

$$\bar{x}_p := \sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}pk}$$
  $0 \le p \le N-1$ 

#### Relation with z-transform:

(for truncated signals  $x_k = 0$  for k < 0 and  $k \ge N$ )

$$X(z) := \sum_{k=0}^{\infty} x_k z^{-k} = \sum_{k=0}^{N-1} x_k z^{-k}$$
$$\bar{x}_p = X(z)_{|z=e^{-j\frac{2\pi}{N}p}}$$

Let's understand the DFT...

Digital signal:  $\{x_k\}$ 

#### Discrete Fourier transform:

$$\bar{x}_p := \sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}pk}$$

Take

$$x := \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{N-1} \end{bmatrix}, \ b(p, N) := \begin{bmatrix} e^{-j\frac{2\pi}{N}p \cdot 0} \\ e^{-j\frac{2\pi}{N}p \cdot 1} \\ \vdots \\ e^{-j\frac{2\pi}{N}p \cdot (N-1)} \end{bmatrix}$$

Then

$$\bar{x}_p := b(p, N)'x$$

(b(p, N)') is the transpose of b(p, N)

 $\bar{x}_p$  is the projection of x on the base b(p, N)!

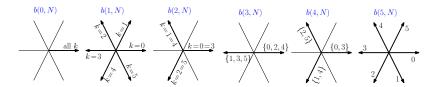
# Digital signal: $\{x_k\}$

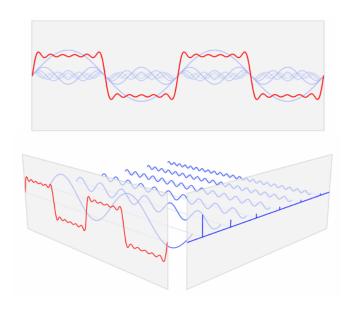
#### Discrete Fourier transform:

$$\bar{x}_{p} := \sum_{k=0}^{N-1} x_{k} e^{-j\frac{2\pi}{N}pk} = b(p, N)'x$$

$$x := \begin{bmatrix} x_{0} \\ x_{1} \\ \vdots \\ x_{N-1} \end{bmatrix}, \quad b(p, N) := \begin{bmatrix} e^{-j\frac{2\pi}{N}p \cdot 0} \\ e^{-j\frac{2\pi}{N}p \cdot 1} \\ \dots \\ e^{-j\frac{2\pi}{N}p \cdot (N-1)} \end{bmatrix}$$

## Example N = 6: Animation





From Wikimedia Commons, by Lucas V. Barbosa

# **Discrete Fourier transform:** $\bar{x}_p := b(p, N)'x$

- one DFT sample = product of two vectors (N operations)
- ▶ N DFT samples = N × N operations.

$$\bar{x} := \begin{bmatrix} \bar{x}_0 \\ \bar{x}_1 \\ \vdots \\ \bar{x}_{N-1} \end{bmatrix} = \underbrace{\begin{bmatrix} b(0, N)' \\ b(1, N)' \\ \dots \\ b(N-1, N)' \end{bmatrix}}_{=:B(N)} x$$

▶ inverse DFT = product by inverse matrix...

$$x := B(N)^{-1}\bar{x}$$

▶ Linearity: if z = (x + y) then  $\bar{z} = \bar{x} + \bar{y}$ . For instance,

$$\bar{z} = B(N)(x+y) = B(N)x + B(N)y = \bar{x} + \bar{y}$$

# Antitransform

#### DFT

#### Inverse DFT

$$\bar{x}_p := \sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}pk}$$

$$x_n := \frac{1}{N} \sum_{p=0}^{N-1} \bar{x}_p e^{j\frac{2\pi}{N}pn}$$

## Proof [inverse DFT]

$$\frac{1}{N} \sum_{p=0}^{N-1} \underbrace{\sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}pk}}_{\bar{x}_p} e^{j\frac{2\pi}{N}pn} = \frac{1}{N} \sum_{p=0}^{N-1} \sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}p(k-n)}$$

$$= \frac{1}{N} \sum_{k=0}^{N-1} x_k \underbrace{\sum_{p=0}^{N-1} e^{-j\frac{2\pi}{N}p(k-n)}}_{0 \text{ if } k \neq n, \\ N \text{ if } k = n.}$$
$$= \frac{1}{N} x_n N = x_n$$

#### DFT

# $\bar{x}_p := \sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}pk}$ $\bar{x}_p := b(p, N)'x$ $\bar{x} = \underbrace{\begin{bmatrix} b(0,N)' \\ b(1,N)' \\ \dots \\ b(N-1,N)' \end{bmatrix}}_{X} x$

#### **Inverse DFT**

$$x_n := \frac{1}{N} \sum_{p=0}^{N-1} \bar{x}_p e^{j\frac{2\pi}{N}pn}$$

$$\Rightarrow$$

$$x_n := \frac{1}{N} b(-n, N)' \bar{x}$$

$$\Rightarrow$$

$$x = \underbrace{\frac{1}{N} \begin{bmatrix} b(0, N)' \\ b(-1, N)' \\ b(-N+1, N)' \end{bmatrix}}_{D(N)} \bar{x}$$

$$b(q,N)' := \left[ \begin{array}{ccc} e^{-j\frac{2\pi}{N}q\cdot 0} & e^{-j\frac{2\pi}{N}q\cdot 1} & \dots & e^{-j\frac{2\pi}{N}q\cdot (N-1)} \end{array} \right]$$

DFT and inverse DFT use the same algorithm!

DFT and inverse DFT share the same properties: periodicity, linearity,...

Proof [inverse DFT, based on b(q, N)]

$$\frac{b(-n,N)'}{N}\bar{x} = \frac{b(-n,N)'}{N} \begin{bmatrix} b(0,N)' \\ b(1,N)' \\ b(N-1,N)' \end{bmatrix} x$$

$$= \frac{b(-n,N)'}{N} \begin{bmatrix} e^{-j\frac{2\pi}{N}0\cdot0} & e^{-j\frac{2\pi}{N}0\cdot1} & \dots & e^{-j\frac{2\pi}{N}0\cdot(N-1)} \\ e^{-j\frac{2\pi}{N}1\cdot0} & e^{-j\frac{2\pi}{N}1\cdot1} & \dots & e^{-j\frac{2\pi}{N}1\cdot(N-1)} \\ \dots & \dots & \dots & \dots & \dots \end{bmatrix} x$$

$$= \frac{b(-n,N)'}{N} \begin{bmatrix} b(0,N) & b(1,N) & \dots & b(N-1,N) \end{bmatrix} x$$

$$= \underbrace{\begin{bmatrix} 0 & \dots & 0 \\ n-1 & 1 & 0 & \dots & 0 \end{bmatrix}}_{N-n} x = x_n$$

since

$$b(-n, N)'b(p, N) = \sum_{k=0}^{N-1} e^{-j\frac{2\pi}{N}(p-n)k} \begin{cases} 0 & p \neq n \\ N & p = n \end{cases}$$

# Properties of the DFT

# **DFT**: $x \stackrel{DFT}{\longrightarrow} \bar{x}$

► Periodicity: (slide 7)

$$\bar{x}_p = \bar{x}_{p+N}$$

► Linearity: (slide 12)

$$DFT(x + y) = DFT(x) + DFT(y)$$

▶ Symmetry: if x is a real sequence then  $\bar{x}_p = \bar{x}^*_{-p} = \bar{x}^*_{N-p}$ 

$$\bar{x}_{-p}^* = \left(\sum_{k=0}^{N-1} x_k e^{j\frac{2\pi}{N}pk}\right)^* = \sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}pk} = \bar{x}_p$$

inverse DFT:  $\bar{x} \stackrel{iDFT}{\longrightarrow} x$ 

▶ the same, DFT and iDFT are similar operations (slide 15)

#### DFT and DTFT - frequency comparison

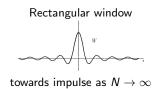
#### Discrete time Fourier transform:

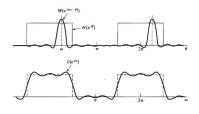
$$\bar{x}_{\omega} := \text{DTFT}(x) = \sum_{k=0}^{\infty} x_k e^{-j\omega Tk}$$

#### Discrete Fourier transform:

$$\bar{x}_p := \sum_{k=0}^{N-1} x_k e^{-j\frac{2\pi}{N}pk}$$

- Finite sampling  $\omega = \frac{2\pi}{NT}$ . No loss: we can always sample at the frequency of interest.
- Finite horizon N. Frequency distortion: rectangular window, convolution in frequency (Lecture 8). Improves for N → ∞.





# Circular convolution

Signal: 
$$\{x_k\} \xrightarrow{DFT} \{\bar{x}_p\}$$
 FIR filter:  $\{g_k\} \xrightarrow{DFT} \{\bar{g}_p\}$ 

The inverse DFT of the **product** of the DFTs

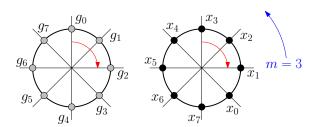
$$\bar{y}_p := \bar{g}_p \bar{x}_p , \qquad \{\bar{y}_p\} \stackrel{iDFT}{\longrightarrow} \{y_m\}$$

is the circular convolution of x and g

$$y_m := \sum_{k=0}^{N-1} g_k x_{mod(m-k,N)}$$

where mod(k - n, N) denotes k - n in modulo N arithmetic

$$\bar{y}_p = \bar{g}_p \bar{x}_p \xrightarrow{iDFT} y_m = \sum_{k=0}^{N-1} g_k x_{mod(m-k,N)}$$



Proof: compute iDFT of  $\{\bar{y}_p\} = \{\bar{g}_p\bar{x}_p\}$ 

$$y_{m} = \frac{1}{N} \sum_{p=0}^{N-1} \bar{g}_{p} \bar{x}_{p} e^{j\frac{2\pi}{N}pm} \quad (iDFT)$$

$$= \frac{1}{N} \sum_{p=0}^{N-1} \left( \sum_{k_{1}=0}^{N-1} g_{k_{1}} e^{-j\frac{2\pi}{N}pk_{1}} \right) \left( \sum_{k_{2}=0}^{N-1} x_{k_{2}} e^{-j\frac{2\pi}{N}pk_{2}} \right) e^{j\frac{2\pi}{N}pm}$$

$$= \frac{1}{N} \sum_{k_{1}=0}^{N-1} \sum_{k_{2}=0}^{N-1} g_{k_{1}} x_{k_{2}} \quad \sum_{p=0}^{N-1} e^{-j\frac{2\pi}{N}p(k_{1}+k_{2}-m)}$$

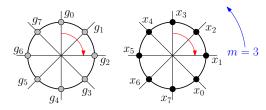
$$= \frac{N}{N} \sum_{k_{1}=0}^{N-1} g_{k_{1}} x_{mod(m-k_{1},N)} = \sum_{k_{2}=0}^{N-1} g_{k} x_{mod(m-k,N)}$$

$$= \frac{N}{N} \sum_{k_{2}=0}^{N-1} g_{k_{1}} x_{mod(m-k_{1},N)} = \sum_{k_{2}=0}^{N-1} g_{k} x_{mod(m-k,N)}$$

Filter response via DFT

#### Circular convolution

$$\bar{y}_p = \bar{g}_p \bar{x}_p \stackrel{iDFT}{\longrightarrow} y_m = \sum_{k=0}^{N-1} g_k x_{mod(m-k,N)}$$



## Filter response (standard/linear convolution)

$$y_{m} = \sum_{k=0}^{\infty} g_{k} x_{m-k}$$

$$g_{1} \quad g_{3} \quad g_{5} \quad g_{7} \quad x_{4} \quad x_{2} \quad x_{0} \quad x_{-2}$$

$$g_{0} \quad g_{2} \quad g_{4} \quad g_{6} \quad x_{5} \quad x_{3} \quad x_{1} \quad x_{-1} \quad m = 3$$

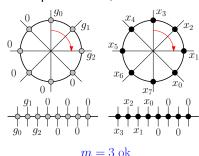
 $\{g_k\}$  FIR filter with  $M+1\ll N$  nonzero coefficients

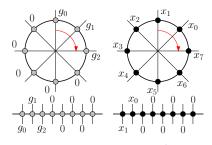
If  $M \leq m < N$ ,

$$\sum_{k=0}^{\infty} g_k x_{m-k} = \sum_{k=0}^{M} g_k x_{m-k} = \sum_{k=0}^{N-1} g_k x_{mod(m-k,N)}$$

#### standard convolution = circular convolution

## Example: M = 2, N = 8





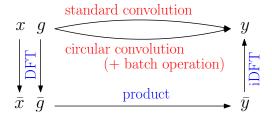
 $\{g_k\}$  FIR filter with  $M+1 \ll N$  nonzero coefficients

If  $M \leq m < N$ ,

$$\sum_{k=0}^{\infty} g_k x_{m-k} = \sum_{k=0}^{M} g_k x_{m-k} = \sum_{k=0}^{N-1} g_k x_{mod(m-k,N)}$$

#### standard convolution = circular convolution

We can use DFT for FIR filtering!





with fast algorithms DFT-product-iDFT may be more efficient than circular convolution to compute the filter response: FFT!

## Example: computation of the filter response via DFT

M = 2 (FIR horizon) and N = 8 (DFT horizon) [on Moodle]

- filter:  $[g_0 \ g_1 \ g_2 \ 0 \ 0 \ 0 \ 0] \xrightarrow{DFT} \bar{g}$
- ▶ frame 1:  $\begin{bmatrix} 0 & 0 & x_0 & x_1 & x_2 & x_3 & x_4 & x_5 \end{bmatrix} \xrightarrow{DFT} \bar{x}^1$
- ▶ frame 2:  $[x_4 \ x_5 \ x_6 \ x_7 \ x_8 \ x_9 \ x_{10} \ x_{11}] \xrightarrow{DFT} \bar{x}^2$

M from previous frame N-M new points

$$\xrightarrow{product, iDFT} y^q = [\underbrace{**}_{remove} | \underbrace{******}_{collect}]$$