

PROPERTIES OF DFT (Continued)

LINEAR AND CIRCULAR CONVOLUTION USING THE DFT

Given, $X_1(n) = \begin{cases} \neq 0, & n=0, \dots, N_1-1 \\ 0, & \text{otherwise} \end{cases}$, $X_2(n) = \begin{cases} \neq 0, & n=0, \dots, N_2-1 \\ 0, & \text{otherwise} \end{cases}$

→ LINEAR CONVOLUTION

$$X_L(n) = X_1(n) * X_2(n) = \sum_{k=0}^{N_1-1} X_1(k) X_2(n-k) = \begin{cases} \neq 0, & 0 \leq n \leq N_1+N_2-2 \\ 0, & \text{otherwise} \end{cases}$$

or in DFT terms:

$$\underline{X_L(w) = X_1(w) X_2(w)}$$

By sampling $X_L(w)$: $X(k) = X_L(w = \frac{2\pi k}{N}) = X_1(k) X_2(k)$

Then we know that: $X(k) \xleftrightarrow{N\text{-IDFT}} \sum_{\ell} X_L(n + \ell N)$

→ CIRCULAR CONVOLUTION

$$X_C(n) = X_1(n) \underset{N}{*} X_2(n) = \left[\sum_{\ell} X_L(n + \ell N) \right] R_N(n), \quad n=0, \dots, N-1$$

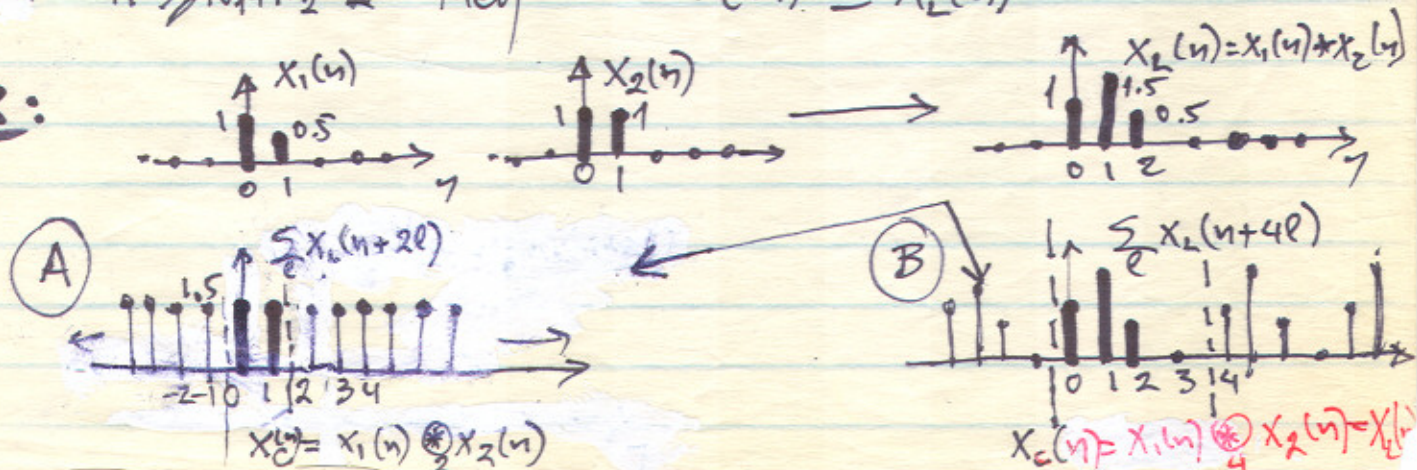
in N-DFT terms

$$\underline{X_C(k) = X_1(k) \cdot X_2(k)}, \quad k=0, \dots, N-1$$

Thus: * In discrete time domain circular convolution is one period^(N) of the periodic extension of linear convolution with period N

* If $N \geq N_1 + N_2 - 1$ then $X_C(n) \equiv X_L(n)$

Ex:



LECTURE 13

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EXERCISE: Given the $x_1(n)$, $x_2(n)$ of previous example.

Perform the steps

- ① $x_1(n) \xrightarrow{2\text{-DFT}} X_1(k)$
 - ② $x_2(n) \xrightarrow{2\text{-DFT}} X_2(k)$
 - ③ $X_c(k) = X_1(k) \cdot X_2(k)$
 - ④ $X_c(k) \xrightarrow{2\text{-IDFT}} x_c(n), n=0,1$ (Verify result in A)
- } $k=0,1$

(Repeat with 4-DFT and 4-IDFT $\rightarrow$ verify result in B).

Convolution in frequency domain.

Based on duality: $x_1(n) \cdot x_2(n) \xleftrightarrow{N\text{-DFT}} \frac{1}{N} X_1(k) \otimes_N X_2(k)$

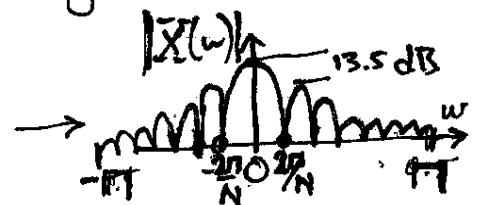
Ex. WINDOWING

Consider the infinite length sequence $x(n)$, $n=0, \dots, \infty$ ($x(n) \leftrightarrow X(\omega)$)

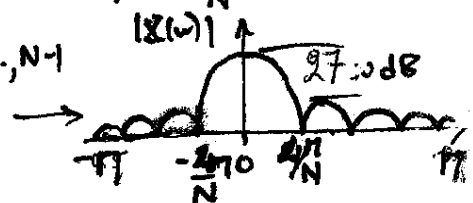
They define the windowed $\begin{cases} \text{DTFT} \\ \text{N-DFT} \end{cases}$ $\begin{aligned} \tilde{X}_w(\omega) &= \sum_{n=0}^{N-1} x(n) \cdot w(n) e^{-j\omega n} = \frac{1}{2\pi} X(\omega) * W(\omega) \\ X_w(k) &= \sum_{n=0}^{N-1} x(n) w(n) e^{-j2\pi kn/N} = \frac{1}{N} X(k) \otimes_N X_2(k) \end{aligned}$

Where $w(n)$: a discrete time window of length N ($n=0, \dots, N-1$)

— Rectangular window (default): $w(n) = \begin{cases} 1, n=0, \dots, N-1 \\ 0, \text{other} \end{cases}$
(brutally truncates signal)



— Bartlett window: $w(n) = \begin{cases} 1 - \frac{|n - N/2|}{N/2}, n=0, \dots, N-1 \\ 0, \text{other} \end{cases}$
(less brutal truncation of signal)



WIDTH OF MAIN LOBE

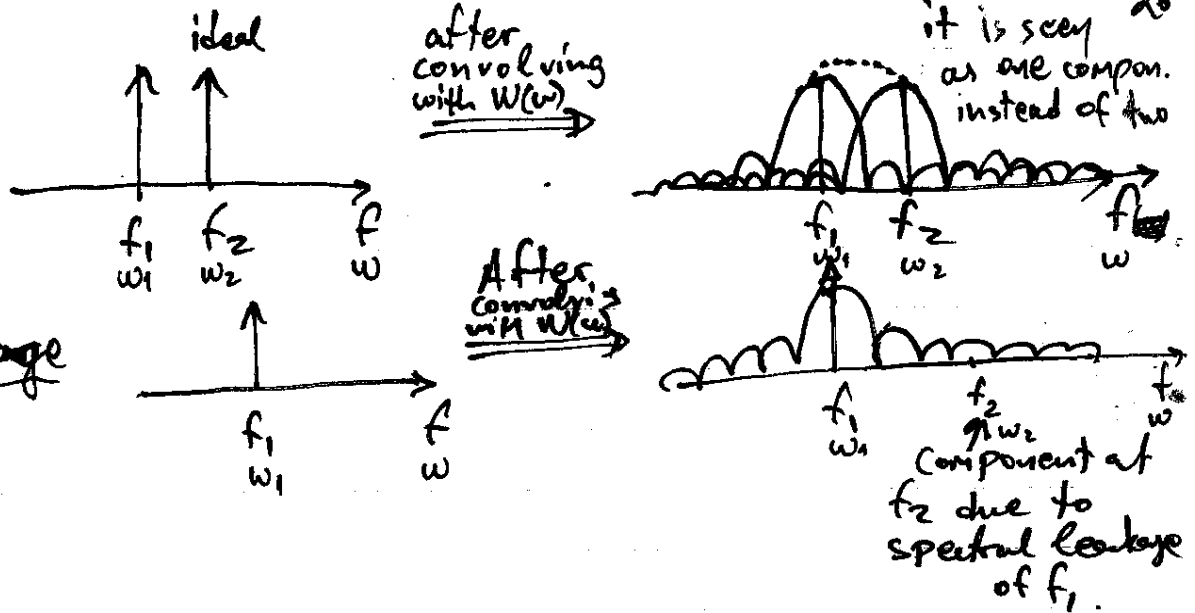
VS

SIZE OF SIDELOBES

(less Resolution due to convolution in frequency domain) VS (Spectral leakage)

Resolution:

Spectral leakage



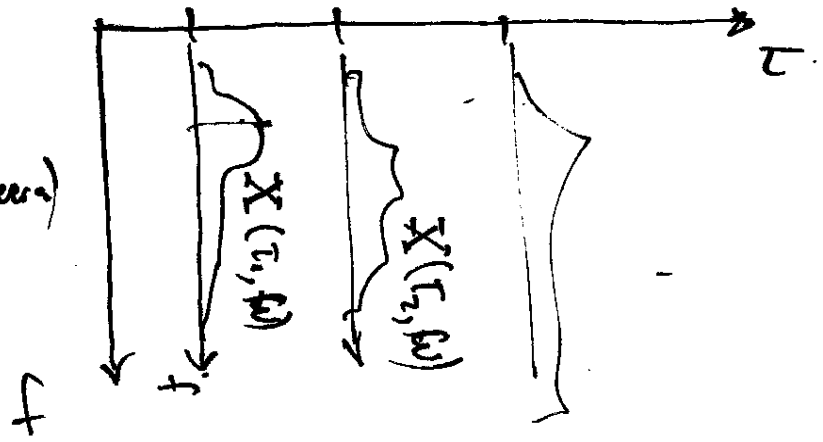
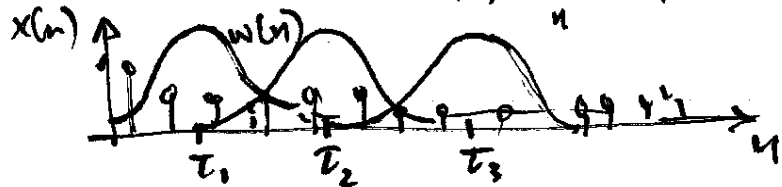
Ex. Short-time Fourier transform
SDTFT or N-SDFT

Consider the transform

S-DTFT $X(\tau, \omega) = \sum_n x(n) w(n-\tau) e^{-j\omega n}$

N-SDFT $\tilde{X}(\tau, k) = \sum_n x(n) w(n-\tau) e^{-j \frac{2\pi k n}{N}}$

Two dimensional sequence (τ, ω)

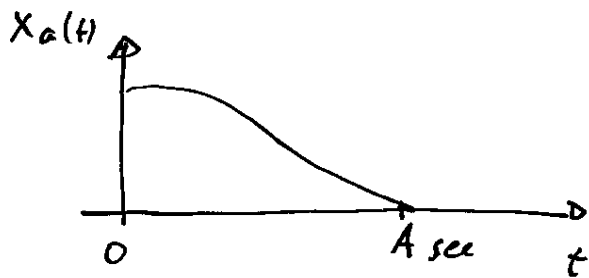


$w(n)$ window of length N
shifted in time by
integer (non-integer in general)
of samples)

* The SDTFT or N-SDFT represent better the local characteristics of a signal (e.g. speech, ... locally stationary)

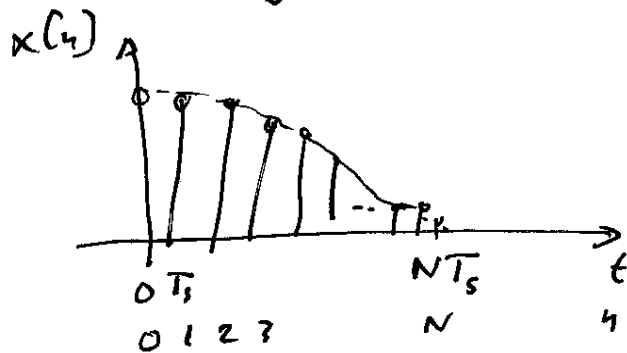
~~SDTFT or N-SDFT~~

MORE ON SPECTRAL RESOLUTION (DISCUSSION)



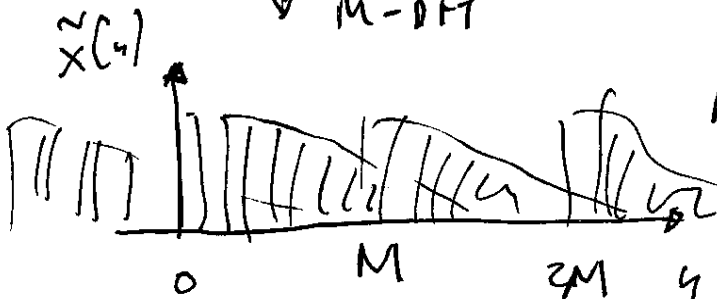
$$\text{Resolution in frequency} = \frac{1}{A \text{ sec.}} \quad (\Delta \Omega)$$

↓ sampling (T_s)



$$\begin{aligned} \text{Resolution in frequency} &= \frac{1}{NT_s} \quad (\Delta \Omega) \\ &= \frac{1}{N} \quad (\Delta \omega) \end{aligned}$$

↓ M-DFT



Actual Resolution in frequency — same
Visual resolution decreases and
is variable depending on M

however

$$\text{visual M-DFT spectral sample distance} = \frac{2\pi}{M}$$

can go to $\rightarrow 0$ as $M \rightarrow \infty$

however this is different from
frequency resolution which remains
unchanged

$X(\omega), X(k)$

VISUAL RESOLUTION $\neq$ FREQUENCY RESOLUTION

