

---

---

ELEN E4810: Digital Signal Processing  
Topic 10:  
The Fast Fourier Transform

1. Calculation of the DFT
2. The Fast Fourier Transform algorithm
3. Short-Time Fourier Transform

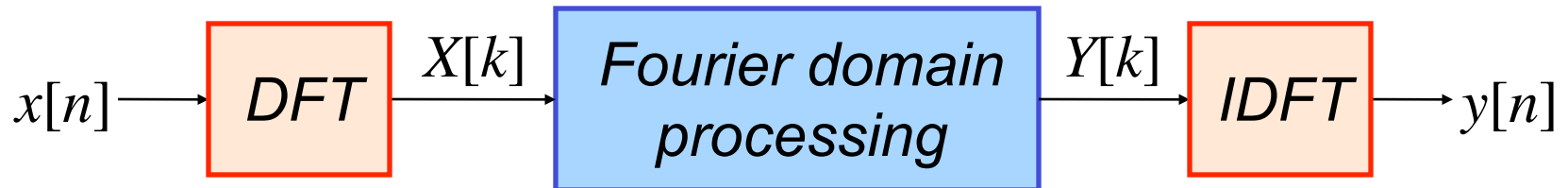


---

---

# 1. Calculation of the DFT

- Filter design so far has been oriented to time-domain processing - cheaper!
- But: frequency-domain processing makes some problems very simple:



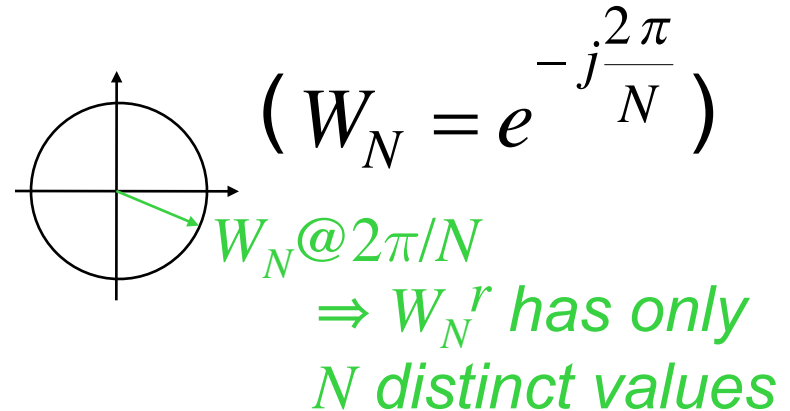
- use all of  $x[n]$ , or use short-time windows
- Need an **efficient** way to calculate DFT



# The DFT

- Recall the DFT:

$$X[k] = \sum_{n=0}^{N-1} x[n] W_N^{kn}$$



- discrete transform of discrete sequence

- Matrix form:

$$\begin{bmatrix} X[0] \\ X[1] \\ X[2] \\ \vdots \\ X[N-1] \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & W_N^1 & W_N^2 & \dots & W_N^{(N-1)} \\ 1 & W_N^2 & W_N^4 & \dots & W_N^{2(N-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & W_N^{(N-1)} & W_N^{2(N-1)} & \dots & W_N^{(N-1)^2} \end{bmatrix} \begin{bmatrix} x[0] \\ x[1] \\ x[2] \\ \vdots \\ x[N-1] \end{bmatrix}$$

Structure  $\Rightarrow$   
 opportunities  
 for  
 efficiency



---

---

# Computational Complexity

$$X[k] = \sum_{n=0}^{N-1} x[n] W_N^{kn}$$

- $N$  complex multiplies  
+  $N-1$  complex adds per point ( $k$ )  
×  $N$  points ( $k = 0.. N-1$ )
  - cpx mult:  $(a+jb)(c+jd) = ac - bd + j(ad + bc)$   
= 4 real mults + 2 real adds
  - cpx add = 2 real adds
- $N$  points:  $4N^2$  real mults,  $4N^2-2N$  real adds



# Goertzel's Algorithm

- Now: 
$$X[k] = \sum_{\ell=0}^{N-1} x[\ell] W_N^{k\ell}$$

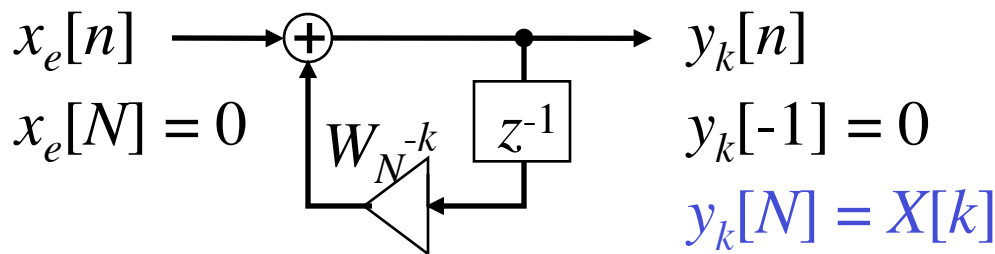
$$= W_N^{kN} \sum_{\ell} x[\ell] W_N^{-k(N-\ell)}$$

*looks like a convolution*

- i.e.  $X[k] = y_k[N]$   
 where  $y_k[n] = x_e[n] \circledast h_k[n]$

$$x_e[n] = \begin{cases} x[n] & 0 \leq n < N \\ 0 & n = N \end{cases}$$

$$h_k[n] = \begin{cases} W_N^{-kn} & n \geq 0 \\ 0 & n < 0 \end{cases}$$



---

---

# Goertzel's Algorithm

- Separate 'filters' for each  $X[k]$ 
  - can calculate for just a few values of  $k$
- No large buffer, no coefficient table
- Same complexity for full  $X[k]$   
( $4N^2$  mults,  $4N^2 - 2N$  adds)
  - but: can **halve** multiplies by making the denominator real:

$$H(z) = \frac{1}{1 - W_N^{-k} z^{-1}} = \frac{1 - W_N^k z^{-1}}{1 - 2 \cos \frac{2\pi k}{N} z^{-1} + z^{-2}}$$

*evaluate only for last step* (pointing to  $1 - W_N^k z^{-1}$ )

*2 real mults per step* (pointing to  $1 - 2 \cos \frac{2\pi k}{N} z^{-1} + z^{-2}$ )



---

---

## 2. Fast Fourier Transform FFT

- Reduce complexity of DFT from  $O(N^2)$  to  $O(N \cdot \log N)$ 
  - grows more slowly with larger  $N$
- Works by **decomposing** large DFT into several stages of smaller DFTs
- Often provided as a highly optimized library



# Decimation in Time (DIT) FFT

- Can rearrange DFT formula in 2 halves:

$$X[k] = \sum_{n=0}^{N-1} x[n] \cdot W_N^{nk}$$

$k = 0..N-1$

Arrange terms in pairs...

$$= \sum_{m=0}^{\frac{N}{2}-1} \left( x[2m] \cdot W_N^{2mk} + x[2m+1] \cdot W_N^{(2m+1)k} \right)$$

Group terms from each pair

$$= \sum_{m=0}^{\frac{N}{2}-1} x[2m] \cdot W_{\frac{N}{2}}^{mk} + W_N^k \sum_{m=0}^{\frac{N}{2}-1} x[2m+1] \cdot W_{\frac{N}{2}}^{mk}$$

$X_0[\langle k \rangle_{N/2}]$

$X_1[\langle k \rangle_{N/2}]$

$N/2$  pt DFT of  $x$  for **even**  $n$

$N/2$  pt DFT of  $x$  for **odd**  $n$





---

---

# Decimation in Time (DIT) FFT

$$\text{DFT}_N \{x[n]\} = \text{DFT}_{\frac{N}{2}} \{x_0[n]\} + W_N^k \text{DFT}_{\frac{N}{2}} \{x_1[n]\}$$

*x[n] for even n*                      *x[n] for odd n*

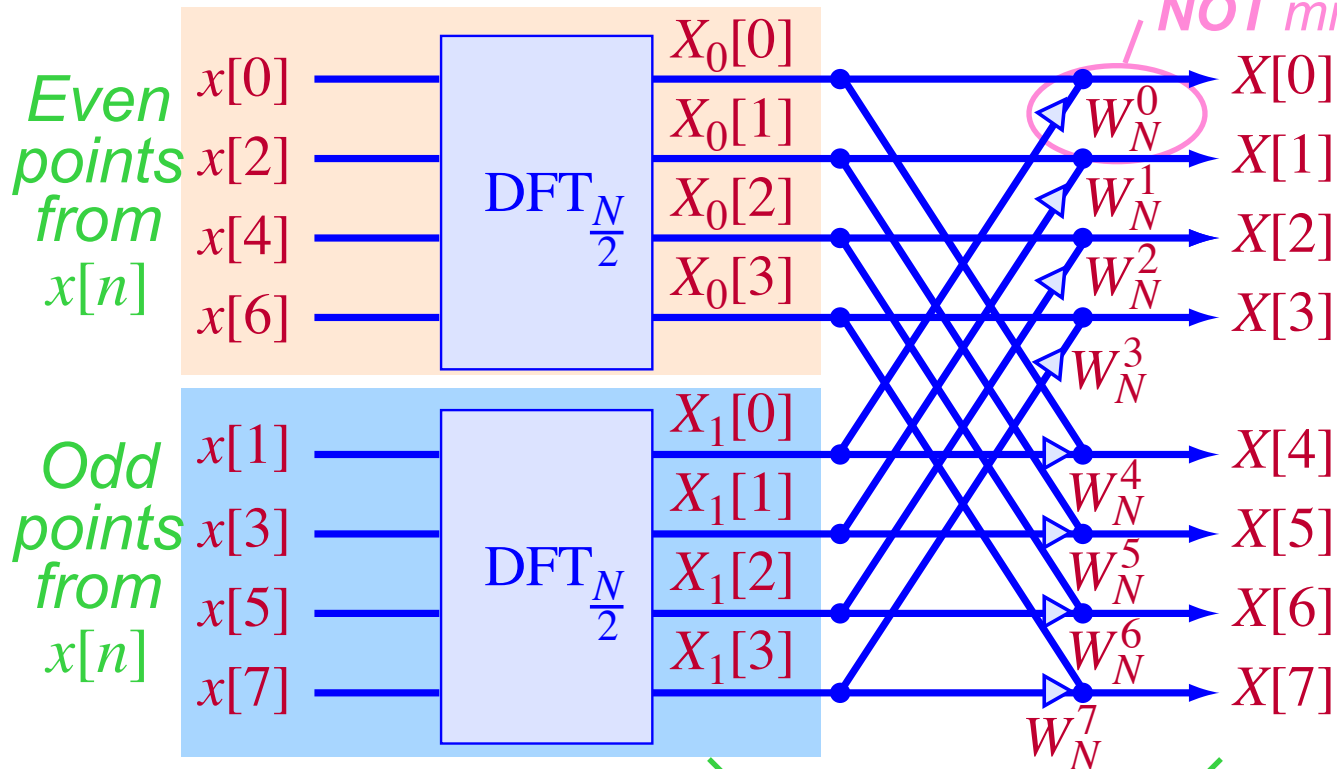
- We can evaluate an  $N$ -pt DFT as two  $N/2$ -pt DFTs (plus a few mults/adds)
  - But if  $\text{DFT}_N\{\bullet\} \sim O(N^2)$   
then  $\text{DFT}_{N/2}\{\bullet\} \sim O((N/2)^2) = 1/4 O(N^2)$
- ⇒ Total computation  $\sim 2 \cdot 1/4 O(N^2)$   
**= 1/2 the computation (+ $\epsilon$ ) of direct DFT**



# One-Stage DIT Flowgraph

$$X[k] = X_0 \left[ \langle k \rangle_{\frac{N}{2}} \right] + W_N^k X_1 \left[ \langle k \rangle_{\frac{N}{2}} \right]$$

*“twiddle factors”:  
always apply to  
odd-terms output  
NOT mirror-image*



*Same as  
 $X[0..3]$   
except for  
factors on  
 $X_1[\cdot]$   
terms*

*Classic FFT structure*



# Multiple DIT Stages

- If **decomposing** one  $\text{DFT}_N$  into two smaller  $\text{DFT}_{N/2}$ 's speeds things up ... Why not **further divide** into  $\text{DFT}_{N/4}$ 's ?

- i.e.  $X[k] = X_0 \left[ \langle k \rangle_{\frac{N}{2}} \right] + W_N^k X_1 \left[ \langle k \rangle_{\frac{N}{2}} \right]$   
 $0 \leq k < N$

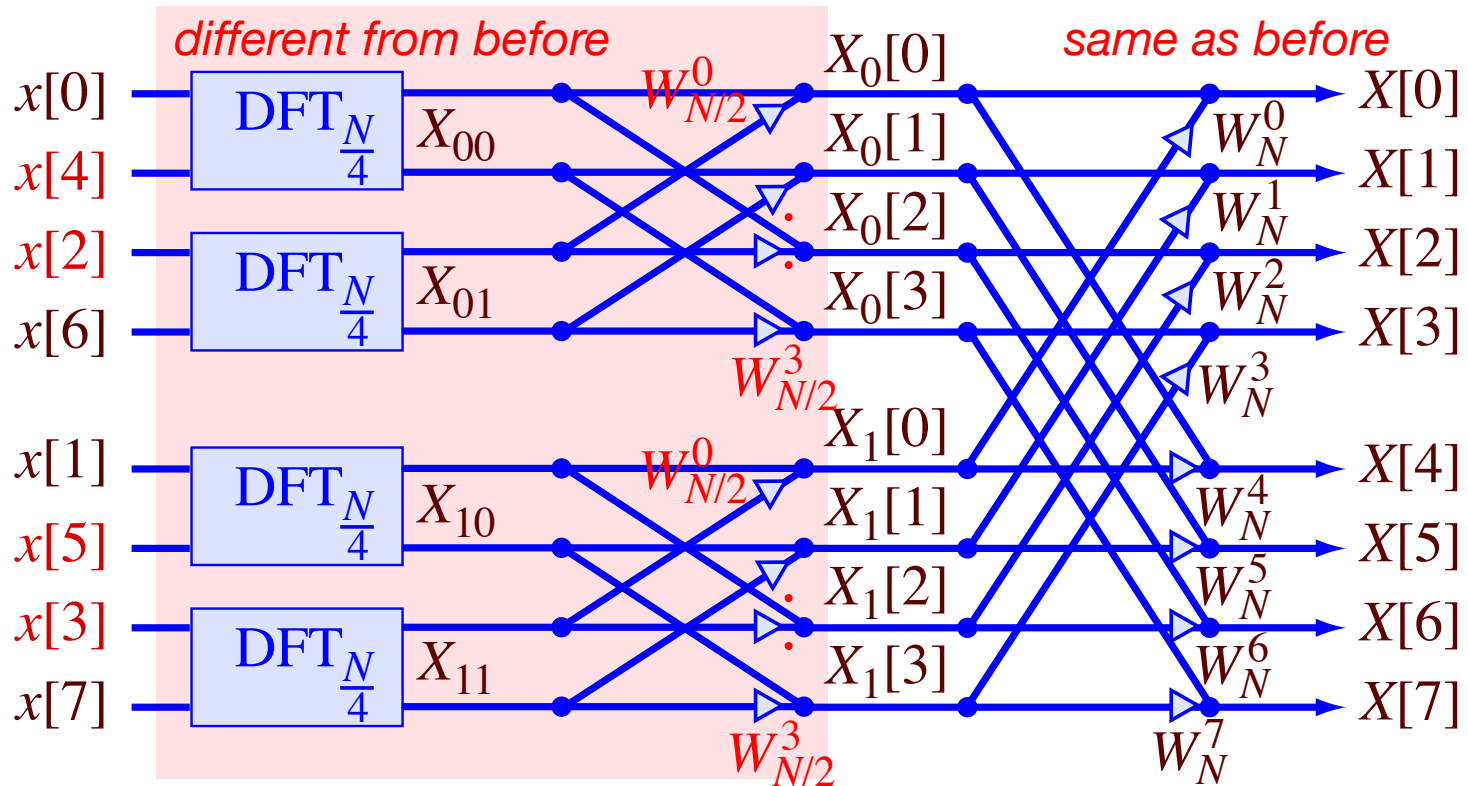
- make:  $X_0[k] = X_{00} \left[ \langle k \rangle_{\frac{N}{4}} \right] + W_{\frac{N}{2}}^k X_{01} \left[ \langle k \rangle_{\frac{N}{4}} \right]$   
 $0 \leq k < N/2$

*$N/4$ -pt DFT of **even points** in **even subset of  $x[n]$***      *$N/4$ -pt DFT of **odd points** from **even subset***

- Similarly,  $X_1[k] = X_{10} \left[ \langle k \rangle_{\frac{N}{4}} \right] + W_{\frac{N}{2}}^k X_{11} \left[ \langle k \rangle_{\frac{N}{4}} \right]$

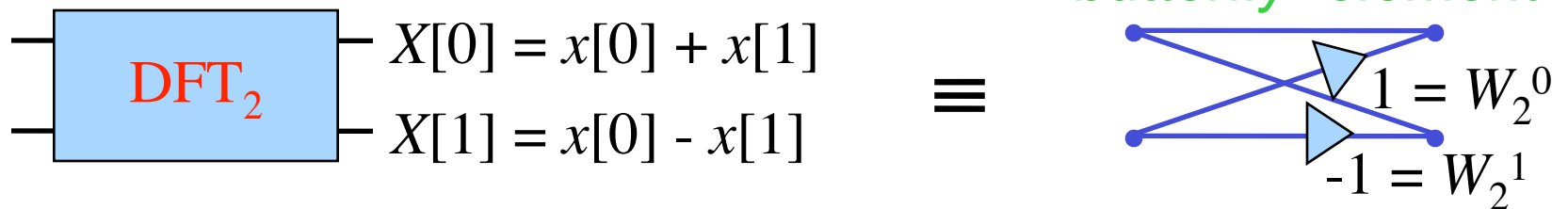


# Two-Stage DIT Flowgraph



# Multi-stage DIT FFT

- Can keep doing this until we get down to 2-pt DFTs:

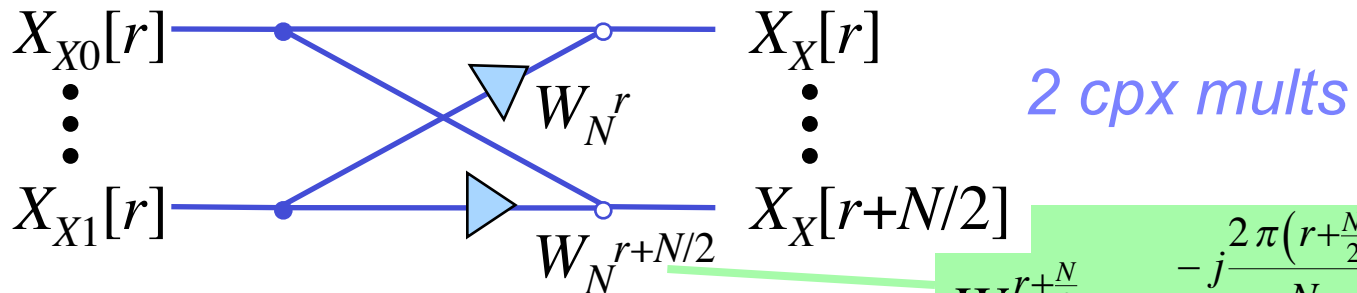


- $N = 2^M$ -pt DFT reduces to  $M$  stages of twiddle factors & summation ( $O(N^2)$  part vanishes)
- real mults  $< M \cdot 4N$ , real adds  $< 2 \cdot M \cdot 2N$
- complexity  $\sim O(N \cdot M) = O(N \cdot \log_2 N)$

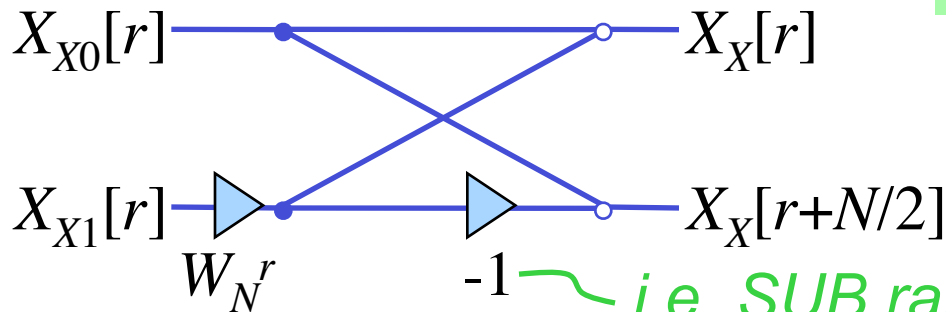


# FFT Implementation Details

- Basic butterfly (at any stage):



- Can simplify:



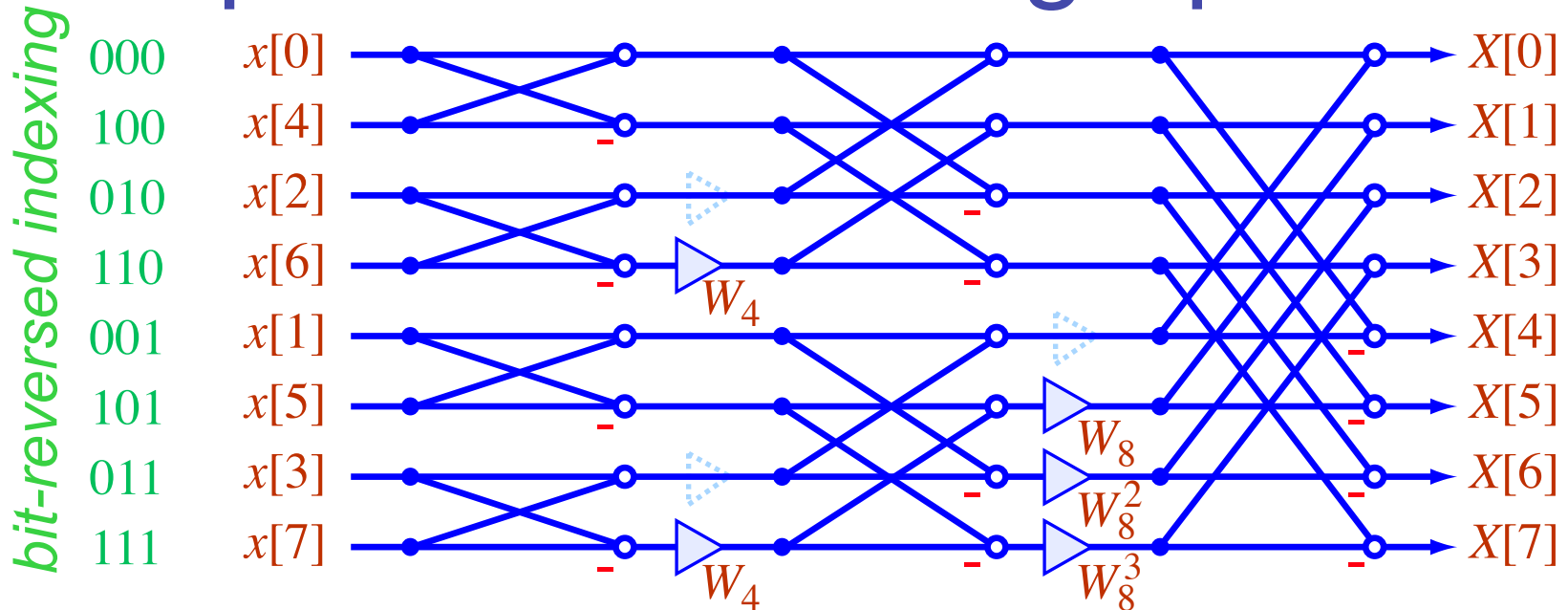
$$\begin{aligned}
 W_N^{r+\frac{N}{2}} &= e^{-j\frac{2\pi(r+\frac{N}{2})}{N}} \\
 &= e^{-j\frac{2\pi r}{N}} \cdot e^{-j\frac{2\pi N/2}{N}} \\
 &= -W_N^r
 \end{aligned}$$

*just one cplx mult!*

*i.e. SUB rather than ADD*



# 8-pt DIT FFT Flowgraph



- -1's absorbed into summation nodes
- $W_N^0$  disappears  $\triangleright$
- 'in-place' algorithm: sequential stages



---

---

# FFT for Other Values of N

- Having  $N = 2^M$  meant we could divide each stage into 2 halves = “radix-2 FFT”
- Same approach works for:
  - $N = 3^M$  radix-3
  - $N = 4^M$  radix-4 - more optimized radix-2
  - etc...
- Composite  $N = a \cdot b \cdot c \cdot d \rightarrow$  mixed radix (different  $N/r$  point FFTs at each stage)
  - .. or just zero-pad to make  $N = 2^M$





# Inverse FFT

*only differences from forward DFT*

- Recall IDFT:  $x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] W_N^{-nk}$

- Thus:

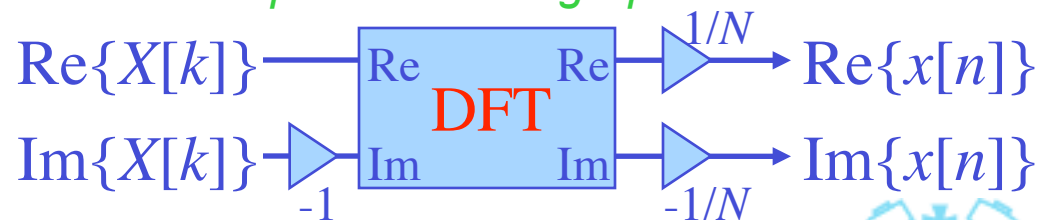
*Forward DFT of  $x'[n] = X^*[k]|_{k=n}$   
i.e. time sequence made from spectrum*

$$Nx^*[n] = \sum_{k=0}^{N-1} \left( X[k] W_N^{-nk} \right)^* = \sum_{k=0}^{N-1} X^*[k] W_N^{nk}$$

- Hence, use FFT to calculate IFFT:

$$x[n] = \frac{1}{N} \left[ \sum_{k=0}^{N-1} X^*[k] W_N^{nk} \right]^*$$

*pure real flowgraph*



---

---

# DFT of Real Sequences

- If  $x[n]$  is pure-real, DFT wastes mult's
- **Real**  $x[n] \rightarrow$  **Conj. symm.**  $X[k] = X^*[-k]$
- Given two real sequences,  $x[n]$  and  $w[n]$   
call  $y[n] = j \cdot w[n]$ ,  $v[n] = x[n] + y[n]$
- $N$ -pt DFT  $V[k] = X[k] + Y[k]$   
but:  $V[k] + V^*[-k] = X[k] + X^*[-k] + Y[k] + Y^*[-k]$   
 $\Rightarrow X[k] = 1/2(V[k] + V^*[-k])$ ,  $W[k] = -j/2(V[k] - V^*[-k])$
- i.e. compute DFTs of **two**  $N$ -pt real sequences with a **single**  $N$ -pt DFT



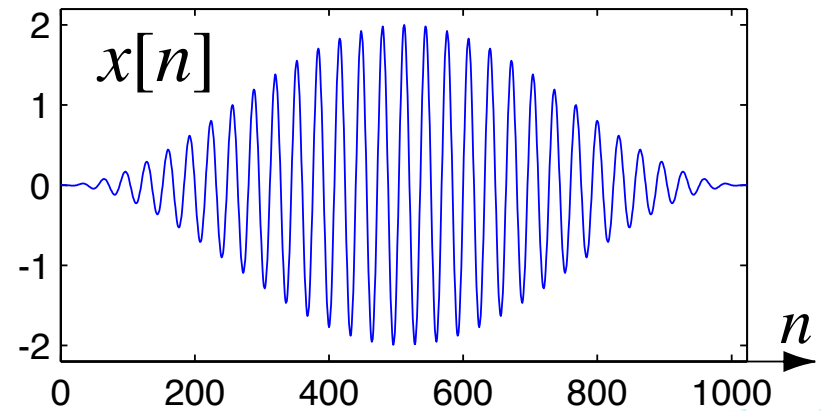
---

---

# 3. Short-Time Fourier Transform (STFT)

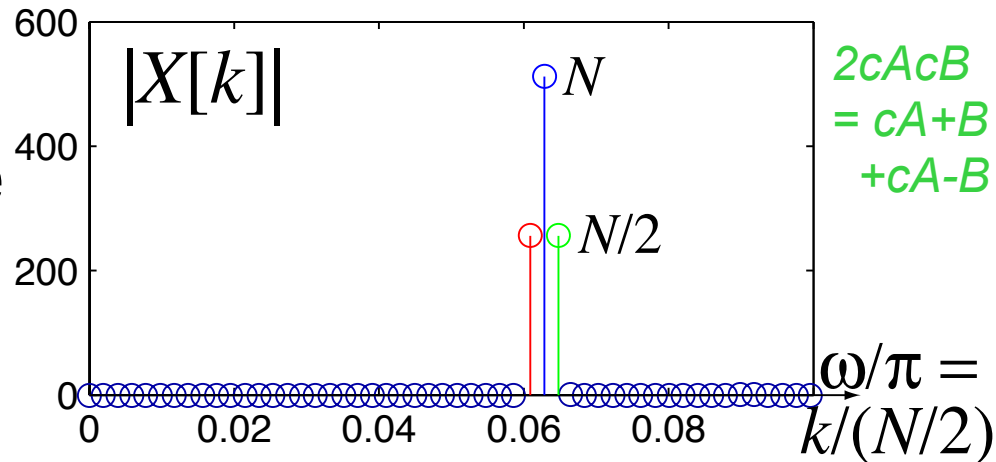
- Fourier Transform (e.g. DTFT) gives spectrum of an entire sequence:
- How to see a **time-varying spectrum**?
- e.g. slow AM of a sinusoid carrier:

$$x[n] = \left(1 - \cos \frac{2\pi n}{N}\right) \cos \omega_0 n$$



# Fourier Transform of AM Sine

- Spectrum of whole sequence indicates modulation indirectly...

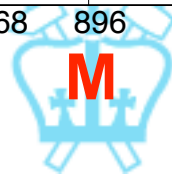
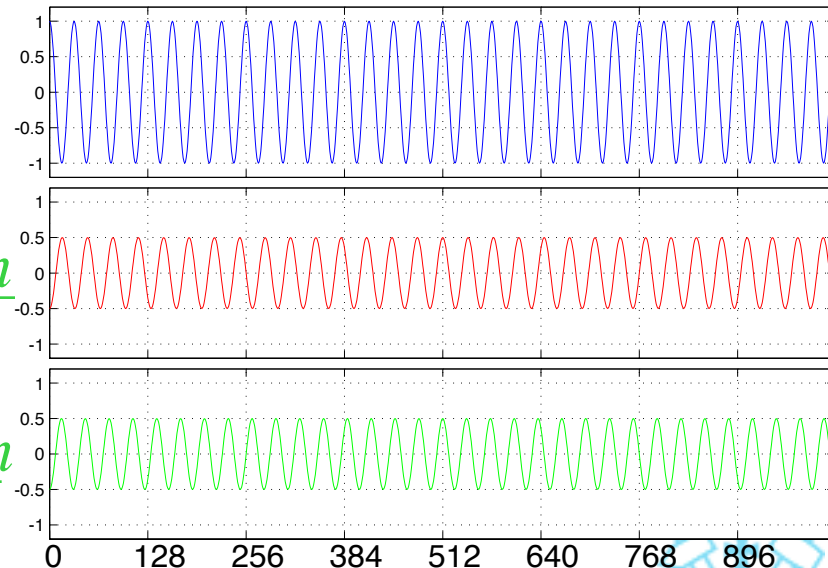


- ... as cancellation between closely-tuned sines

$$N \frac{\sin 2\pi kn}{N}$$

$$\frac{-N \sin 2\pi(k-1)n}{2} \frac{1}{N}$$

$$\frac{-N \sin 2\pi(k+1)n}{2} \frac{1}{N}$$



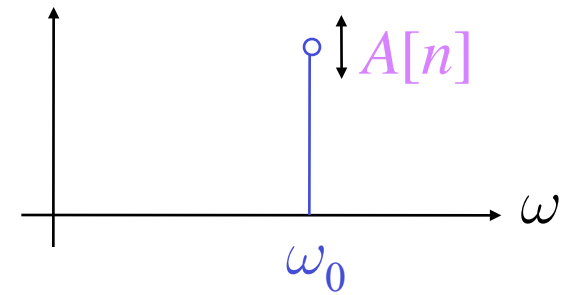
---

---

# Fourier Transform of AM Sine

- Sometimes we'd rather separate modulation and carrier:

$$x[n] = A[n] \cos \omega_0 n$$

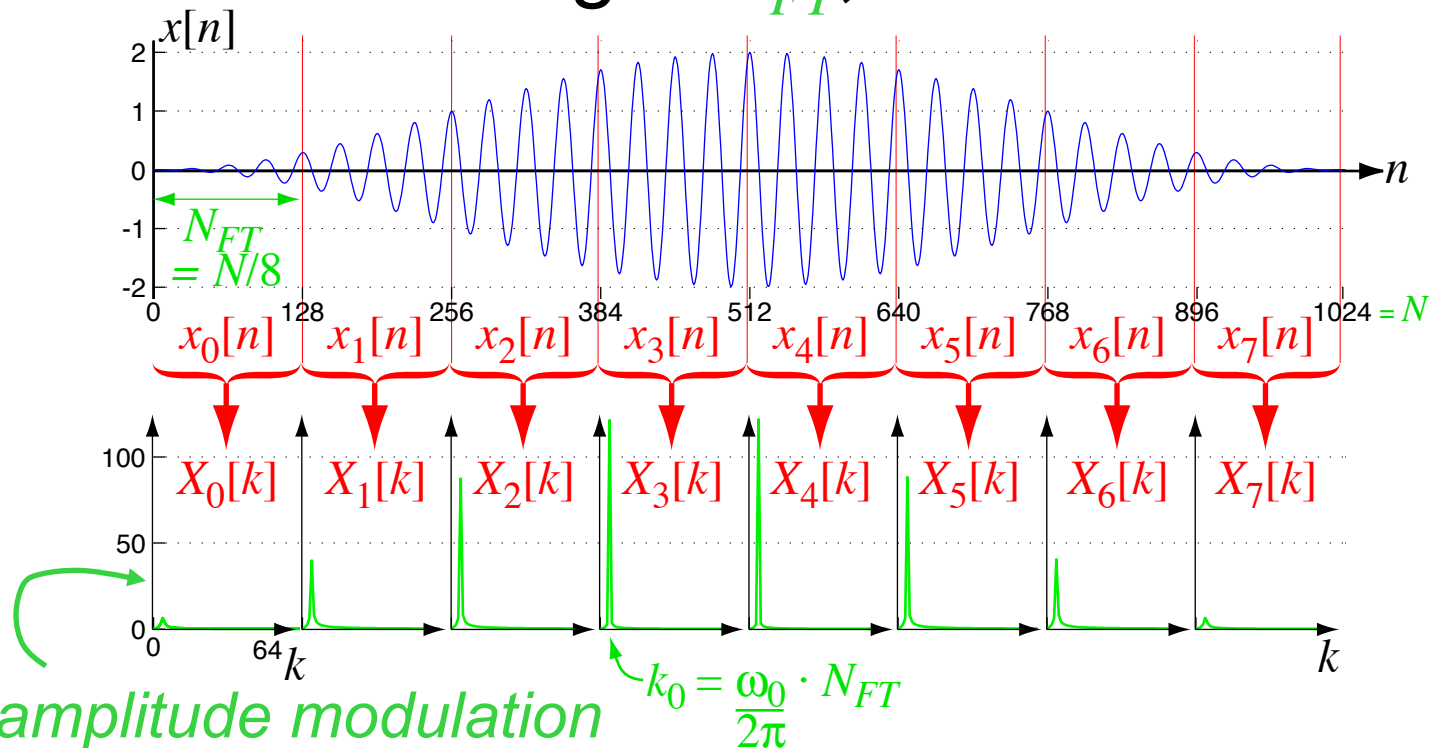


- $A[n]$  varies on a different (slower) timescale
- One approach:
  - chop  $x[n]$  into short sub-sequences ..
  - .. where slow modulator is  $\sim$  constant
  - DFT spectrum of pieces  $\rightarrow$  show variation



# FT of Short Segments

- Break up  $x[n]$  into successive, shorter chunks of length  $N_{FT}$ , then DFT each:

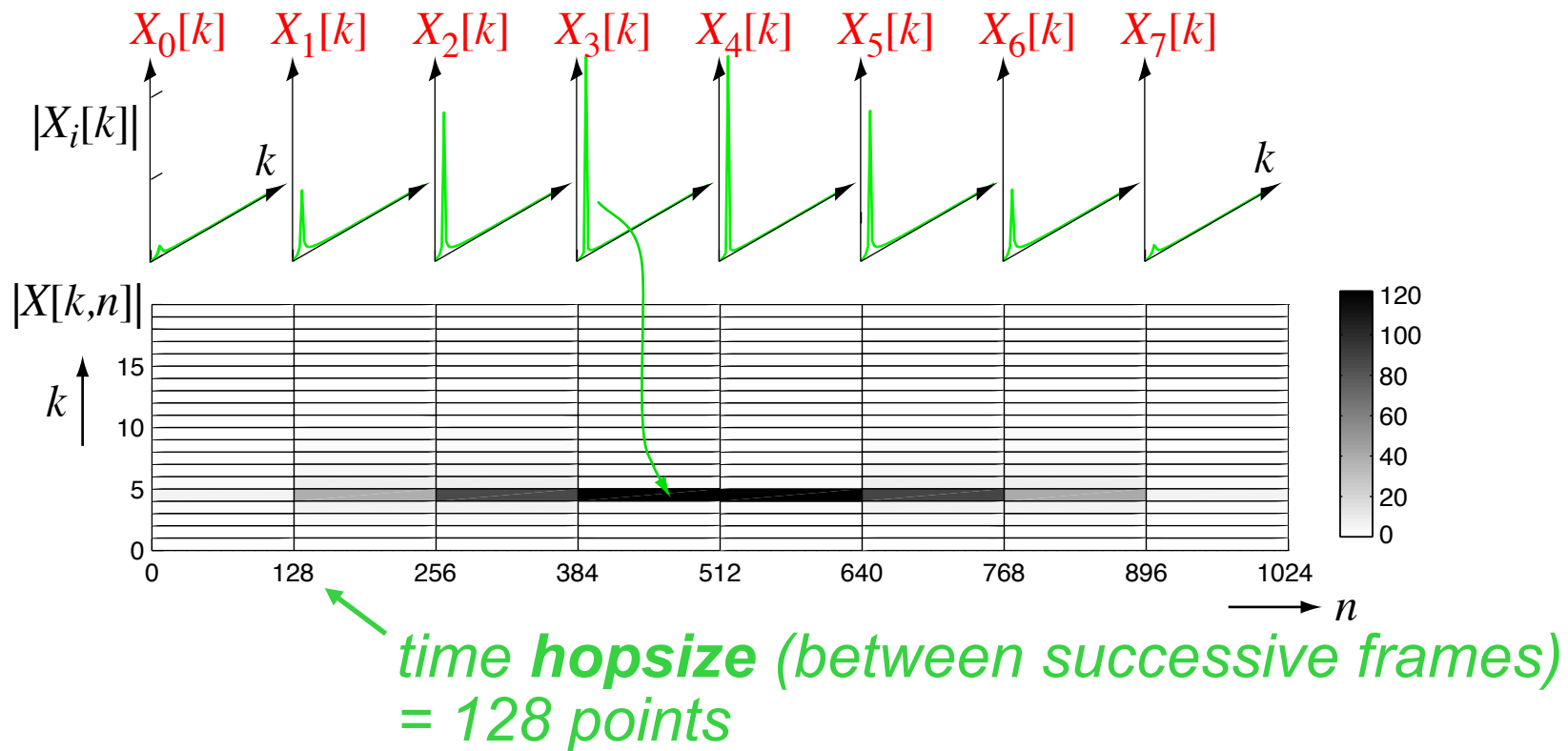


Shows amplitude modulation  
of  $\omega_0$  energy



# The Spectrogram

- Plot successive DFTs in time-frequency:



- This image is called the **Spectrogram**



---

---

# Short-Time Fourier Transform

- Spectrogram = **STFT magnitude** plotted on time-frequency plane
- **STFT** is (DFT form):

$$X[k, n_0] = \sum_{n=0}^{N_{FT}-1} x[n_0 + n] \cdot w[n] \cdot e^{-j \frac{2\pi kn}{N_{FT}}}$$

*frequency index* (red arrow pointing to  $k$ )

*time index* (yellow arrow pointing to  $n_0$ )

*$N_{FT}$  points of  $x$  starting at  $n_0$*  (green arrow pointing to the summation range)

*window* (green arrow pointing to  $w[n]$ )

*DFT kernel* (green arrow pointing to  $e^{-j \frac{2\pi kn}{N_{FT}}}$ )

- **intensity** as a function of **time** & **frequency**

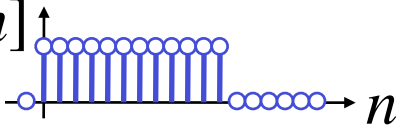




---

---

# STFT Window Shape

- $w[n]$  provides ‘time localization’ of STFT
  - e.g. rectangular   
selects  $x[n]$ ,  $n_0 \leq n < n_0 + N_W$
- But: resulting spectrum has same problems as **windowing for FIR design**:

*DTFT form of STFT*

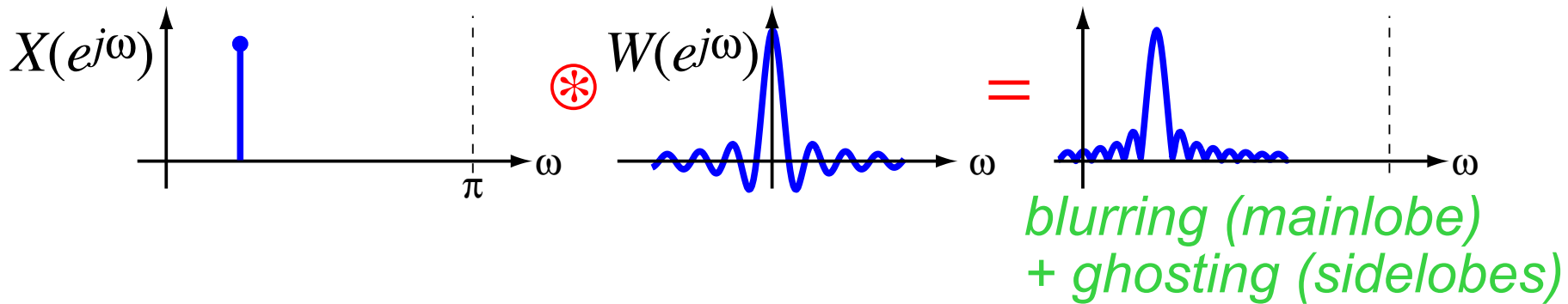
$$\begin{aligned} X(e^{j\omega}, n_0) &= \text{DTFT}\{x[n_0 + n] \cdot w[n]\} \\ &= \int_{-\pi}^{\pi} e^{j\theta n_0} X(e^{j\theta}) W(e^{j(\omega-\theta)}) d\theta \end{aligned}$$

*spectrum of short-time window  
is convolved with (twisted) parent spectrum*



# STFT Window Shape

- e.g. if  $x[n]$  is a pure sinusoid,

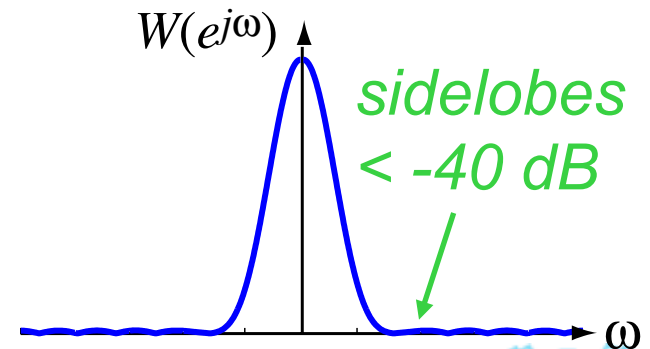
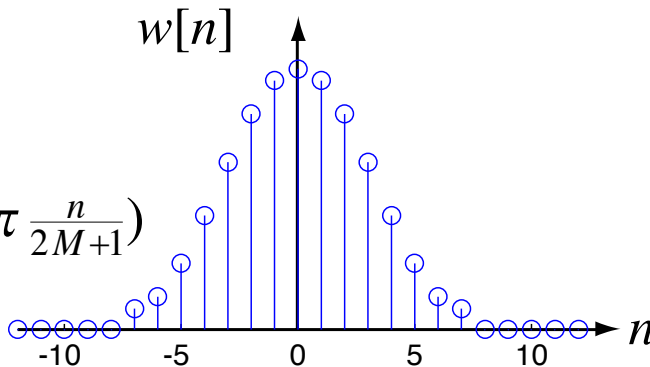


- Hence, use **tapered window** for  $w[n]$

e.g. Hamming

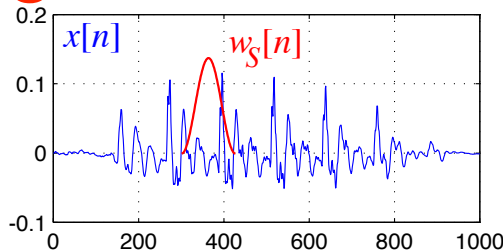
$$w[n] =$$

$$0.54 + 0.46 \cos\left(2\pi \frac{n}{2M+1}\right)$$

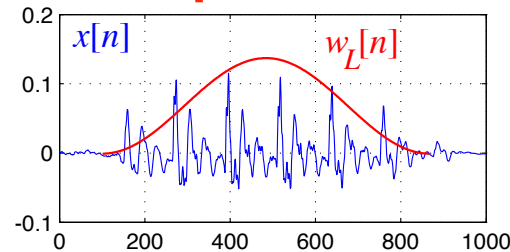


# STFT Window Length

- Length of  $w[n]$  sets temporal resolution

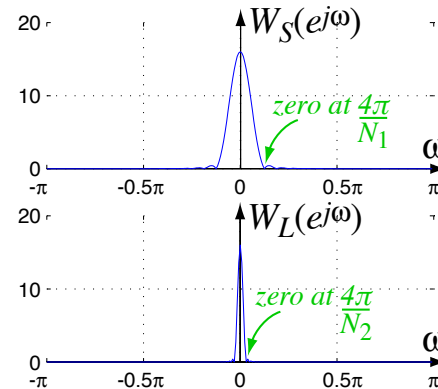
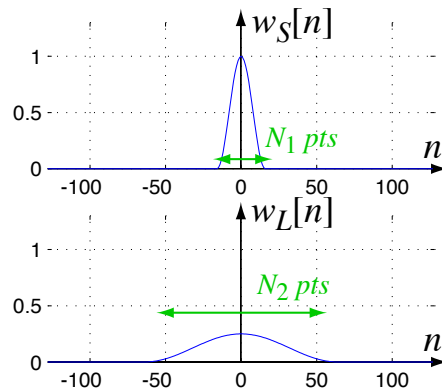


short window measures only local properties



longer window averages spectral character

- Window length  $\propto 1/(\text{Mainlobe width})$



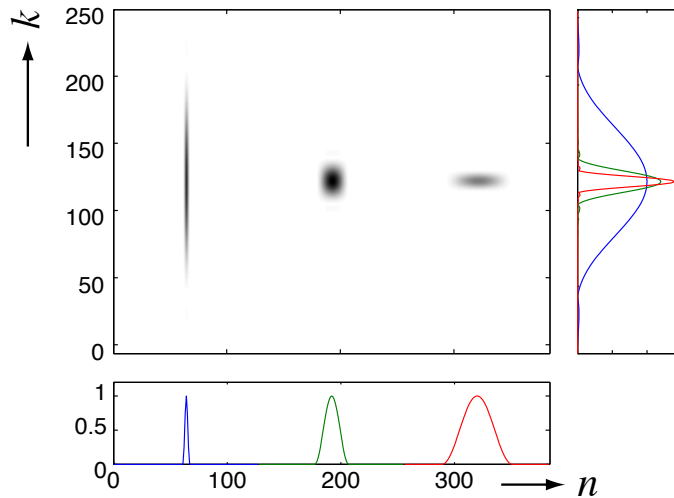
shorter window  $\rightarrow$  more blurred spectrum

- more time detail  $\leftrightarrow$  less frequency detail



# STFT Window Length

- Can illustrate time-frequency tradeoff on the time-frequency plane:

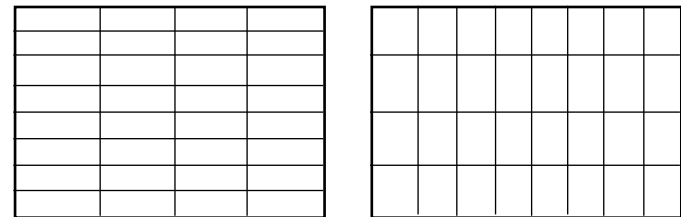


*disks show 'blurring' due to window length; area of disk is constant*

→ **Uncertainty principle:**

$$\delta f \cdot \delta t \geq k$$

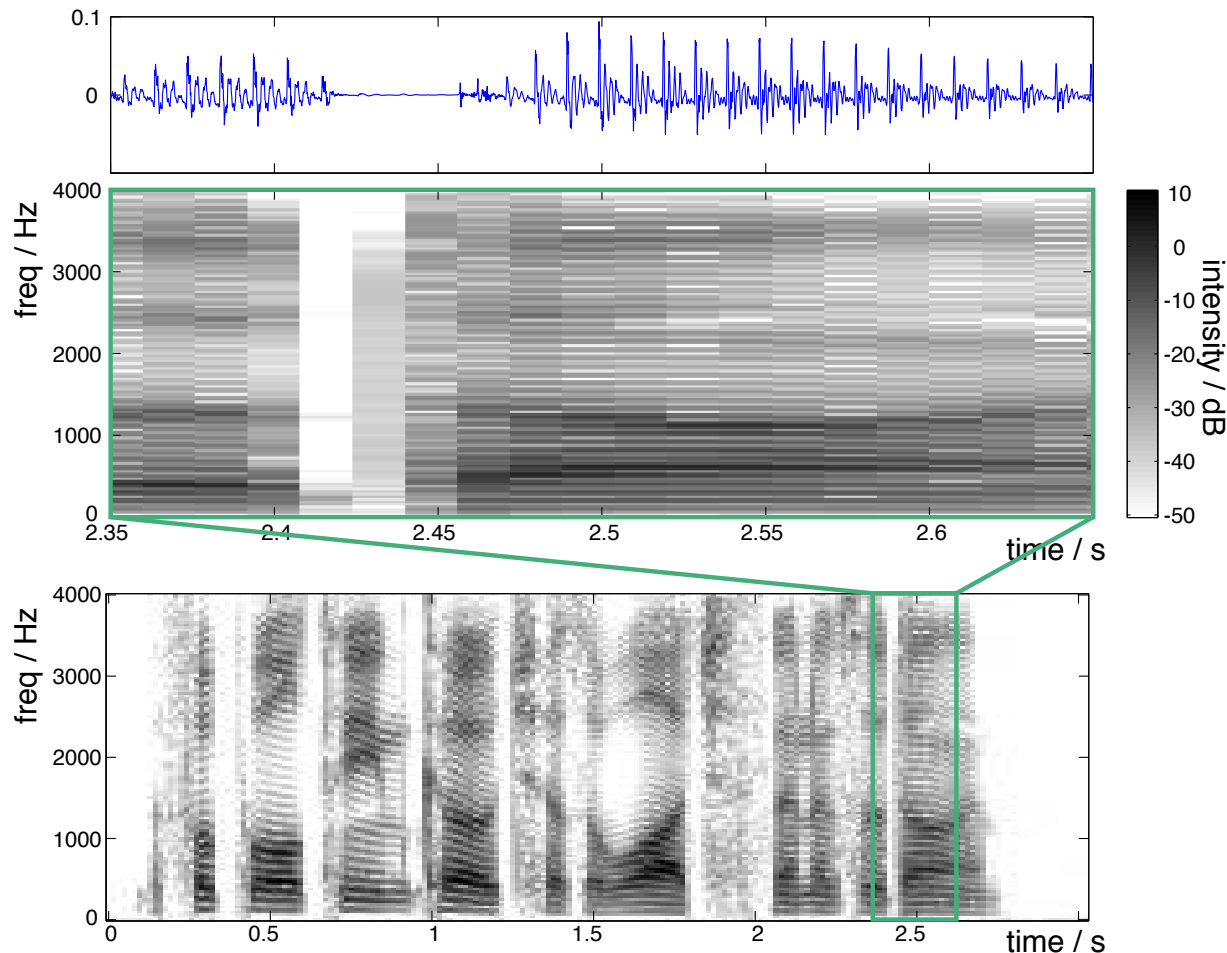
- Alternate tilings of time-freq:



*half-length window → half as many DFT samples*



# Spectrograms of Real Sounds



*time-domain*

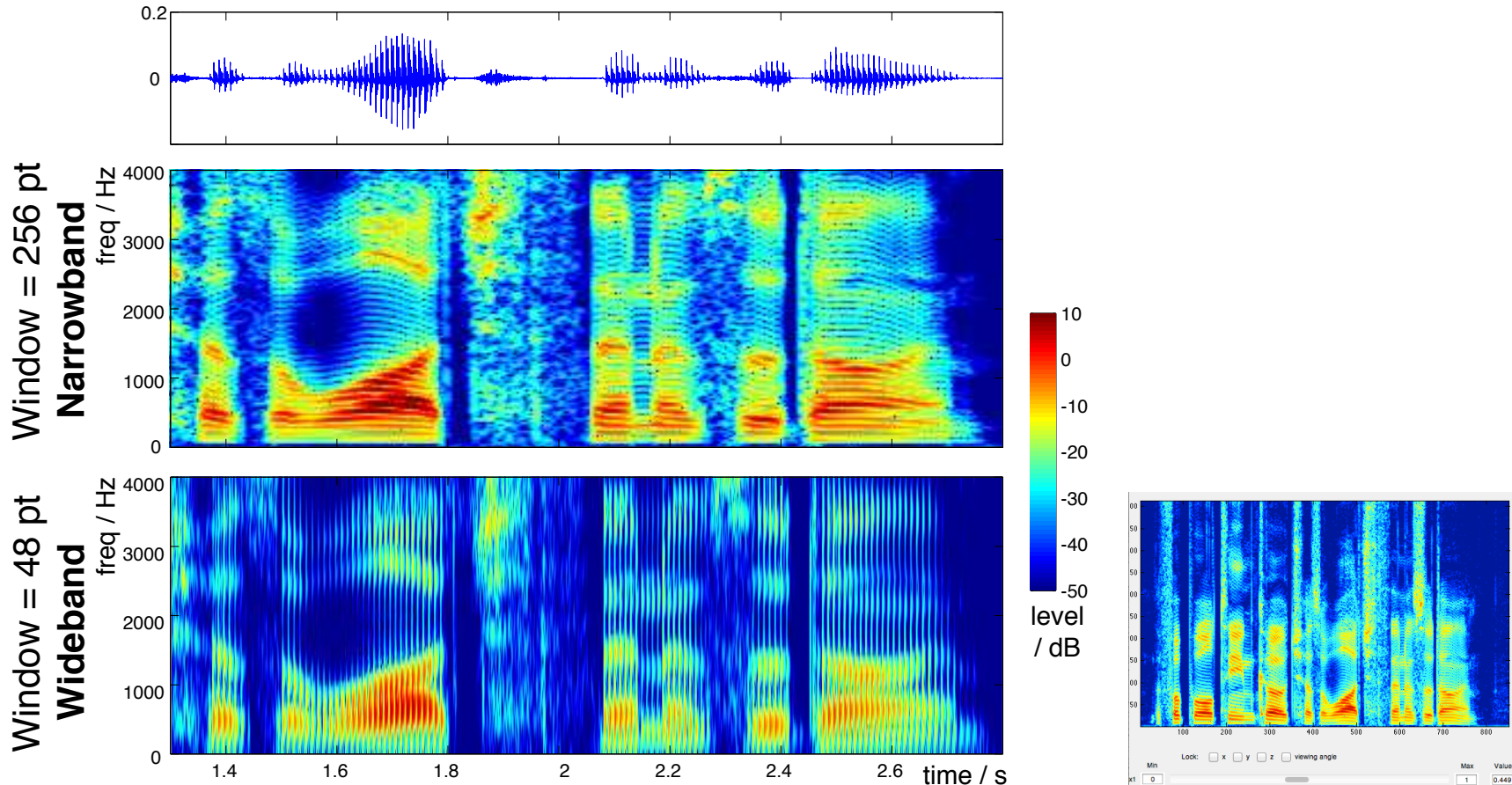
*successive  
short  
DFTs*

*individual t-f  
cells merge  
into continuous  
image*



# Narrowband vs. Wideband

- Effect of varying window length:

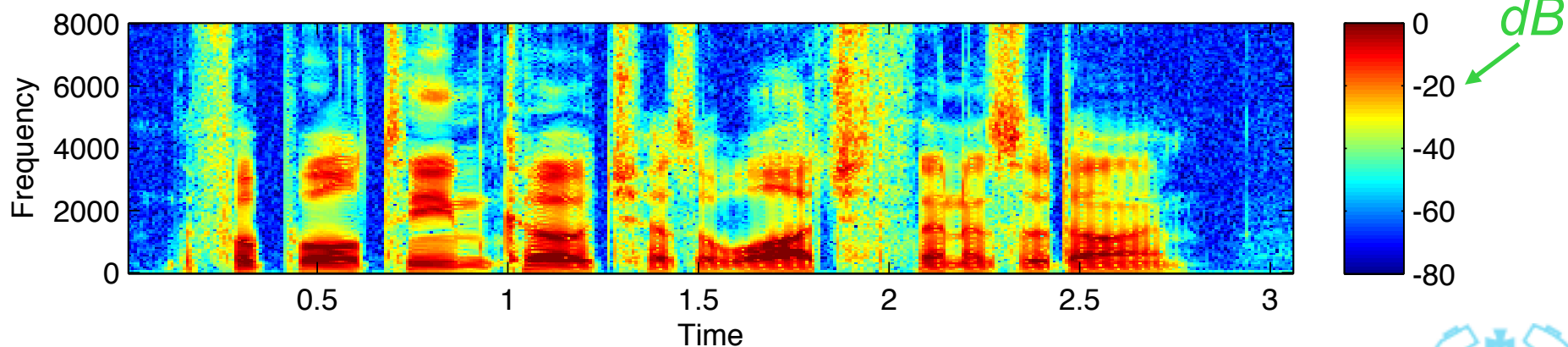


# Spectrogram in Matlab

```
>> [d, sr]=wavread('mpgr1_sx419.wav');  
>> Nw=256;  
>> specgram(d, Nw, sr)  
>> caxis([-80 0])  
>> colorbar
```

*(hann) window length*

*actual sampling rate  
(to label time axis)*



# STFT as a Filterbank

- Consider one 'row' of STFT:

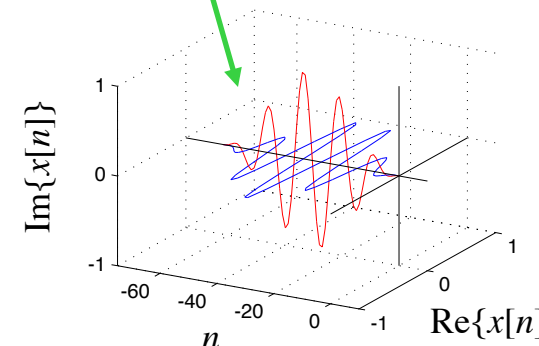
$$X_k[n_0] = \sum_{n=0}^{N-1} x[n_0 + n] \cdot w[n] \cdot e^{-j\frac{2\pi kn}{N}}$$

*just one freq.*

$$= \sum_{m=0}^{-(N-1)} h_k[m] x[n_0 - m]$$

*convolution with complex IR*

where  $h_k[n] = w[-n] \cdot e^{j\frac{2\pi kn}{N}}$



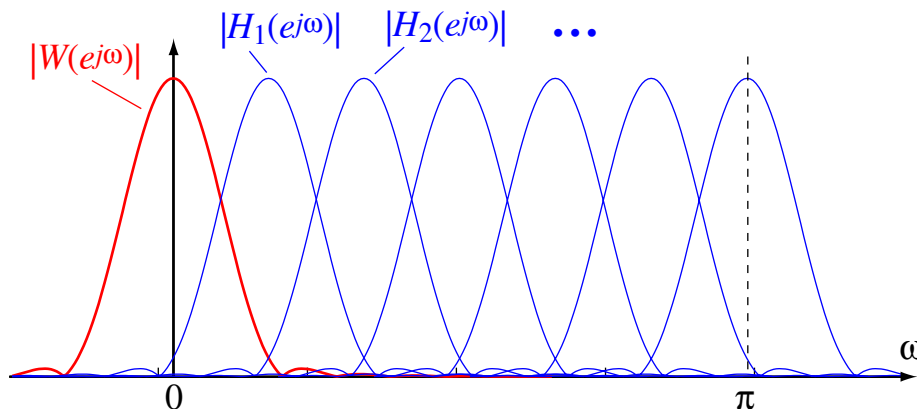
- Each STFT row is output of a **filter** (subsampled by the STFT hop size)





# STFT as a Filterbank

- If  $h_k[n] = w[(-)n] \cdot e^{j\frac{2\pi kn}{N}}$   
then  $H_k(e^{j\omega}) = W(e^{(-)j(\omega - \frac{2\pi k}{N})})$  *shift-in- $\omega$*
- Each STFT row is the same **bandpass** response defined by  $W(e^{j\omega})$ ,  
**frequency-shifted** to a given DFT bin:



*A bank of identical, frequency-shifted bandpass filters: “filterbank”*

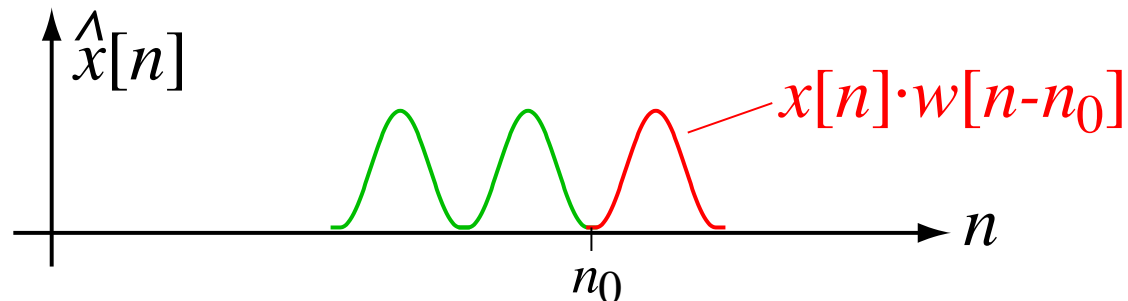


---

---

# STFT Analysis-Synthesis

- IDFT of STFT frames can **reconstruct** (part of) original waveform
- e.g. if  $X[k, n_0] = \text{DFT}\{x[n_0 + n] \cdot w[n]\}$   
then  $\text{IDFT}\{X[k, n_0]\} = x[n_0 + n] \cdot w[n]$
- Can shift by  $n_0$ , combine, to get  $\hat{x}[n]$ :



- Could divide by  $w[n - n_0]$  to recover  $x[n]$ ...



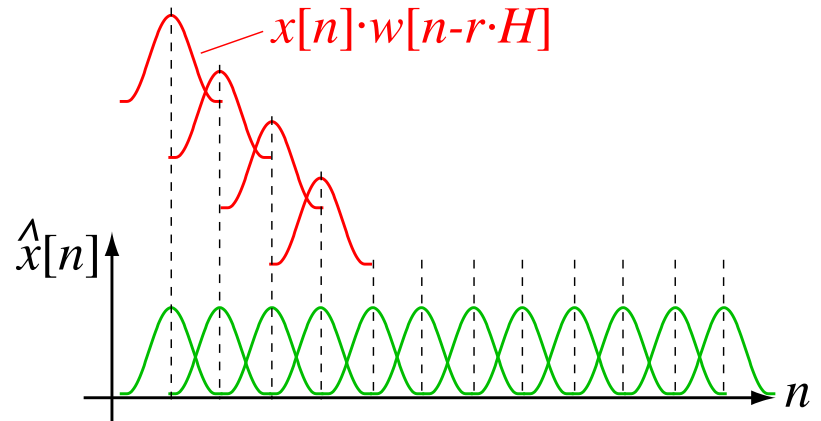
# STFT Analysis-Synthesis

- Dividing by small values of  $w[n]$  is bad

- Prefer to **overlap** windows:

i.e. sample  $X[k, n_0]$

at  $n_0 = r \cdot H$  where  $H = N/2$  (for example)  
*hopsize* *window length*



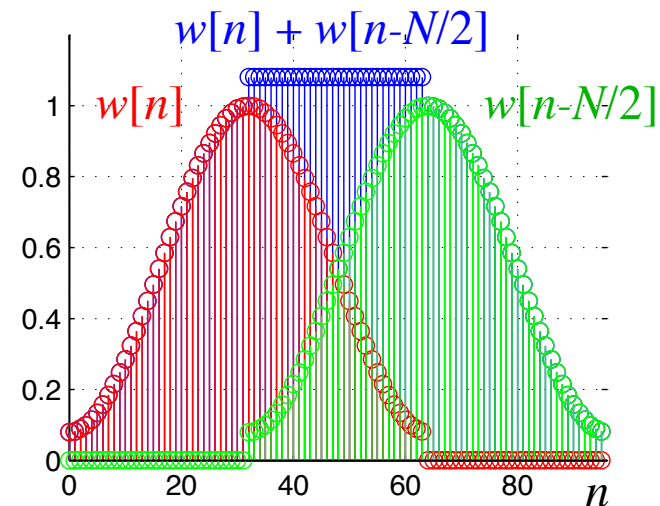
- Then  $\hat{x}[n] = \sum_r x[n]w[n - rH]$   
 $= x[n]$  if  $\sum_{\forall r} w[n - rH] = 1$



# STFT Analysis-Synthesis

- Hann or Hamming windows with 50% overlap sum to constant

$$\left(0.54 + 0.46 \cos\left(2\pi \frac{n}{N}\right)\right) + \left(0.54 + 0.46 \cos\left(2\pi \frac{n-N/2}{N}\right)\right) = 1.08$$



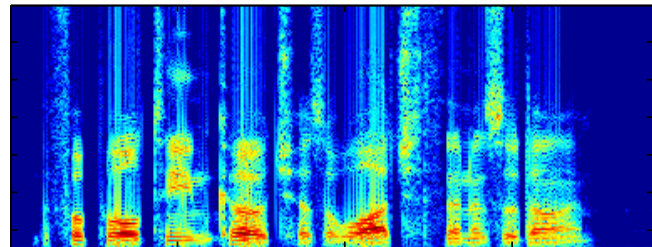
- Can modify individual frames of  $X[k,n]$  and then reconstruct
  - complex, time-varying modifications
  - tapered overlap makes things OK



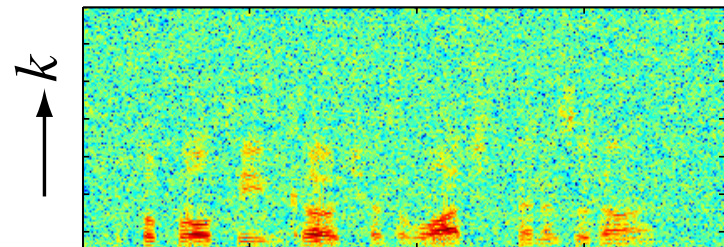
# STFT Analysis-Synthesis

- e.g. Noise reduction:

*STFT of  
original speech*



*Speech corrupted  
by white noise*



*Energy threshold  
mask*

