

Computation of DFT

- Efficient *algorithms* for computing DFT – Fast Fourier Transform.
 - (a) Compute only a few points out of all N points
 - (b) Compute all N points
- What are the efficiency criteria?
 - Number of multiplications
 - Number of additions
 - Chip area in VLSI implementation

✧ DFT as a Linear Transformation

- Matrix representation of DFT

Definition of DFT:

$$X(k) = \sum_{n=0}^{N-1} x(n)W_N^{kn}, \quad k = 0, 1, \dots, N-1$$

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k)W_N^{-kn}, \quad n = 0, 1, \dots, N-1$$

where

$$\text{Let } \mathbf{x}_N = \begin{bmatrix} x(0) \\ x(1) \\ \vdots \\ x(N-1) \end{bmatrix}, \quad \mathbf{X}_N = \begin{bmatrix} X(0) \\ X(1) \\ \vdots \\ X(N-1) \end{bmatrix},$$

and

$$\mathbf{W}_N = \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & W_N & W_N^2 & \cdots & W_N^{N-1} \\ 1 & W_N^2 & W_N^4 & \cdots & W_N^{2(N-1)} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & W_N^{(N-1)} & W_N^{2(N-1)} & \cdots & W_N^{(N-1)(N-1)} \end{bmatrix}$$

Thus,

$$\begin{aligned} \mathbf{X}_N &= \mathbf{W}_N \mathbf{x}_N && N - \text{point DFT} \\ \mathbf{x}_N &= \mathbf{W}_N^{-1} \mathbf{X}_N && N - \text{point IDFT} \\ &= \frac{1}{N} \mathbf{W}_N^* \mathbf{X}_N \end{aligned}$$

Because the matrix (transformation) \mathbf{W}_N has a specific structure and because W_N^k has particular values (for some k and n), we can reduce the number of arithmetic operations for computing this transform.

Example $x[n] = [0 \ 1 \ 2 \ 3]$

$$\mathbf{W}_4 = \begin{bmatrix} W_4^0 & W_4^0 & W_4^0 & W_4^0 \\ W_4^0 & W_4^1 & W_4^2 & W_4^3 \\ W_4^0 & W_4^2 & W_4^4 & W_4^6 \\ W_4^0 & W_4^3 & W_4^6 & W_4^9 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & W_4^1 & W_4^2 & W_4^3 \\ 1 & W_4^2 & W_4^0 & W_4^2 \\ 1 & W_4^3 & W_4^2 & W_4^1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -j & -1 & j \\ 1 & -1 & 1 & -1 \\ 1 & j & -1 & -j \end{bmatrix}$$

Only additions are needed to compute this specific transform.

(This is a well-known *radix-4 FFT*)

$$\text{Thus, the DFT of } x[n] \text{ is } \mathbf{X}_4 = \mathbf{W}_4 \mathbf{x}_4 = \begin{bmatrix} 6 \\ -2+2j \\ -2 \\ -2-2j \end{bmatrix}$$

❖ Fast Fourier Transform

- Highly efficient algorithms for computing DFT
- General principle: *Divide-and-conquer*
- Specific properties of W_N^k
 - Complex conjugate symmetry: $W_N^{-kn} = (W_N^{kn})^*$
 - Symmetry: $W_N^{k+N/2} = -W_N^k$
 - Periodicity: $W_N^{k+N} = W_N^k$
 - Particular values of k and n : e.g., radix-4 FFT (no multiplications)
- Direct computation of DFT

$$\begin{aligned} X[k] &= \sum_{n=0}^{N-1} x[n] \cdot W_N^{kn}, \quad k = 0, 1, \dots, N-1 \\ &= \sum_{n=0}^{N-1} \left\{ \begin{bmatrix} \operatorname{Re}(x[n]) \cdot \operatorname{Re}(W_N^{kn}) - \operatorname{Im}(x[n]) \cdot \operatorname{Im}(W_N^{kn}) \\ j[\operatorname{Re}(x[n]) \cdot \operatorname{Im}(W_N^{kn}) + \operatorname{Im}(x[n]) \operatorname{Re}(W_N^{kn})] \end{bmatrix} \right\} \end{aligned}$$

For each k , we need N complex multiplications and $N-1$ complex additions. $\rightarrow 4N$ real multiplications and $4N-2$ real additions.

We will show how to use the properties of W_N^k to reduce computations.

- Radix-2 algorithms: Decimation-in-time; Decimation-in-frequency
- Composite N algorithms: Cooley-Tukey; Prime factor
- Winograd algorithm
- Chirp transform algorithm

✧ Radix-2 Decimation-in-time Algorithms

-- Assume N -point DFT and $N = 2^\nu$

- Idea: N -point DFT $\rightarrow N/2$ -point DFT $\rightarrow N/4$ -point DFT

$N/4$ -point DFT

$N/2$ -point DFT $\rightarrow N/4$ -point DFT

$N/4$ -point DFT

- Sequence: $x[0] \ x[1] \ x[2] \ x[3] \ \dots \ x[N/2] \ \dots \ x[N-1]$

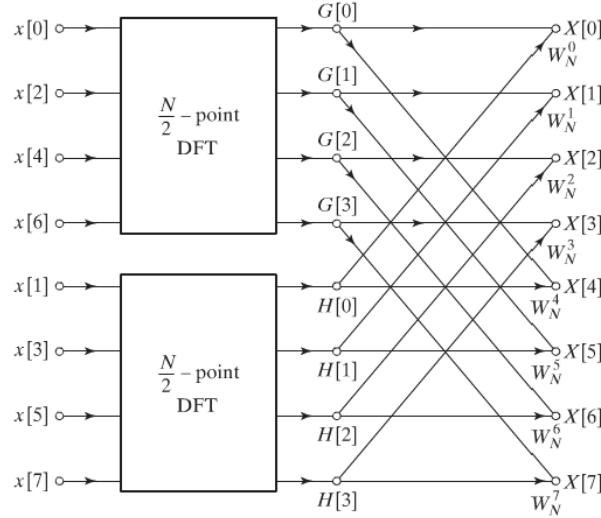
Even index: $x[0] \ x[2] \ \dots \ x[N-2]$

Odd index: $x[1] \ x[3] \ \dots \ x[N-1]$

$$\begin{aligned} X[k] &= \sum_{n=0}^{N-1} x[n] W_N^{kn}, \quad k = 0, 1, \dots, N-1 \\ &= \underbrace{\sum_{\substack{n \text{ even} \\ n=2r}} x[n] W_N^{kn}} + \underbrace{\sum_{\substack{n \text{ odd} \\ n=2r+1}} x[n] W_N^{kn}} \\ &= \sum_{r=0}^{\frac{N}{2}-1} x[2r] W_N^{2rk} + \sum_{r=0}^{\frac{N}{2}-1} x[2r+1] W_N^{(2r+1)k} \end{aligned}$$

$$\therefore W_N^2 = e^{-2j\left(\frac{2\pi}{N}\right)} = e^{-2j\left(\frac{\pi}{N/2}\right)} = W_{N/2}$$

$$\begin{aligned} X[k] &= \underbrace{\sum_{r=0}^{\frac{N}{2}-1} x[2r] W_{N/2}^{rk}} + \underbrace{W_N^k \sum_{r=0}^{\frac{N}{2}-1} x[2r+1] W_{N/2}^{rk}} \\ &= G[k] + W_N^k H[k] \end{aligned}$$



■ Comparison:

(a) Direct computation of N -point DFT (N frequency samples):

$$\sim N^2 \text{ complex multiplications and } N^2 \text{ complex adds}$$

(b) Direct computation of $\frac{N}{2}$ -point DFT:

$$\sim \left(\frac{N}{2}\right)^2 \text{ complex multiplications and } \left(\frac{N}{2}\right)^2 \text{ complex adds}$$

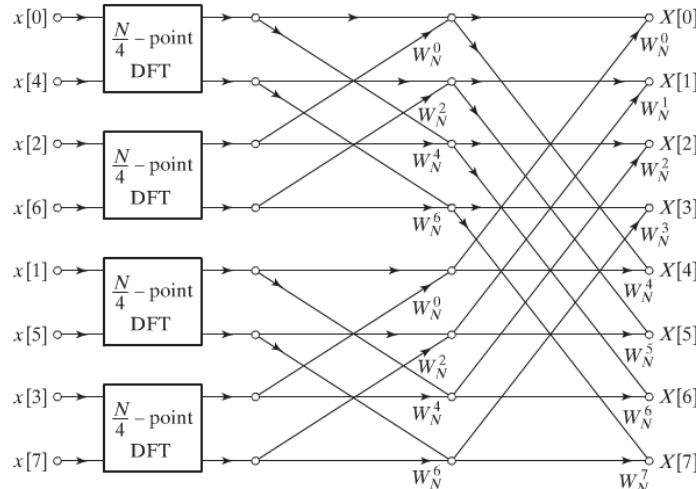
+ additional N complex multis and N complex adds

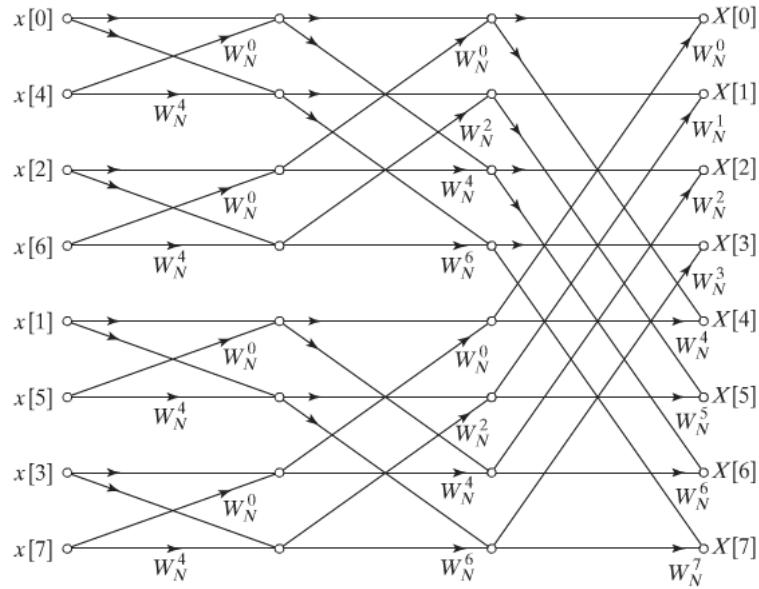
$$\sim (\text{Total:}) N + 2\left(\frac{N}{2}\right)^2 = N + \frac{N^2}{2} \text{ complex multis and adds}$$

(c) $\log_2 N$ -stage FFT

Since $N = 2^\nu$, we can further break $\frac{N}{2}$ -point DFT into two $\frac{N}{4}$ -point DFT and

so on.





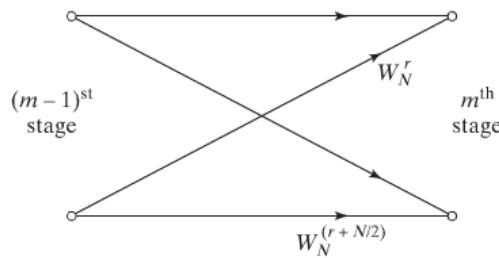
At each stage: $\sim N$ complex multis and adds

Total: $\sim N \log_2 N$ complex multis and adds ($\sim \frac{N}{2} \log_2 N$)

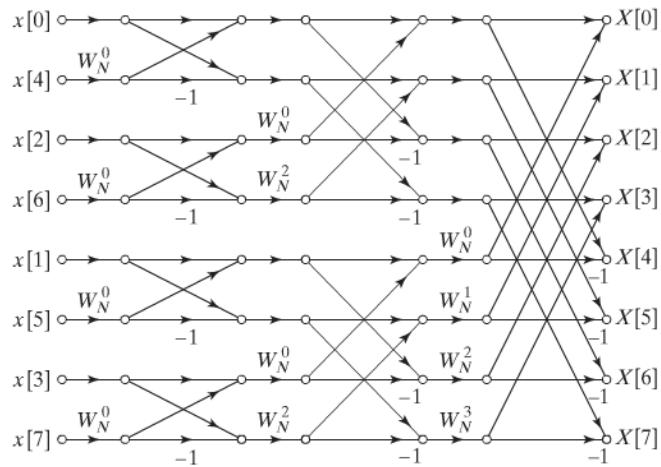
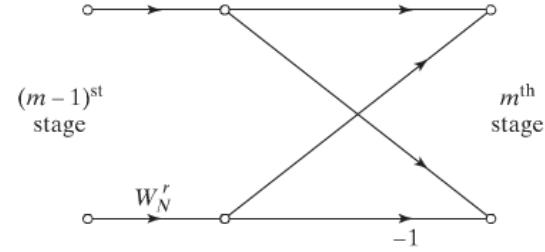
| Number of points, N | Direct Computation: Complex Multis | FFT: Complex Multis | Speed Improvement Factor |
|-----------------------|---------------------------------------|------------------------|--------------------------|
| 4 | 16 | 4 | 4.0 |
| 8 | 64 | 12 | 5.3 |
| 16 | 256 | 32 | 8 |
| 64 | 4,096 | 192 | 21.3 |
| 256 | 65,536 | 1,024 | 64.0 |
| 1024 | 1,048,576 | 5,120 | 204.8 |

■ Butterfly: Basic unit in FFT

Two multiplications:



One multiplication:

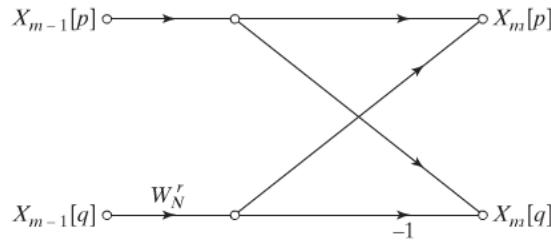


■ In-place computations

Only two registers are needed for computing a butterfly unit.

$$X_m[p] = X_{m-1}[p] + W_N^r X_{m-1}[q]$$

$$X_m[q] = X_{m-1}[p] - W_N^r X_{m-1}[q]$$



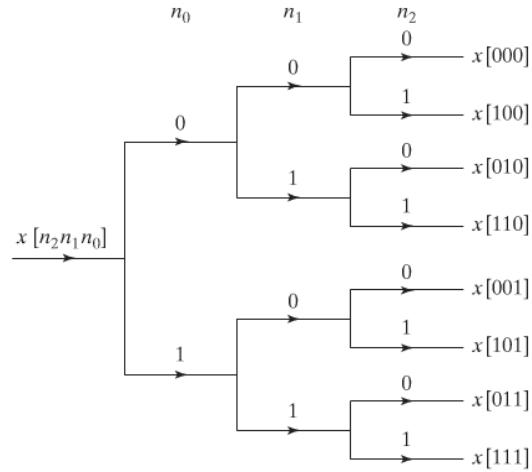
Advantage: less storage!

- In order to retain the in-place computation property, the input data are accessed in the **bit-reversed** order.

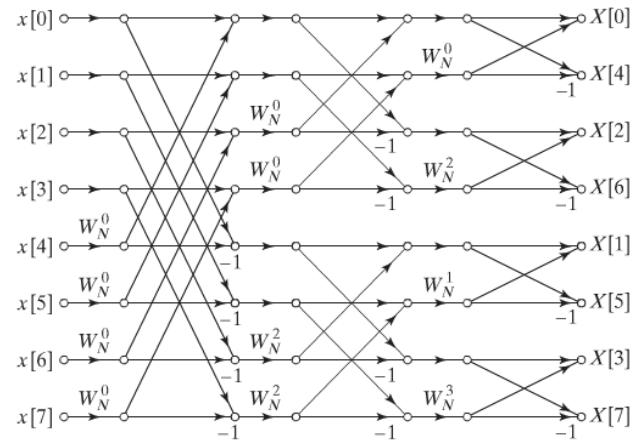
Note: The outputs are in the normal order (same as the “position”)

| Position | Binary equivalent | Bit reversed | Sequence index |
|----------|-------------------|--------------|----------------|
| 6 | 110 | 011 | 3 |
| 2 | 010 | 010 | 2 |

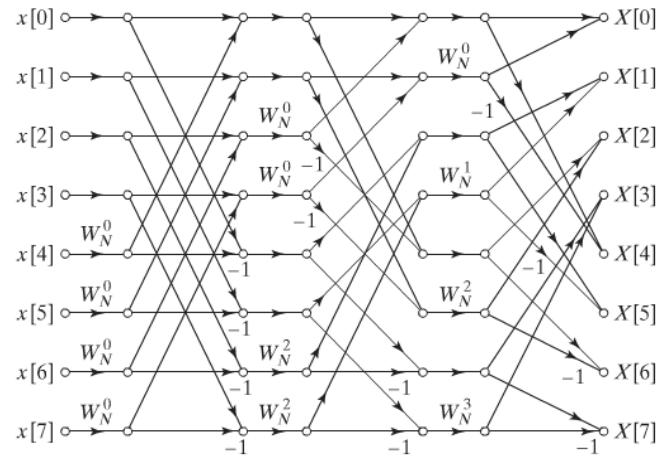
Remark: Index 3 input data is placed at position 6.

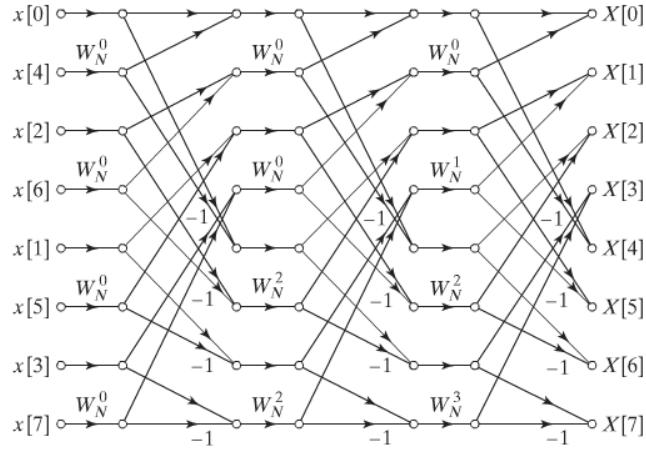


We may also place the inputs in the normal order; then the outputs are in the bit-reversed order.



- If we try to maintain the normal order of both inputs and outputs, then in-place computation structure is destroyed.





✧ Radix-2 Decimation-in-frequency Algorithms

- Dividing the output sequence $X[k]$ into smaller pieces.

$$X(k) = \sum_{n=0}^{N-1} x(n) W_N^{kn}, \quad k = 0, 1, \dots, N-1$$

If k is even, $k = 2r$.

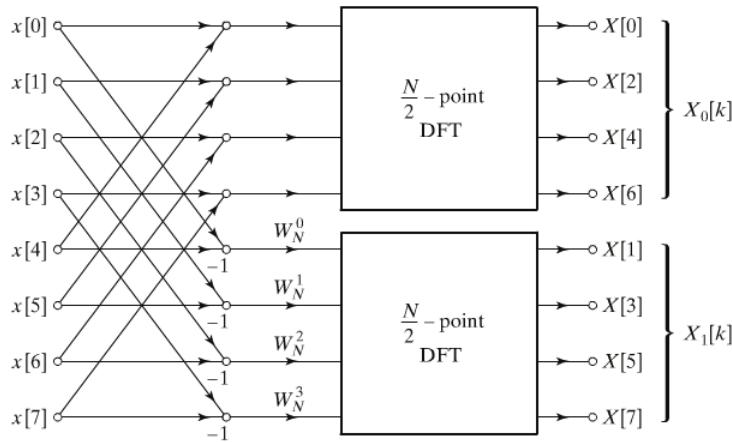
$$\begin{aligned} X[2r] &= \sum_{n=0}^{N-1} x[n] W_N^{kn}, \quad r = 0, 1, \dots, \frac{N}{2}-1 \\ &= \sum_{n=0}^{\frac{N}{2}-1} x[n] W_N^{2nr} + \sum_{n=\frac{N}{2}}^{N-1} x[n] W_N^{2nr} \quad n \leftarrow (n + \frac{N}{2}) \\ &= \sum_{n=0}^{\frac{N}{2}-1} x[n] W_N^{2nr} + \sum_{n=0}^{\frac{N}{2}-1} x\left[n + \frac{N}{2}\right] \cdot W_N^{2r\left(n + \frac{N}{2}\right)} \\ &\because W_N^{2r[n+\frac{N}{2}]} = W_N^{2rn} W_N^{rN} = W_N^{2rn} \\ &= \sum_{n=0}^{\frac{N}{2}-1} \left(x[n] + x\left[n + \frac{N}{2}\right] \right) \cdot W_N^{2nr} \\ &= \sum_{n=0}^{\frac{N}{2}-1} \left(x[n] + x\left[n + \frac{N}{2}\right] \right) \cdot W_{N/2}^{nr} \end{aligned}$$

Similarly, if k is odd, $k = 2r+1$.

$$X[2r+1] = \sum_{n=0}^{\frac{N}{2}-1} \left(x[n] - x\left[n + \frac{N}{2}\right] \right) \cdot W_N^n \cdot W_{N/2}^{nr}$$

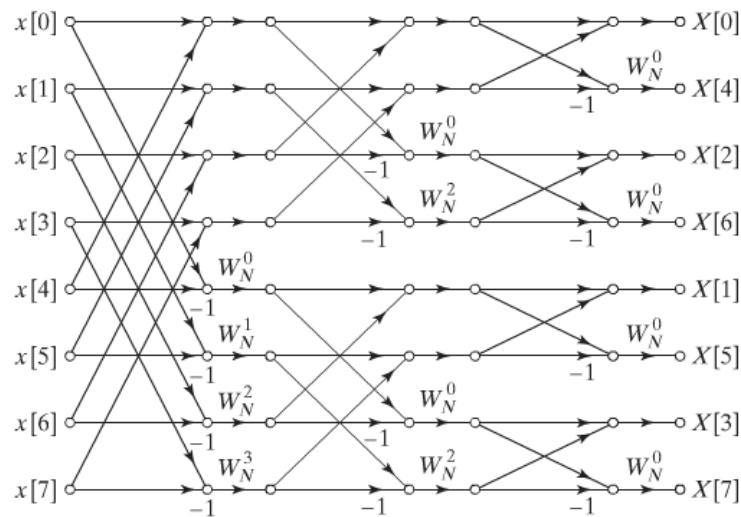
$$\left\{ \begin{array}{l} X[2r] = \sum_{n=0}^{\frac{N}{2}-1} \left(x[n] + x\left[n + \frac{N}{2}\right] \right) \cdot W_{N/2}^{nr} \\ X[2r+1] = \sum_{n=0}^{\frac{N}{2}-1} \left(x[n] - x\left[n + \frac{N}{2}\right] \right) \cdot W_N^n \cdot W_{N/2}^{nr} \end{array} \right.$$

Let $\begin{cases} g[n] = x[n] + x\left[n + \frac{N}{2}\right] \\ h[n] = x[n] - x\left[n + \frac{N}{2}\right] \end{cases}$



We can further break $X[2r]$ into even and odd groups ...

Again, we can reduce the two-multiplication butterfly into one multiplication. Hence, the computational complexity is about $\frac{N}{2} \log_2 N$. The in-place computation property holds if the outputs are in bit-reversed order (when inputs are in the normal order).



❖ FFT for Composite N

-- Cooley-Tukey Algorithm: $N = N_1 N_2$

$$\left\{ \begin{array}{l} \text{Time index : } n = N_2 n_1 + n_2 \quad \begin{cases} 0 \leq n_1 \leq N_1 - 1 \\ 0 \leq n_2 \leq N_2 - 1 \end{cases} \\ \text{Freq. index : } k = k_1 + N_1 k_2 \quad \begin{cases} 0 \leq k_1 \leq N_1 - 1 \\ 0 \leq k_2 \leq N_2 - 1 \end{cases} \end{array} \right.$$

Remark: $n \leftrightarrow (n_1, n_2)$ and $k \leftrightarrow (k_1, k_2)$

■ Goal: Decompose N -point DFT into two stages:

$$N_1\text{-point DFT} \otimes N_2\text{-point DFT}$$

$$\begin{aligned} X[k] &= \sum_{n=0}^{N-1} x[n] W_N^{kn}, \quad 0 \leq k \leq N-1 \\ &= X[k_1 + N_1 k_2] \\ &= \sum_{n_2=0}^{N_2-1} \sum_{n_1=0}^{N_1-1} x[N_2 n_1 + n_2] \cdot W_N^{(k_1+N_1 k_2)(N_2 n_1 + n_2)} \\ &= \sum_{n_2=0}^{N_2-1} \sum_{n_1=0}^{N_1-1} x[N_2 n_1 + n_2] \cdot \underbrace{W_N^{N_2 k_1 n_1}}_{W_{N_1}^{k_1 n_1}} \cdot \underbrace{W_N^{k_1 n_2}}_{W_{N_2}^{k_2 n_2}} \cdot \underbrace{W_N^{k_1 N_1 n_2}}_{\text{twiddle factor}} \cdot \underbrace{W_N^{N_1 N_2 k_2 n_1}}_1 \\ &= \sum_{n_2=0}^{N_2-1} \underbrace{\left[\sum_{n_1=0}^{N_1-1} x[N_2 n_1 + n_2] \cdot W_{N_1}^{k_1 n_1} \right]}_{N_1\text{-point}} \cdot \underbrace{W_{N_2}^{k_1 n_2}}_{\text{twiddle factor}} \cdot W_{N_2}^{k_2 n_2} \end{aligned}$$

■ Procedure

(1) Compute N_1 -point DFT: (row transform)

$$G[n_2, k_1] = \sum_{n_1=0}^{N_1-1} x[N_2 n_1 + n_2] \cdot W_{N_1}^{k_1 n_1}$$

(2) Multiply twiddle factors:

$$\tilde{G}[n_2, k_1] = W_{N_2}^{k_1 n_2} \cdot G[n_2, k_1]$$

(3) Compute N_2 -point DFT: (column transform)

$$X[k_1 + N_1 k_2] = \sum_{n_2=0}^{N_2-1} \tilde{G}[n_2, k_1] \cdot W_{N_2}^{k_2 n_2}$$

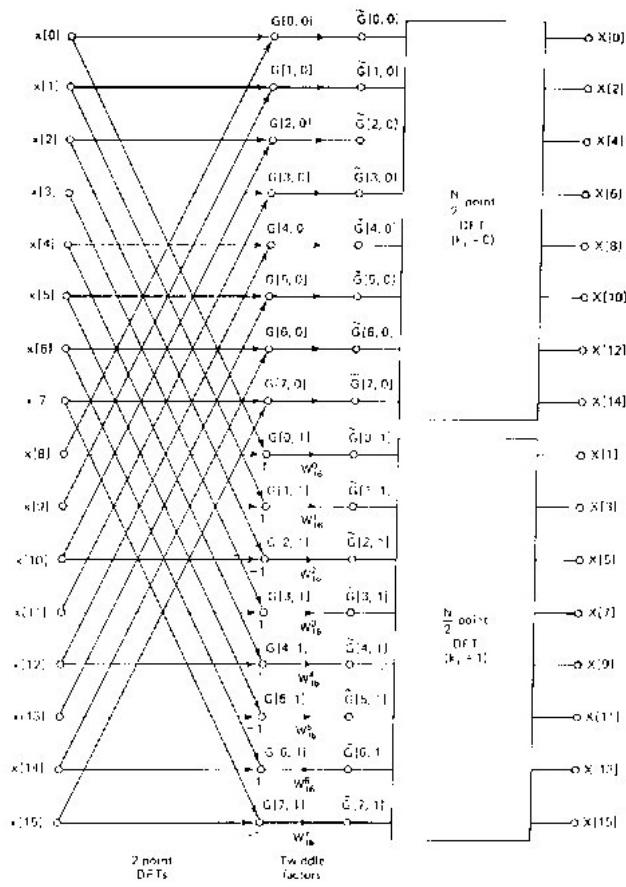
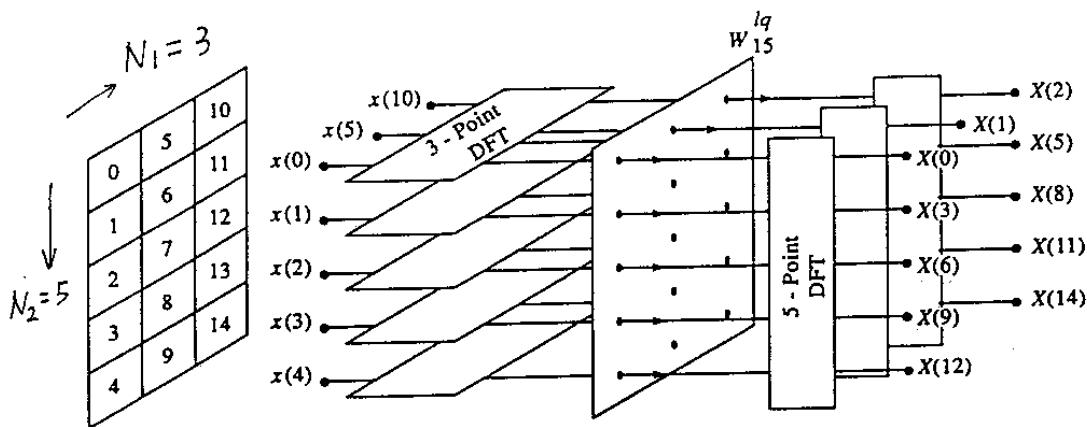


Figure 9.27 Flow graph of decomposition of an N -point DFT into two $(N/2)$ -point DFTs ($N = 16$)

(Computation of $N=15$ -point DFT by means of 3-point and 5-point DFTs.)



■ **Extension:** $N = N_1 N_2 \cdots N_v$

Let $\mu(N) \equiv$ number of multiplications for N - point DFT

If $N = N_1 N_2$

$$\begin{cases} 1. \text{ row transform : } & N_2 \cdot \mu(N_1) \\ 2. \text{ twiddle factors : } & N_1 N_2 = N \\ 3. \text{ column transfrm : } & N_1 \cdot \mu(N_2) \end{cases}$$

$$\begin{aligned} \mu(N) &= N_2 \cdot \mu(N_1) + N_1 \cdot \mu(N_2) + N \\ &= N \left(\frac{\mu(N_1)}{N_1} + \frac{\mu(N_2)}{N_2} + 1 \right) \end{aligned}$$

$$\text{In general, } \mu(N) = N \left(\sum_{i=1}^v \frac{\mu(N_i)}{N_i} + (v-1) \right)$$

In fact, the term $(v-1)$ should be $\frac{(v-1)}{2}$ because rearranging the butterfly structure would make half of the branches becoming “1”.

■ **Special Case:** $N_1 = N_2 = \cdots = N_v = 2$

Radix-2: $N_1 = N_2 = \cdots = N_v = 2$ and $v = \log_2 N$

$\mu(N) = \frac{N(v-1)}{2}$ multiplications because $\mu(2)$ requires no multiplications.

Radix-4: $N_1 = N_2 = \cdots = N_v = 4$ and $v = \log_4 N$

$\mu(N) = \frac{N(v-1)}{2}$ multiplications because $\mu(4)$ requires no multiplications. This FFT

has fewer stages than Radix-2 ==> fewer multiplications.

$$\mathbf{W}_4 = \begin{bmatrix} W_4^0 & W_4^0 & W_4^0 & W_4^0 \\ W_4^0 & W_4^1 & W_4^2 & W_4^3 \\ W_4^0 & W_4^2 & W_4^4 & W_4^6 \\ W_4^0 & W_4^3 & W_4^6 & W_4^9 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & W_4^1 & W_4^2 & W_4^3 \\ 1 & W_4^2 & W_4^0 & W_4^2 \\ 1 & W_4^3 & W_4^2 & W_4^1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -j & -1 & j \\ 1 & -1 & 1 & -1 \\ 1 & j & -1 & -j \end{bmatrix}$$

✧ Inverse FFT

■ IDFT: $x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] \cdot W_N^{-kn}$ (*)

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

Hence, take the conjugate of (*) :

$$\begin{aligned} x^*[n] &= \frac{1}{N} \left(\sum_{k=0}^{N-1} X[k] \cdot W_N^{-kn} \right)^* \\ &= \frac{1}{N} \sum_{k=0}^{N-1} (X[k] \cdot W_N^{-kn})^* \\ &= \frac{1}{N} \sum_{k=0}^{N-1} (X^*[k] \cdot W_N^{kn}) \\ &= \frac{1}{N} \text{DFT}[X^*(k)] \end{aligned}$$

Take the conjugate of the above equation:

$$\begin{aligned} x[n] &= \frac{1}{N} (\text{DFT}[X^*(k)])^* \\ &= \frac{1}{N} (\text{FFT}[X^*(k)])^* \end{aligned}$$

Thus, we can use the FFT algorithm to compute the inverse DFT.

✧ The Goertzel Algorithm

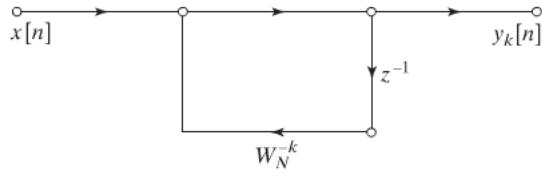
$$W_N^{-kN} = e^{j(\frac{2\pi}{N})Nk} = e^{j2\pi k} = 1$$

$$X[k] = W_N^{-kN} \sum_{r=0}^{N-1} x[r] W_N^{kr} = \sum_{r=0}^{N-1} x[r] W_N^{-k(N-r)}$$

If we define $x[n] = 0$ for $n < 0$ and $n \geq N$

and $y_k[n] = \sum_{r=-\infty}^{\infty} x[r] W_N^{-k(N-r)} u[n-r] = x[n] * (W_N^{-kn} u[n])$,

$$\Rightarrow X[k] = y_k[n] \Big|_{n=N}$$



$$H_k(z) = \frac{1}{1 - W_N^{-k} z^{-1}}$$

If $x[n]$ is complex, we need 4 real multiplications and 4 real additions to compute each $y_k[n]$.

To compute $y_k[N]$, we need to compute $y_k[1], y_k[2], \dots, y_k[N-1]$.

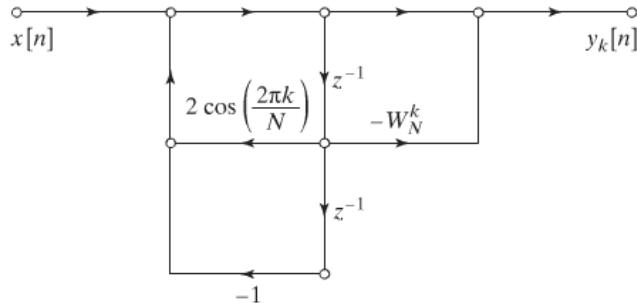
\Rightarrow We need $4N$ real multiplications and $4N$ real additions to compute $X[k]$.

Remarks:

- less efficient than the direct method.
- Avoid the computation or storage of the coefficients W_N^{kn} .

To reduce the number of multiplications,

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



If $x[n]$ is complex, we only need 2 real multiplications and 4 real additions to implement the poles of the system.

(The complex multiplication by $-W_N^k$ needs not be performed at every iteration.)

\Rightarrow To compute $X[k]$, we need $2N$ real multiplications and $4N$ real additions for the poles and 4 real multiplications and 4 real additions for the zero.

Remarks:

- Avoid the computation or storage of the coefficients W_N^{kn} .
- Only need to compute and save W_N^k and $\cos(2\pi k/N)$.