ESE 5310: Digital Signal Processing

Lecture 20: April 6, 2023 Fast Fourier Transform



Fast Fourier Transform Algorithms

We are interested in efficient computing methods for the DFT and inverse DFT:

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

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



- □ Fast Fourier transform algorithms enable computation of an N-point DFT (or inverse DFT) with the order of just N · log₂ N complex multiplications.
 - This can represent a huge reduction in computational load, especially for large N.

N	N ²	$N \cdot \log_2 N$	$\frac{N^2}{N \cdot \log_2 N}$
16	256	64	4.0
128	16,384	896	18.3
1,024	1,048,576	10,240	102.4
8,192	67,108,864	106,496	630.2
$6 imes 10^6$	$36 imes 10^{12}$	$135 imes 10^6$	$2.67 imes 10^{5}$

* 6Mp image size

Eigenfunction Properties

■ Most FFT algorithms exploit the following properties of W_N^{kn} : $W_N^0 = W_N^N = W_N^{2N} =$

Conjugate Symmetry

$$W_N^0 = W_N^N = W_N^{2N} = \dots = 1$$
$$W_N^{k+N} = W_N^k$$

$$W_N^{k(N-n)} = W_N^{-kn} = (W_N^{kn})^*$$

• Periodicity in n and k

$$W_N^{kn} = W_N^{k(n+N)} = W_N^{(k+N)n}$$

Power

$$W_N^2 = W_{N/2}$$

FFT Algorithms via Decimation

- Most FFT algorithms decompose the computation of a DFT into successively smaller DFT computations.
 - Decimation-in-time algorithms decompose x[n] into successively smaller subsequences.
 - Decimation-in-frequency algorithms decompose X[k] into successively smaller subsequences.
- Note: Assume length of x[n] is power of 2 (N = 2^v). If not, zero-pad to closest power of 2.



• We start with the DFT

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

• Separate the sum into even and odd terms:

$$X[k] = \sum_{n \text{ even}} x[n] W_N^{kn} + \sum_{n \text{ odd}} x[n] W_N^{kn}$$

These are two DFTs, each with half the number of samples (N/2)



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$$X[k] = \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk} + W_N^k \sum_{r=0}^{(N/2)-1} x[2r+1] W_{N/2}^{rk}$$



Hence:

$$X[k] = \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk} + W_N^k \sum_{r=0}^{(N/2)-1} x[2r+1] W_{N/2}^{rk}$$
$$\triangleq G[k] + W_N^k H[k], \quad k = 0, \dots, N-1$$

where we have defined:

$$G[k] \triangleq \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk} \Rightarrow \text{DFT of even samples}$$

$$H[k] \triangleq \sum_{r=0}^{(N/2)-1} x[2r+1] W_{N/2}^{rk} \Rightarrow \text{DFT of odd samples}$$















Both G[k] and H[k] are periodic, with period N/2. For example

$$G[k] \triangleq \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk}$$

• Decimation-in-Time FFT

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$$G[k + N/2] = \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{r(k+N/2)}$$

$$= \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk} W_{N/2}^{r(N/2)} = 1$$

$$= \sum_{r=0}^{(N/2)-1} x[2r] W_{N/2}^{rk}$$

$$= G[k]$$



□ So,

$$G[k + (N/2)] = G[k]$$

 $H[k + (N/2)] = H[k]$

The periodicity of G[k] and H[k] allows us to further simplify. For the first N/2 points we calculate G[k] and W_N^kH[k], and then compute the sum

$$X[k] = G[k] + W_N^k H[k] \qquad \forall \{k : 0 \le k < \frac{N}{2}\}.$$







How does periodicity help for
$$\frac{N}{2} \le k < N$$
?
 $X[k] = G[k] + W_N^k H[k] \qquad \forall \{k : 0 \le k < \frac{N}{2}\}.$

for
$$\frac{N}{2} \leq k < N$$
:

ł

$$W_N^{k+(N/2)} = ?$$

X[k + (N/2)] = ?



$X[k + (N/2)] = G[k] - W_N^k H[k]$

• We previously calculated G[k] and $W_N^kH[k]$.

Now we only have to compute their difference to obtain the second half of the spectrum. No additional multiplies are required.







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Penn ESE 5310 Spring 2023 – Khanna Adapted from M. Lustig, EECS Berkeley $X[0] = G[0] + W_N^0 H[0]$



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Penn ESE 5310 Spring 2023 – Khanna Adapted from M. Lustig, EECS Berkeley $X[4] = G[0] - W_N^0 H[0]$



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Decimation-in-Time FFT

- Note that the inputs have been reordered so that the outputs come out in their proper sequence.
- We can define a *butterfly operation*, e.g., the computation of X[k] and X[k+N/2] from G[k] and H[k]:





• Still $O(N^2)$ operations.... What should we do?





We can use the same approach for each of the N/2 point DFT's. For the N = 8 case, the N/2 DFTs look like



*Note that the inputs have been reordered again.



 At this point for the 8 sample DFT, we can replace the N/4 = 2 sample DFT's with a single butterfly. The fundamental eigenfunction is:

$$W_{N/4} = W_{8/4} = W_2 = e^{-j\pi} = -1$$



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Replace N/2-point DFT with 2-point DFT and butterfly operations





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• $3 = \log_2(N) = \log_2(8)$ stages

- 4=N/2=8/2 multiplications in each stage
 - 1st stage has trivial multiplication
Decimation-in-Time FFT

- □ In general, there are log_2N stages of decimation-in-time.
- Each stage requires N/2 complex multiplications, some of which are trivial.
- □ The total number of complex multiplications is $(N/2) \log_2 N$, or is $O(N \log_2 N)$

Decimation-in-Time FFT

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- Each stage requires N/2 complex multiplications, some of which are trivial.
- □ The total number of complex multiplications is $(N/2) \log_2 N$, or is $O(N \log_2 N)$
- The order of the input to the decimation-in-time FFT algorithm must be permuted.
 - Net effect is reversing the bit order of indexes

This is illustrated in the following table for N = 8.

Decimal	Binary	Bit-Reversed Binary	Bit-Reversed Decimal
0	000	000	0
1	001	100	4
2	010	010	2
3	011	110	6
4	100	001	1
5	101	101	5
6	110	011	3
7	111	111	7



Combining all these stages, the diagram for the 8 sample DFT is:





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$$X[2r] = \sum_{n=0}^{N-1} x[n] W_N^{n(2r)}$$

We split this into two sums, one over the first N/2 samples, and the second of the last N/2 samples.

$$X[2r] = \sum_{n=0}^{(N/2)-1} x[n] W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2] W_N^{2r(n+N/2)}$$

Decimation-in-Frequency FFT

But
$$W_N^{2r(n+N/2)} = W_N^{2rn} W_N^{rN} = W_N^{2rn}$$

We can then write

$$X[2r] = \sum_{n=0}^{(N/2)-1} x[n] W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2] W_N^{2r(n+N/2)}$$
$$= \sum_{n=0}^{(N/2)-1} x[n] W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2] W_N^{2rn}$$

Decimation-in-Frequency FFT

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$$W_N^{2r(n+N/2)} = W_N^{2rn} W_N^{rN} = W_N^{2rn} = W_{N/2}^{rn}$$
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We can then write

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=
$$\sum_{n=0}^{(N/2)-1} x[n] W_N^{2rn} + \sum_{n=0}^{(N/2)-1} x[n+N/2] W_N^{2rn}$$

=
$$\sum_{n=0}^{(N/2)-1} (x[n] + x[n+N/2]) W_{N/2}^{rn}$$

This is the N/2-length DFT of first and second half of x[n] summed.

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$$X[2r] = \mathsf{DFT}_{\frac{N}{2}} \{ (x[n] + x[n + N/2]) \}$$

$$X[2r+1] = \mathsf{DFT}_{\frac{N}{2}} \{ (x[n] - x[n + N/2]) W_N^n \}$$

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(By a similar argument that gives the odd samples)

 Continue the same approach on the N/2 DFTs, and N/4 DFTs until we reach the 2-point DFT, which is a simple butterfly operation



The diagram for and 8-point decimation-in-frequency DFT is as follows



This is just the decimation-in-time algorithm reversed! The inputs are in normal order, and the outputs are bit reversed.



Combining all these stages, the diagram for the 8 sample DFT is:



• $3 = \log_2(N) = \log_2(8)$ stages

- 4=N/2=8/2 multiplications in each stage
 - 1st stage has trivial multiplication



- A similar argument applies for any length DFT, where the length N is a composite number
- For example, if N=6, with decimation-in-frequency you could compute three 2-point DFTs followed by two 3-point DFTs



























Non-Power-of-2 FFTs

- Good component DFTs are available for lengths up to 20(ish). Many of these exploit the structure for that specific length
 - For example, a factor of

$$W_N^{N/4} = e^{-j\frac{2\pi}{N}(N/4)} = e^{-j\frac{\pi}{2}} = -j$$

Just swaps the real and imaginary components of a complex number. Hence a DFT of length 4 doesn't require any complex multiples.

- Half of the multiples of an 8-point DFT also don't require multiplication
- Composite length FFTs can be very efficient for any length that factors into terms of this order



- Historically, the power-of-two FFTs were much faster (better written and implemented).
- For non-power-of-two length, it was faster to zero pad to power of two.
- Recently this has changed. The free FFTW package implements very efficient algorithms for almost any filter length. Matlab has used FFTW since version 6





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- □ What if the signal x[n] has a k sparse frequency
 - A. Gilbert et. al, "Near-optimal sparse Fourier representations via sampling
 - H. Hassanieh et. al, "Nearly Optimal Sparse Fourier Transform"
 - Others...
 - O(K Log N) instead of O(N Log N)



From: http://groups.csail.mit.edu/netmit/sFFT/paper.html



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 Compare the *total number of multiplications* required in your scheme to that in the direct implementation of FIR filtering. (Consider the case r = 10, m = 10).





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(a) Suppose N = 10. You want to evaluate both $X(e^{j2\pi 7/12})$ and $X(e^{j2\pi 3/8})$. The only computation you can perform is one DFT, on any one input sequence of your choice. Can you find the desired DTFT values? (Show your analysis and explain clearly.)



(b) Suppose N is large. You want to obtain $X(e^{j\omega})$ at the following 2M frequencies:

$$\omega = \frac{2\pi}{M}m, m = 0, 1, ..., M - 1$$
 and $\omega = \frac{2\pi}{M}m + \frac{2\pi}{N}, m = 0, 1, ..., M - 1.$
Here $M = 2^{\mu} \ll N = 2^{\nu}$

A standard radix-2 FFT algorithm is available. You may execute the FFT algorithm *once* or *more than once*, and *multiplications* and *additions* outside of the FFT are *allowed*, if necessary.

(i) You want to get the 2*M* DTFT values with as few *total multiplications* as possible (*including those in the FFT*). Give explicitly the best method you can find for this, with an estimate of the *total number of multiplications* needed in terms of *M* and *N*.



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- (ii) Does your result change if extra multiplications outside of FFTs are not allowed?

Chirp Transfer Algorithm



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Chirp Transform Algorithm

- Uses convolution to evaluate the DFT
- This algorithm is not optimal in minimizing any measure of computational complexity, but it has been useful in a variety of applications, particularly when implemented in technologies that are well suited to doing convolution with a fixed, prespecified impulse response.
- The CTA is also more flexible than the FFT, since it can be used to compute *any* set of equally spaced samples of the Fourier transform on the unit circle.

Chirp Transform Algorithm



• Example: Chirp Transform Parameters

We have a finite-length sequence x[n] that is nonzero only on the interval n = 0, ..., 25, (Length N=26) and we wish to compute 16 samples of the DTFT X(e^{jω}) at the frequencies ω_k = 2π/27 + 2πk/1024 for k = 0, ..., 15.








$$h_1[n] = \begin{cases} W^{-(n-N+1)^2/2}, & n = 0, 1, \dots, M+N-2, \\ 0, & \text{otherwise.} \end{cases}$$



 $X(e^{j\omega_n}) = y_1[n+N-1], \qquad n = 0, 1, \dots, M-1.$

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- Fast Fourier Transform
 - Enable computation of an N-point DFT (or DFT⁻¹) with the order of just N · log₂ N complex multiplications.
 - Most FFT algorithms decompose the computation of a DFT into successively smaller DFT computations.
 - Decimation-in-time algorithms
 - Decimation-in-frequency
 - Historically, power-of-2 DFTs had highest efficiency
 - Modern computing has led to non-power-of-2 FFTs with high efficiency
 - Sparsity leads to reduced computation on order $K \cdot \log N$
- Design DSP methods to minimize computations!

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- □ HW 8 due 4/11
- □ Project 2 posted on 4/11
 - Can work in pairs

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