



Part-two Outlines Discrete Transforms

- Fourier Series
- Fourier Transform
- •Discrete Fourier Transform (DFT)
- **•**DFT inverse
- •Properties of DFT
- Complexity of DFT

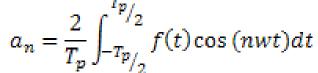




Any periodic continuous waveform f(t) can be represented as the sum of an infinite number of sinusoidal and cosinusoidal terms, together with a constant term, this representation being the Fourier series given by

$$f(t) = a_0 + \sum_{n=1}^{\infty} a_n \cos(nwt) + \sum_{n=1}^{\infty} b_n \sin(nwt)$$

$$a_0 = \frac{1}{T_p} \int_{-T_{p/2}}^{T_{p/2}} f(t)dt \qquad b_n = \frac{2}{T_p} \int_{-T_{p/2}}^{T_{p/2}} f(t)\sin(nwt)dt$$





The frequencies $n\omega$ are known as the *n*th harmonics of ω .







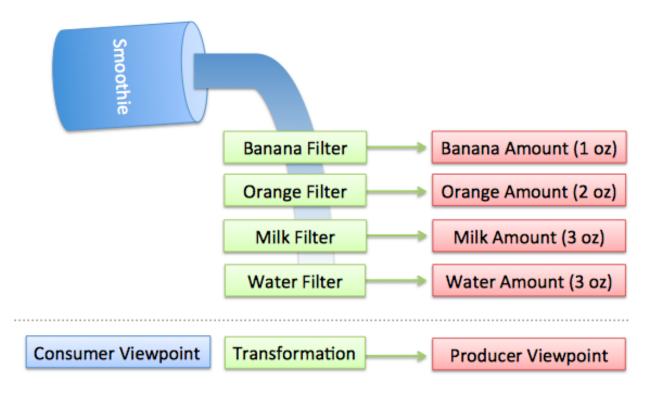


- ❖ The Fourier Transform changes our perspective from consumer to producer, turning What I see ?, into How was it made ?
 - What does the Fourier Transform do? Given a smoothie, it finds the recipe.
 - **How?** Run the smoothie through filters to extract each ingredient.
 - Why? Recipes are easier to analyze, compare, and modify than the smoothie itself.
 - How do we get the smoothie back? Blend the ingredients.
 - Filters must be independent. The banana filter needs to capture bananas, and nothing else. Adding more oranges should never affect the banana reading.
 - Filters must be complete. We won't get the real recipe if we leave out a filter ("There were mangoes too!"). Our collection of filters must catch every last ingredient.
 - Ingredients must be combine-able. Smoothies can be separated and re-combined without issue (A cookie? Not so much. Who wants crumbs?). The ingredients, when separated and combined in any order, must make the same result.





Smoothie to Recipe



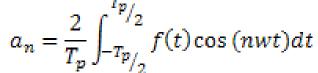




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where t is an independent variable which often represents time but could, for example, represent distance or any other quantity, f(t) is often a varying voltage versus time waveform, but could be any other waveform, $\omega = 2\pi/T_p$ is known as the first harmonic, or fundamental, angular frequency, related to the fundamental frequency, f, by $\omega = 2\pi f$, T_p is the repetition period of the waveform,

❖This series can be written more compactly using exponential notation and the advantage in that form is that it is more easily manipulated mathematically the series that becomes

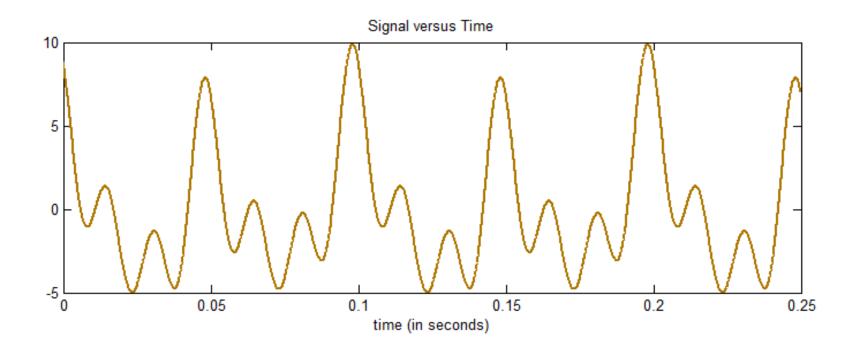
$$f(t) = \sum_{n=-\infty}^{\infty} d_n e^{jn\omega t}$$

$$d_n = \frac{1}{T_p} \int_{-T_p/2}^{T_p/2} f(t) e^{-jn\omega t} dt$$



 \bullet is complex and $|d_n|$ has the unit of volts.

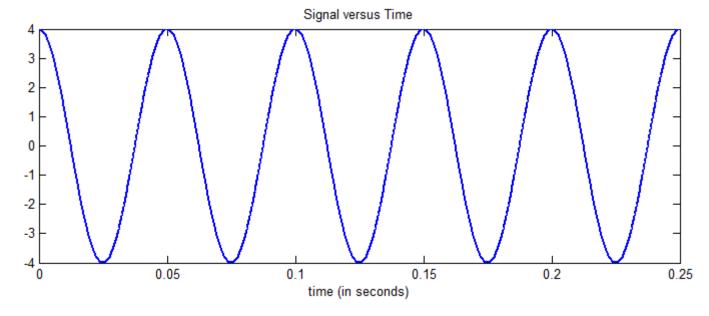








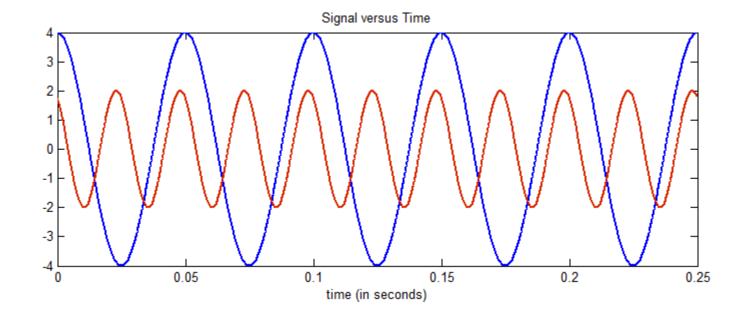
- F= 20 HZ
- A=4
- **Θ**=0







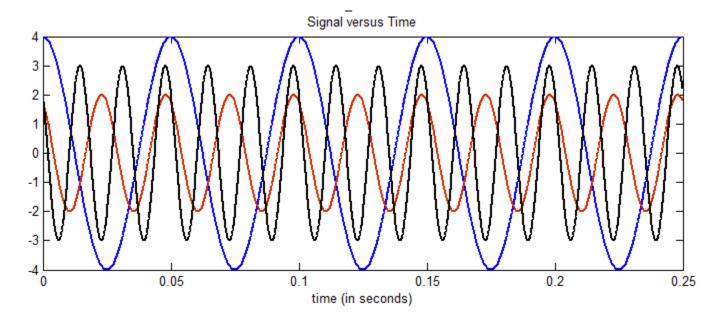
- F= 20 HZ
- A=4
- $\Theta=0$ rad
- F= 40 HZ
- A=2
- Θ =0.5 rad







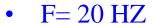
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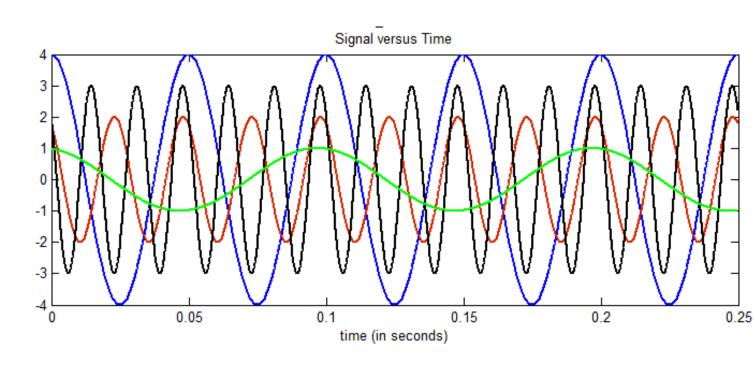
- F=60 HZ
- A=3
- Θ =0.8 rad





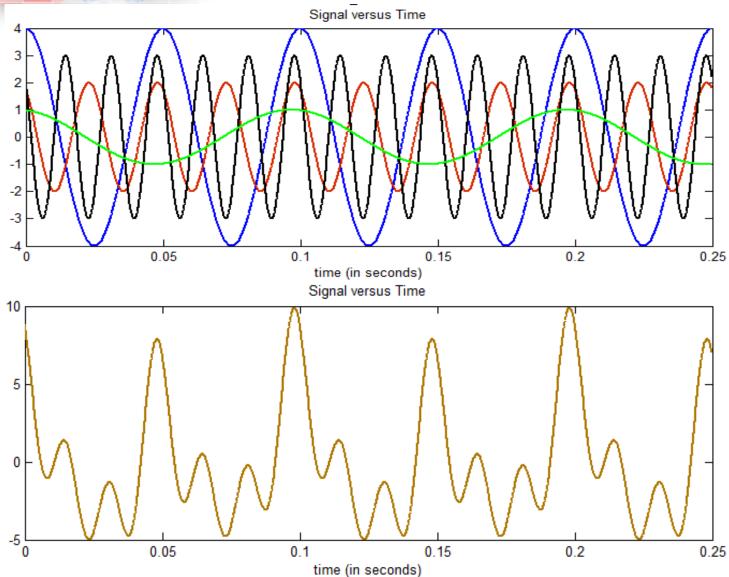


- A=4
- <u>Θ</u>=0
- F=40 HZ
- A=2
- Θ =0.5 rad
- F=60 HZ
- A=3
- Θ =0.8 rad
- F= 10 HZ
- A=1
- Θ =0.2 rad













Fourier Transform, Non-periodic Signals

❖By increasing the period T_p to be infinite. As T_p is increased the spacing between the harmonic components, $1/T_p = w/2\pi$, decreases to $dw/2\pi$ eventually becoming zero. This corresponds to a change from the discrete frequency variable nw to the continuous variable w, and the amplitude and phase spectra become continuous. Thus d_n -> d(w) as T_p -> ∞. With this modifications,

$$d(\omega) = \frac{d\omega}{2\pi} \int_{-\infty}^{\infty} f(t) e^{-j\omega t} dt$$

$$\frac{d(\omega)}{d\omega/2\pi} = F(j\omega) = \int_{-\infty}^{\infty} f(t) e^{-j\omega t} dt$$

$$F(j\omega) = \operatorname{Re}(j\omega) + j\operatorname{Im}(j\omega) = |F(j\omega)| e^{j\phi(\omega)}$$

$$|F(j\omega)| = [\operatorname{Re}^{2}(j\omega) + \operatorname{Im}^{2}(j\omega)]^{1/2}$$

$$\phi(\omega) = \tan^{-1}[\operatorname{Im}(j\omega)/\operatorname{Re}(j\omega)]$$



IMS'

Discrete Fourier Transform, (DFT)

Assume that a waveform has been sampled at regular time intervals T to produce the sample sequence $\{x(nT)\} = x(0), x(T), ..., x[(N-1)T]$ Of N sample values, where n is the sample number from n=0 to n=N-1. The DFT of x(nT) is then defined as the sequence of complex values $\{X(k\Omega)\} = X(0), X(\Omega), ..., X[(N-1)\Omega]$ in the frequency Domain where Ω is the first harmonic frequency given by $\Omega = 2\pi/NT$. Thus, the $X(k\Omega)$ have real and imagery components in general so that for the kth harmonic

$$X(k) = R(k) + jI(k)$$

$$|X(k)| = [R^{2}(k) + I^{2}(k)]^{1/2}$$

$$\phi(k) = \tan^{-1}[I(k)/R(k)]$$



TMS'

Discrete Fourier Transform, (DFT)

❖ N real data values (in time domain) transform to N complex DFT values in (frequency domain). The DFT values, X(k) are given by

$$X(k) = F_{D}[x(nT)] = \sum_{n=0}^{N-1} x(nT)e^{-jk\Omega nT}, k = 0, 1, ..., N-1$$



D IMS'

Discrete Fourier Transform, DFT

Sometimes we don't know the value of T but may be eliminated using $\Omega = 2\pi/NT$ giving

$$X(k) = \sum_{n=0}^{N-1} x(nT)e^{-jk\Omega nT}$$
$$= \sum_{n=0}^{N-1} x(nT)e^{-jk2\pi n/N}$$



DFT

Problems

1) Compute the DFT for the following sequence $x(n) = \{1, 0, 0, 1\}$.

$$X(k) = \sum_{n=0}^{N-1} x(nT)e^{-jk2\pi n/N}$$

$$X(0) = 1 + 0 + 0 + 1 = 2$$

$$X(1) = 1 + 0 + 0 + 1e^{-j2\pi 3/4} = 1 + e^{-j3\pi/2}$$

$$= 1 + \cos\left(\frac{3\pi}{2}\right) - j\sin\left(\frac{3\pi}{2}\right) = 1 + j$$

$$X(2) = 1 + 0 + 0 + 1e^{-j4\pi^{3/4}} = 1 + 0 + 0 + e^{-j3\pi} = 1 - 1 = 0$$

$$X(3) = 1 + 0 + 0 + e^{-j9\pi/2} = 1 - j$$

It has therefore been shown that the time series $\{1, 0, 0, 1\}$ has the DFT given by the complex sequence $\{2, 1 + j, 0, 1 - j\}$.





DFT

Problems

2) Compute the DFT for the following sequence $x(n) = \{0, 1, 2, 3\}$.

Ans: $X(k) = \{ 6, -2+2j, -2, -2-2j \}$





Relation between FT & DFT

 \bullet by putting x(nT)=f(t), kΩ=w and nT= t, so the two transforms may be expected to have similar properties. The transforms are not however equal. Thus, making these substitutions and putting dt= T and replacing the integral by a summation gives

$$\sum_{n=0}^{N-1} x(nT) e^{-jk\Omega nT} T = F(j\omega) \qquad 0 \le t \le (N-1)T.$$

This reveals

$$F(j\omega) = TX(k)$$

Showing that the Fourier transform components are related to the DFT components by sampling interval, and may be obtained by multiplying the DFT components by the sampling interval.



Important Properties, of DFT

An important property of the DFT may be deduced if the kth component of DFT, X(k) is compared with (K+N)th component, X(k+N) thus,

$$X(k) = \sum_{n=0}^{N-1} x(nT) e^{-jk\Omega nT}$$

$$= \sum_{n=0}^{N-1} x(nT) e^{-jk2\pi n/N}$$

$$X(k+N) = \sum_{n=0}^{N-1} x(nT) e^{-jk2\pi n/N} e^{-jN2\pi n/N}$$

$$= \sum_{n=0}^{N-1} x(nT) e^{-jk2\pi n/N} e^{-j2\pi n}$$

$$= \sum_{n=0}^{N-1} x(nT) e^{-jk2\pi n/N} = X(k)$$





Important Properties, of DFT

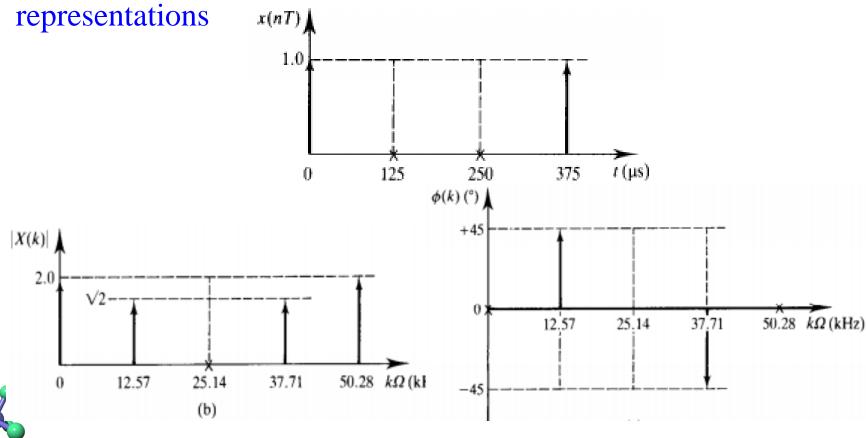
- ❖The fact that X(k+N)=X(k) shows that the DFT is periodic with period N. this is the cyclical property of the DFT. The values of DFT are repetitive.
- ❖ the amplitude spectrum distribution of N-point DFT is symmetrical about harmonic N/2. similarly the phase function being odd exhibits anti-symmetry about harmonic N/2
- The harmonic N/2 represents F_{max} the maximum frequency present in the signal. Thus all the signal components are fully represented in an amplitude spectrum plotted up to F_{max} (harmonic N/2) and it is unnecessary to plot further points.
- ❖Thus, N real points data transform to N/2 complex DFT values of practical significance.



DFT

Problems

If T for the sequence {1, 0, 0, 1} equals 125µs then the sampling frequency equals 8kHz and we can have the following

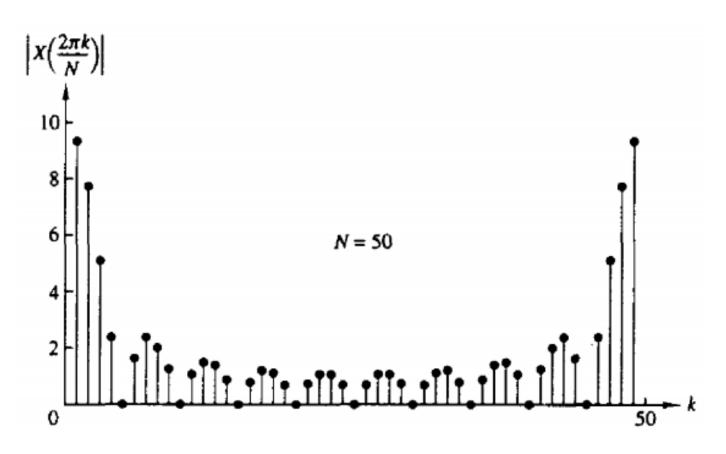




DFT

Examples

Amplitude



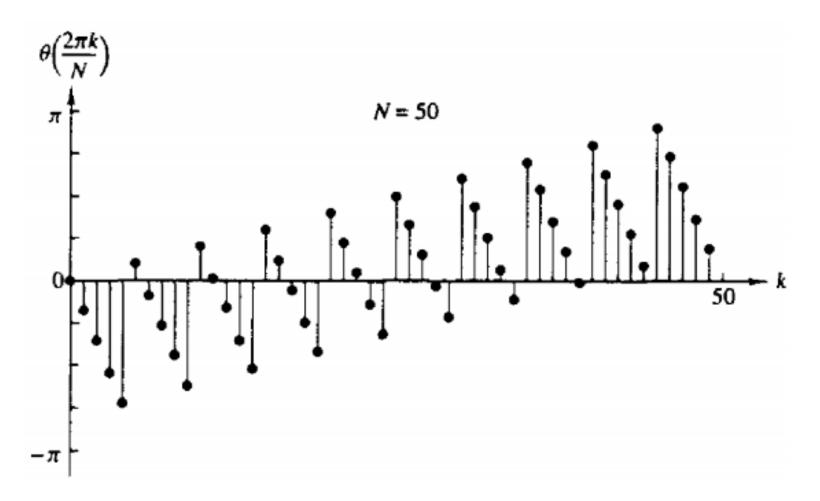




DFT.

Examples

Phase

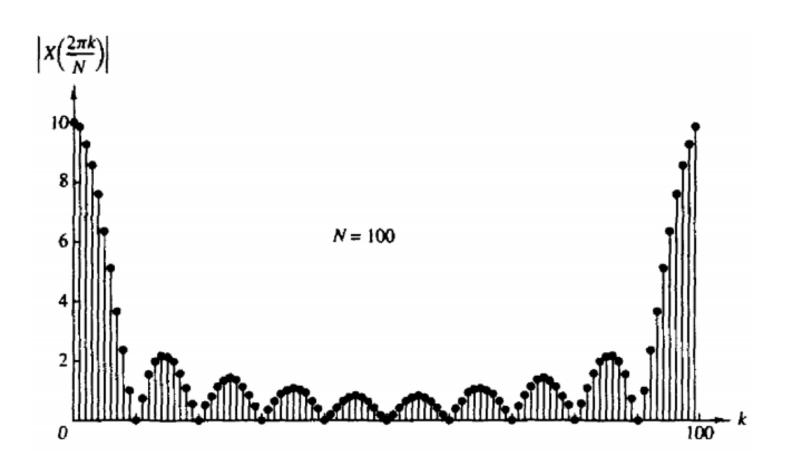






DFT Examples

Amplitude



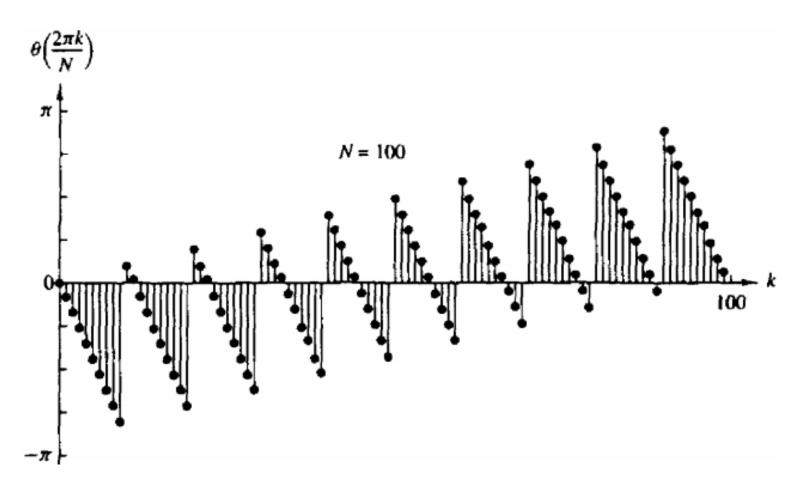




DFT.

Examples

Phase







Inverse DFT (IDFT)

❖ It is necessary to be able to carry out discrete transformation from the frequency to the time domain. This may be achieved using the inverse discrete Fourier transform (IDFT), defined by

$$x(nT) = F_{D}^{-1}[X(k)] = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{jk\Omega nT}, n = 0, 1, ..., N-1$$

The analogy for the inverse Fourier transform is obvious, obtained by dividing IDFT by N.





IDFT. Problems

1) Compute the data sequence back from its DFT components $\{2, 1+j, 0, 1-j\}$





IDFT Problems

$$= \frac{1}{4}[X(0) + X(1) + X(2) + X(3)]$$

= $\frac{1}{4}[2 + (1 + j) + 0 + (1 - j)] = 1$

as expected. With n = 1,

$$x(nT) = x(T) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{jk\Omega T}$$

$$= \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{jk2\pi/N} = \frac{1}{4} \sum_{k=0}^{N-1} X(k) e^{jk\pi/2}$$

$$= \frac{1}{4} [2 + (1+j)e^{j\pi/2} + 0 + (1-j)e^{j3\pi/2}]$$

$$= \frac{1}{4} [2 + (1+j)j + (1-j)(-j)]$$

$$= \frac{1}{4} (2+j-1-j-1) = 0$$

as expected. With n = 2,

$$x(nT) = x(2T) = \frac{1}{N} \sum_{k=0}^{N-1} x(k) e^{jk\pi}$$

= $\frac{1}{4} [2 + (1+j)e^{j\pi} + (1-j)e^{j3\pi}] = \frac{1}{4} [2 - (1+j) - (1-j)]$
= 0

again, as expected. Finally, with n = 3,

$$x(nT) = x(3T) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{jk3\pi/2}$$

$$= \frac{1}{4} [2 + (1+j)e^{j3\pi/2} + (1-j)e^{j9\pi/2}]$$

$$= \frac{1}{4} [2 + (1+j)(-j) + (1-j)j] = \frac{1}{4} (2-j+1+j+1) = 1$$





IDFT. Problems

2) Compute the data sequence back from its DFT components { 6, -2+2j, -2, -2-2j}





IDFT. Problems

2) Compute the data sequence back from its DFT components { 6, -2+2j, -2, -2-2j}





Time & Frequency. Domains

- ➤ Time domain: All time information (samples) is available but no information about frequency components.
- Frequency domain: Frequency components are known but no information about time.
- ➤ Do we need sometimes information about both time & frequency ??
 - YES, when we need to when a specific frequency occurs since it doesn't exist all the time





Low & High. Frequencies

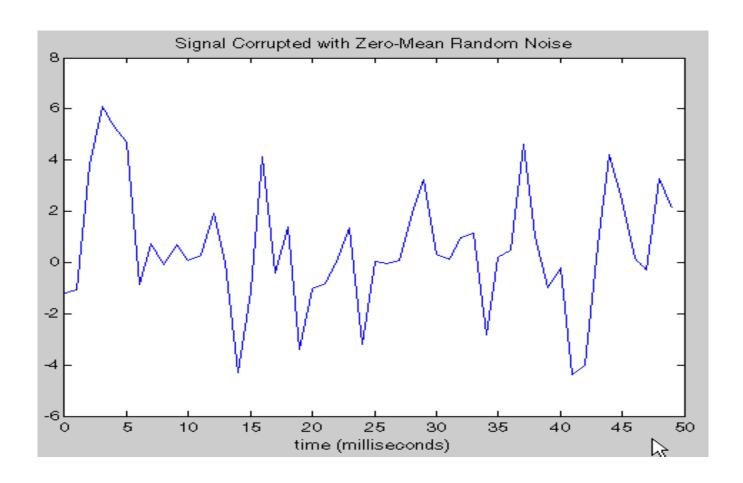
- ➤ Low Frequencies: Slow small change in values signal → smooth image -> blurring
- ➢ High Frequencies: Sudden noticeable change in values
 signal → includes sharp peaks image → includes sharp edges
- ➤ Smoothing of signals and images preserves low frequencies

 Smoothing → Moving average or low pass filters
- ➤ Sharpening of signals and images preserves high frequencies
 Sharpening → Derivative or high pass filters





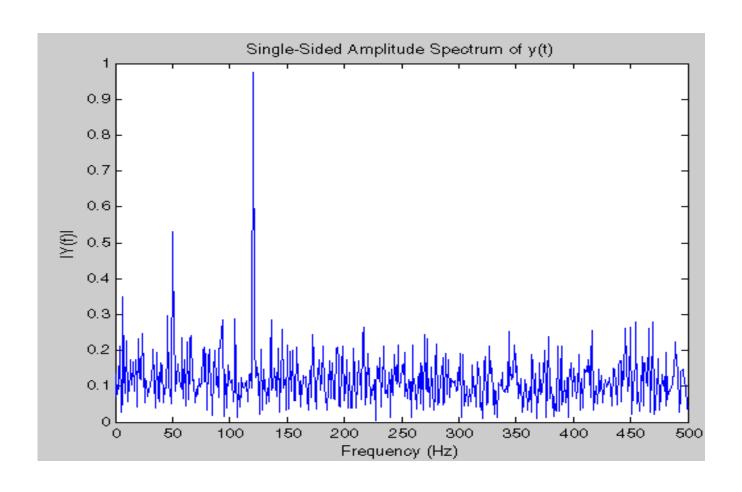
Frequency Selection (noise removal)







Frequency Selection (noise removal)





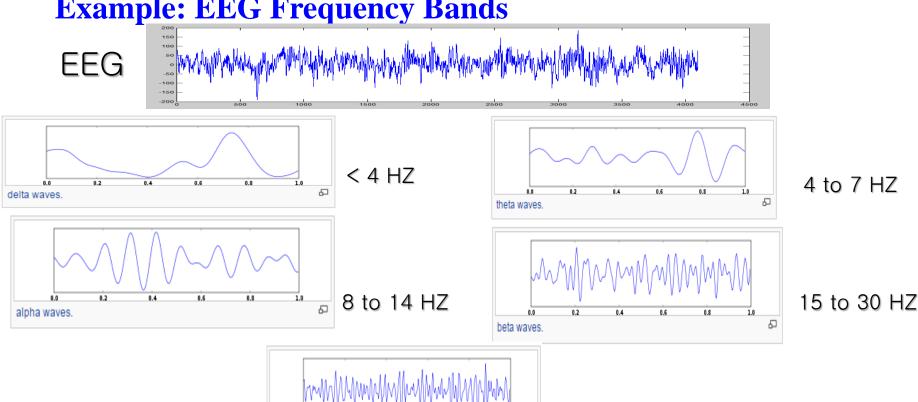


Frequency Selection (Band Selection)

> Sometimes we need to concentrate on a specific frequency band and neglect the others. Band pass filters can be used.

Example: EEG Frequency Bands

gamma waves.









DC Component Removal (mean removal)

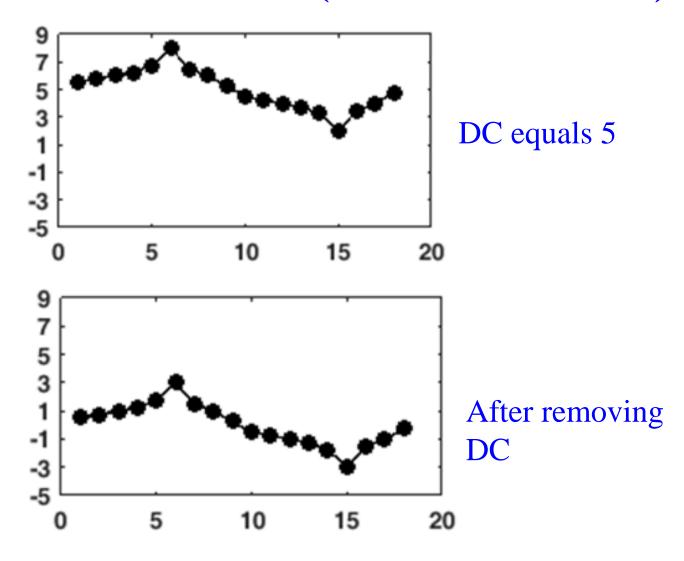
- ➤ The DC component if it is not equal zero, it makes the signal oscillates on a horizontal line rather than the X axis. Thus, the signal is shifted upwards or downwards.
- ➤ We are usually interested in removing the shift and allow the signal to oscillate back on the X axis.
- ➤ For time Domain → Subtract the mean of the signal from it.
- \rightarrow For Frequency domain \rightarrow remove the first harmonic X(0).





DC Component Removal

(mean removal)





Computational Complexity of DFT

- ❖ Each term consists of a multiplication of an exponential term which is always complex by another term which is real or complex. Each of the product terms is added together. Therefore, for N points DFT there will be N complex multiplication and N-1 complex additions to be calculated. There are also N points to be evaluated. Thus, N² complex multiplications and N(N-1) complex additions.
- ♦ What happens if we have N=1000 or N = 10000 ??
 Huge computation
- **Can we reduce the computation ?? Yes**



