



Advanced biomedical signal and image processing

Master: Plasturgy & Biomedical Engineering

2025-2026

Faculté de Science Meknes

Professor Omar ELOUTASSI

Section 1 :

Introduction to Digital Signal and Image Processing

Chapter 2:

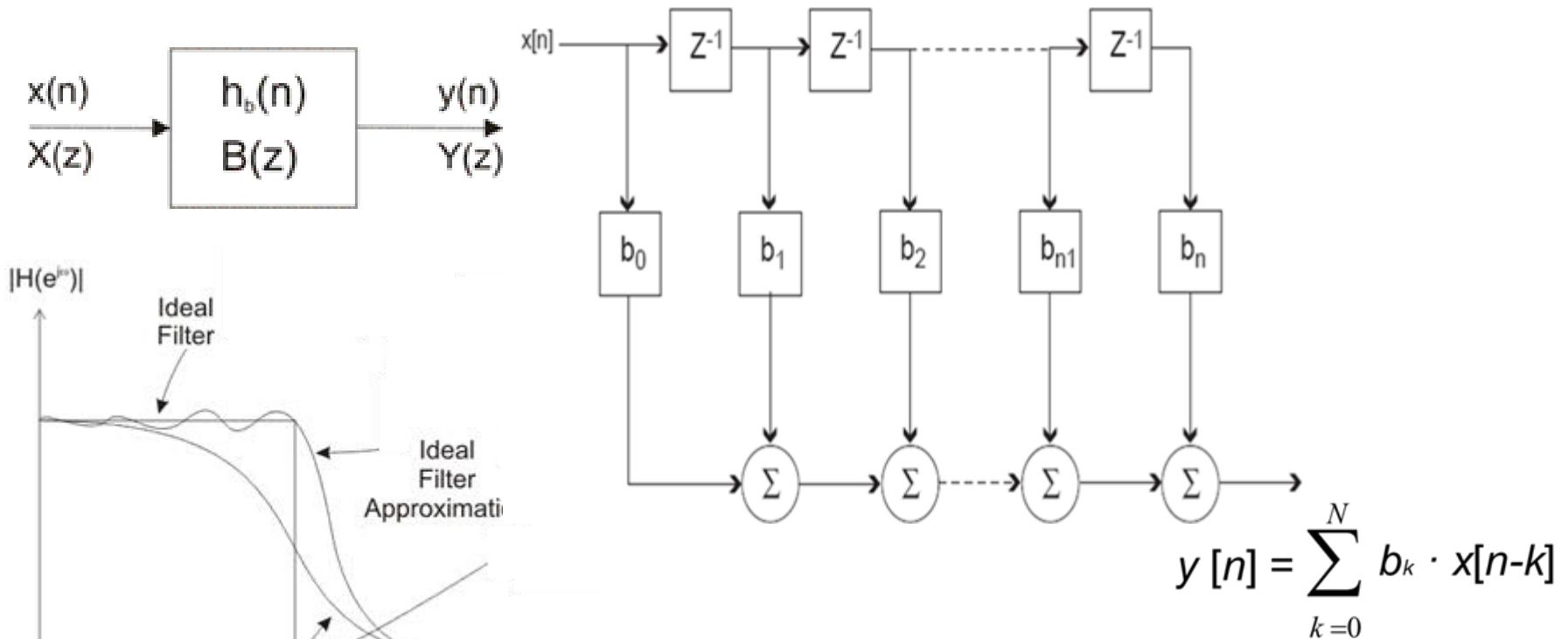
Chapter 2: Fourier analysis of continuous-time signals

Filters

Other signal processing techniques

Wavelet transformation

Digital Filters – FIR filters



Ideal low-pass filter approximation

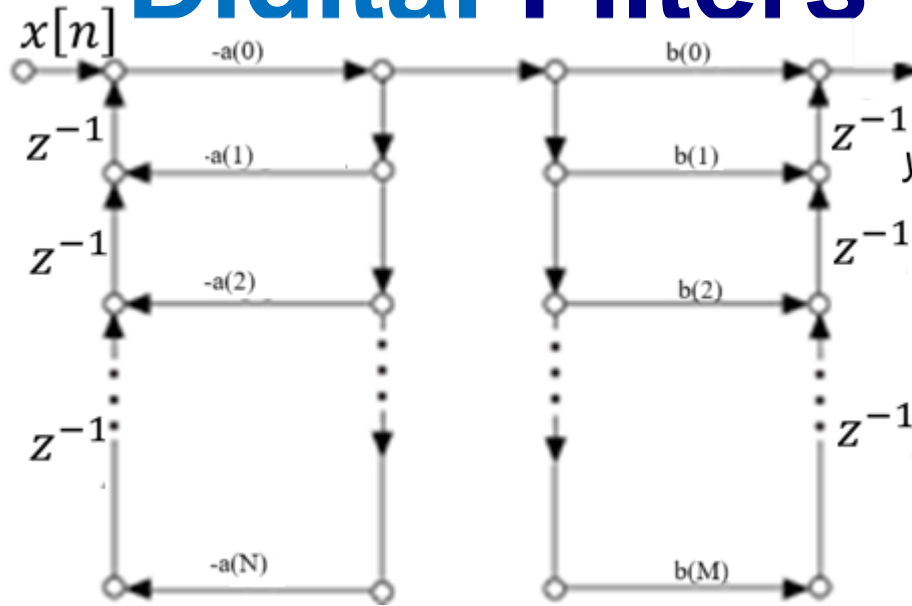
- finite impulse response, no recursion (output does not depend on the input)
- described by multiplication coefficients
- less sufficient (need higher order)

Digital Filters – FIR filters

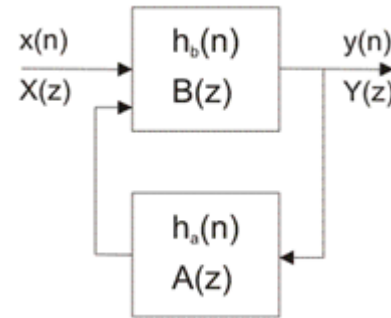
Finite Impulse Response (FIR) filters are widely used in biosignal processing due to several key advantages

- Linear Phase Response that is critical for medical applications like ECG (Electrocardiogram), EEG (Electroencephalogram), and EMG (Electromyogram).
- FIR filters are integrally stable. This stability is crucial for long-term signal monitoring and real-time applications.
- Less oscillations or artifacts in biosignals, which reduce misinterpretation in medical diagnoses.
- Precise control over the frequency response, making them suitable for applications such as: noise removal
- Easy to implement in real-time digital signal processing (DSP) applications, including portable and embedded biomedical devices.
- Suitability for adaptive filtering

Digital Filters – IIR filters



$$y[n] = \sum_{k=0}^N b_k \cdot x[n-k] + \sum_{m=1}^M -a_m \cdot y[n-m]$$

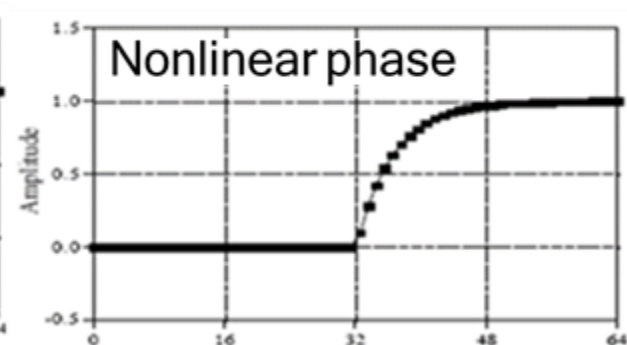
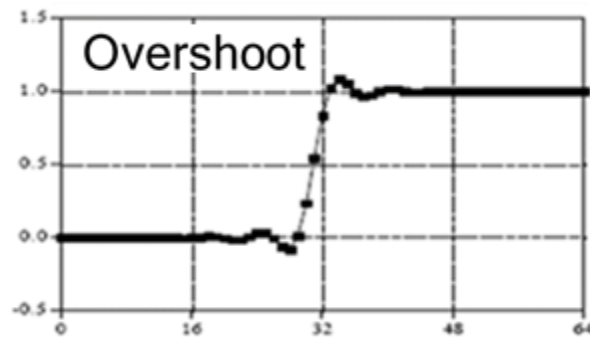
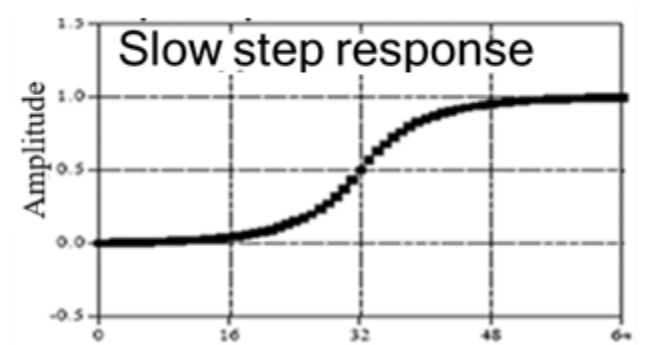


- infinite impulse response, truncated at a certain precision
- use previously calculated values from the output (recursion)
- described by recursion coefficients
- more efficient
- can be unstable

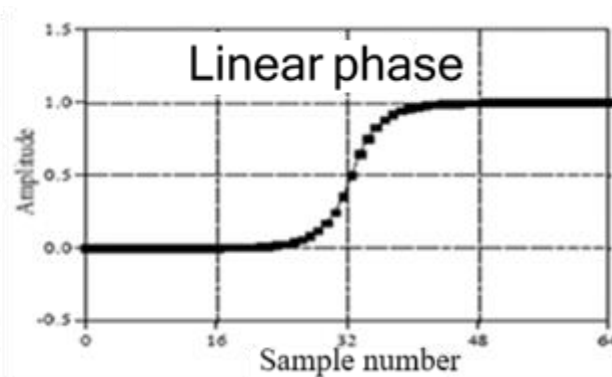
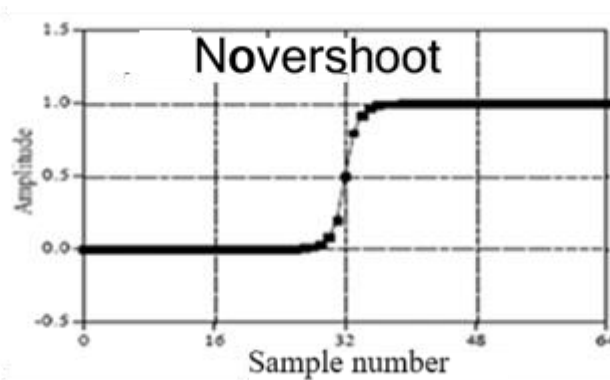
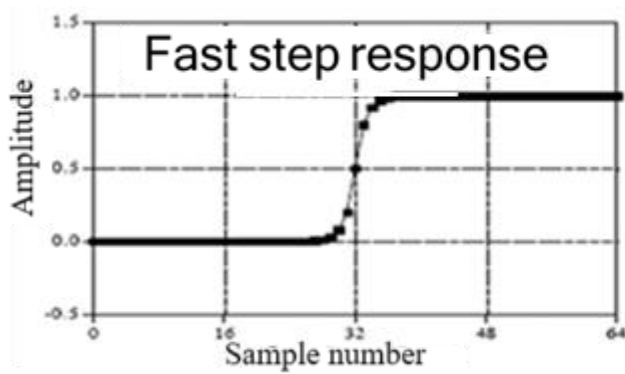
Digital Filter Characteristics

Performance in Time Domain

Poor



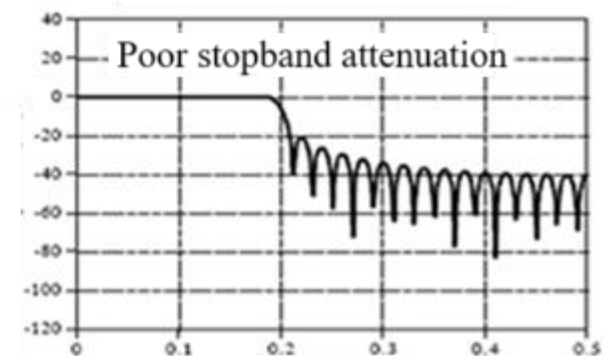
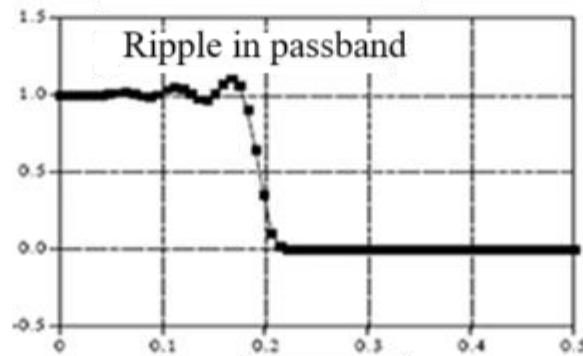
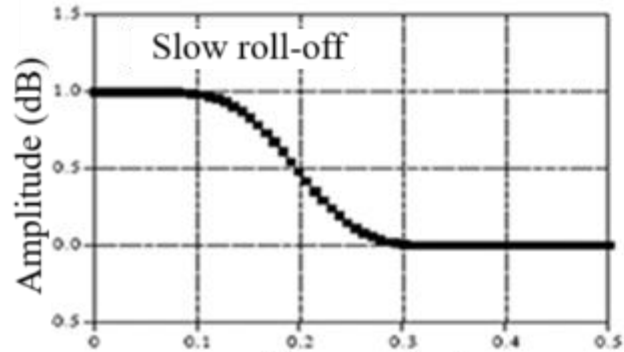
Good



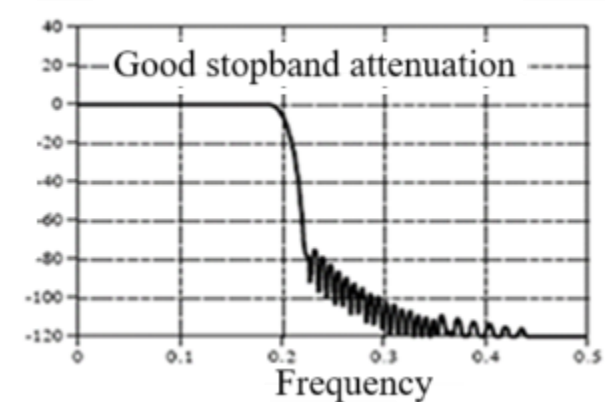
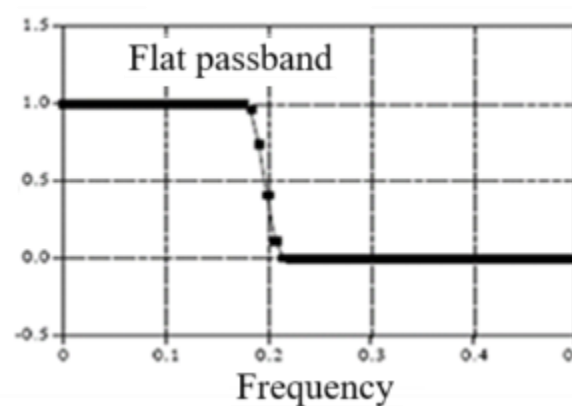
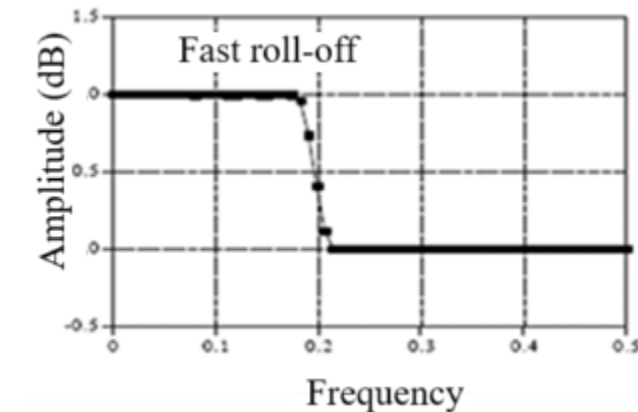
Digital Filter Characteristics

Performance in Frequency Domain

Poor

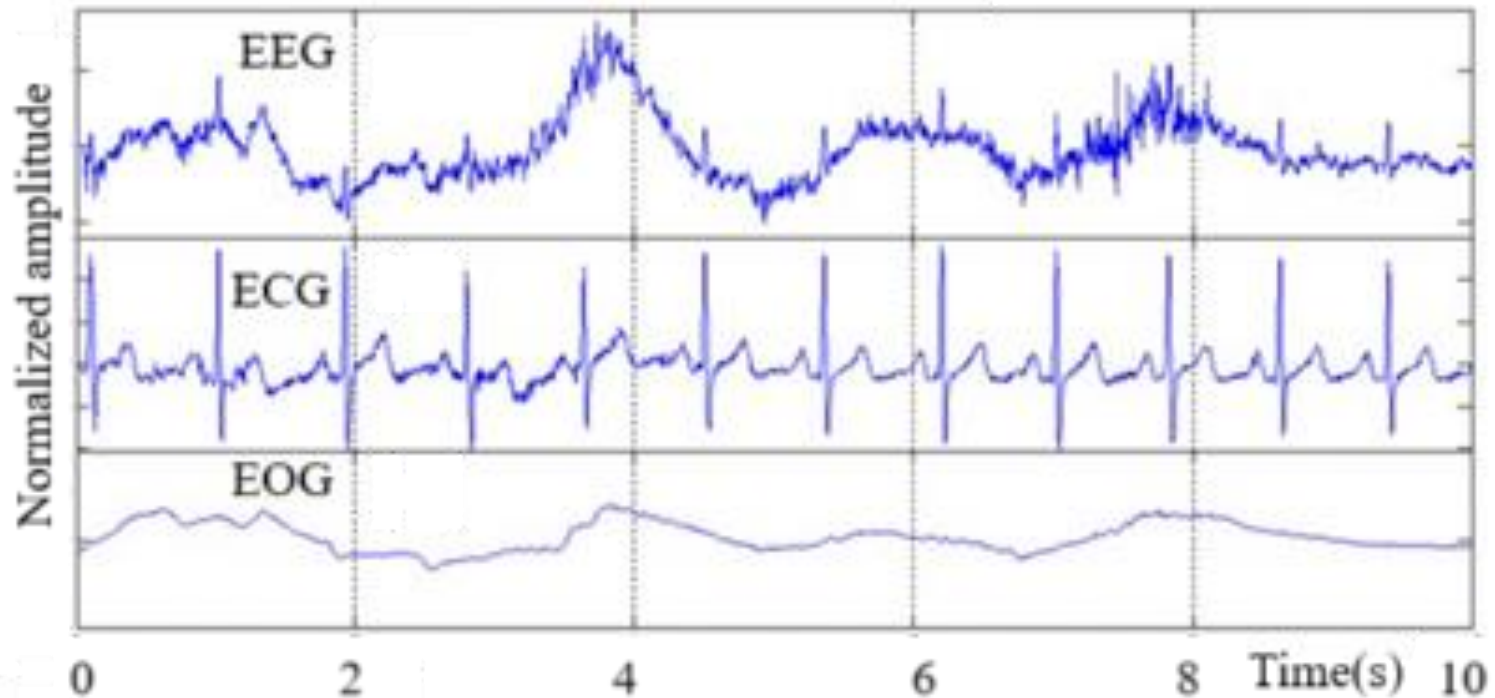


Good



Digital Filter Characteristics-Examples

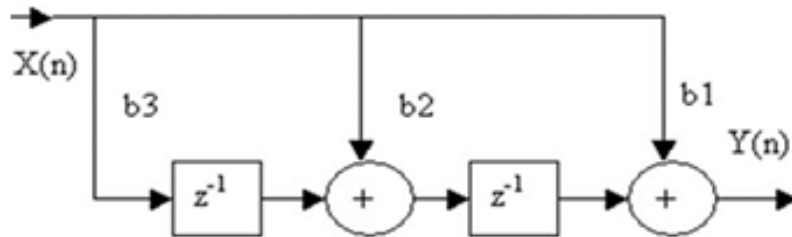
Examples of three biological signals with their frequency spectrum



Digital FIR Filters

example: Finite Impulse Response Notch Filter

System function:



Transfer function:

$$H(z) = \frac{Y(z)}{X(z)} = \frac{(z - z_1) \cdot (z - z_2)}{z^2}$$
$$= \frac{z^2 - z \cdot z_2 - z_1 \cdot z + z_1 \cdot z_2}{z^2}$$

$$= 1 - z^{-1} \cdot (z_2 + z_1) + z^{-2} \cdot z_1 \cdot z_2$$

$$z_1 = \cos(\omega_0) + j \cdot \sin(\omega_0)$$

$$z_2 = \cos(\omega_0) - j \cdot \sin(\omega_0) \longrightarrow H(z) = 1 + z^{-1}(-2(\cos(\omega_0))) + z^{-2}$$

$$= b_1 + b_2 z^{-1} + b_3 z^{-2}$$

Filter Coefficients:

$$b_1 = 1$$

$$b_2 = -2 \cdot \cos(\omega_0)$$

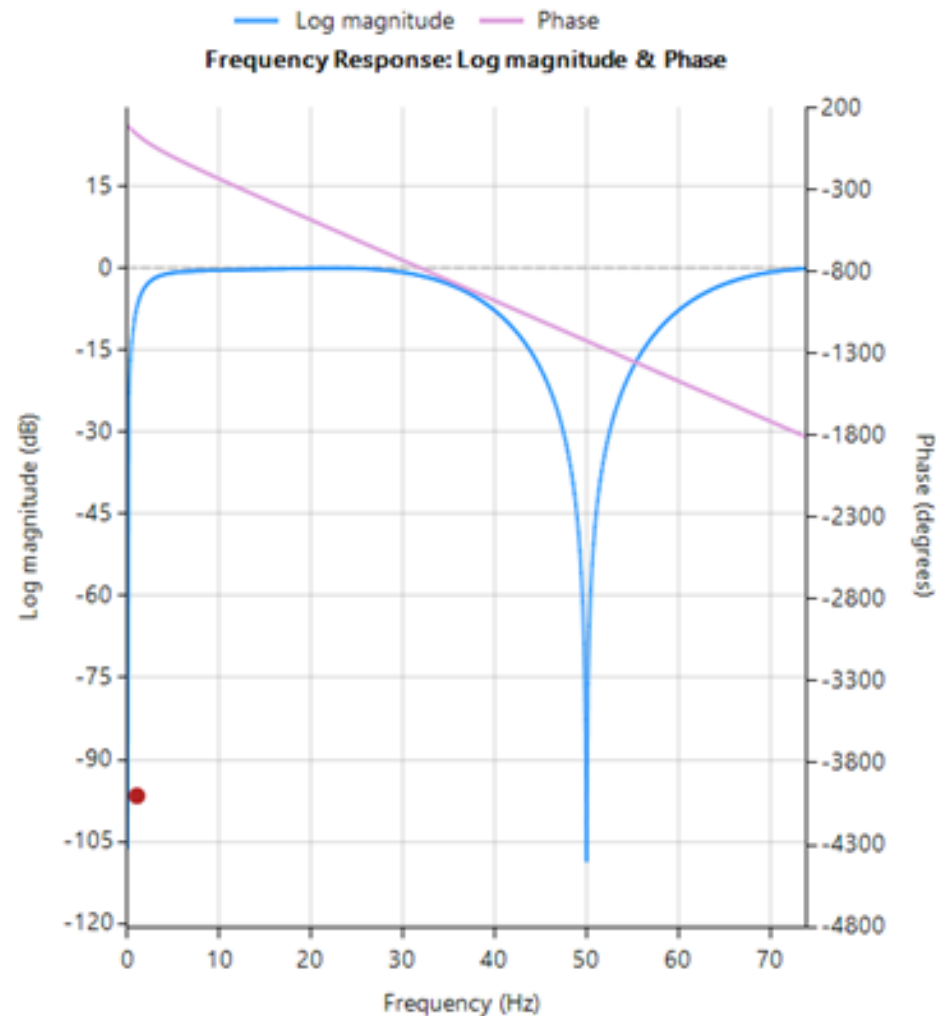
$$b_3 = 1$$

Scaling coefficient

$$G = \frac{1}{(2 - 2 \cos(\omega_0))}$$

Digital FIR Filters

60 Hz notch filter characteristics



Design Digital FIR Filters

60 Hz notch filter example

Frequencies that define complex zeros:

$f_0=60\text{Hz}$ - power supply frequency

$f_s=500\text{Hz}$ - sampling rate

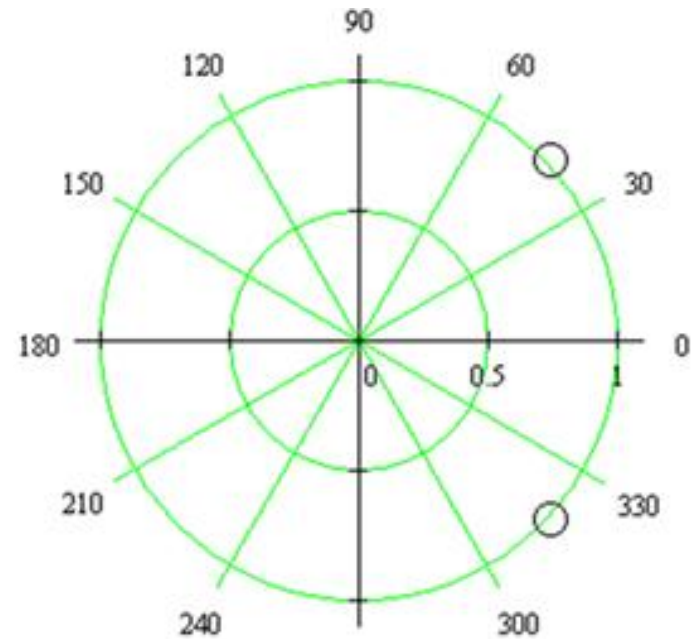
$$\omega_0 = 2 \cdot \pi \cdot \frac{f_0}{f_s}$$

we get $\omega_0 = 0.754$

Positions of complex zeros:

$$z_1 = \cos(\omega_0) + j \cdot \sin(\omega_0)$$

$$z_2 = \cos(\omega_0) - j \cdot \sin(\omega_0)$$

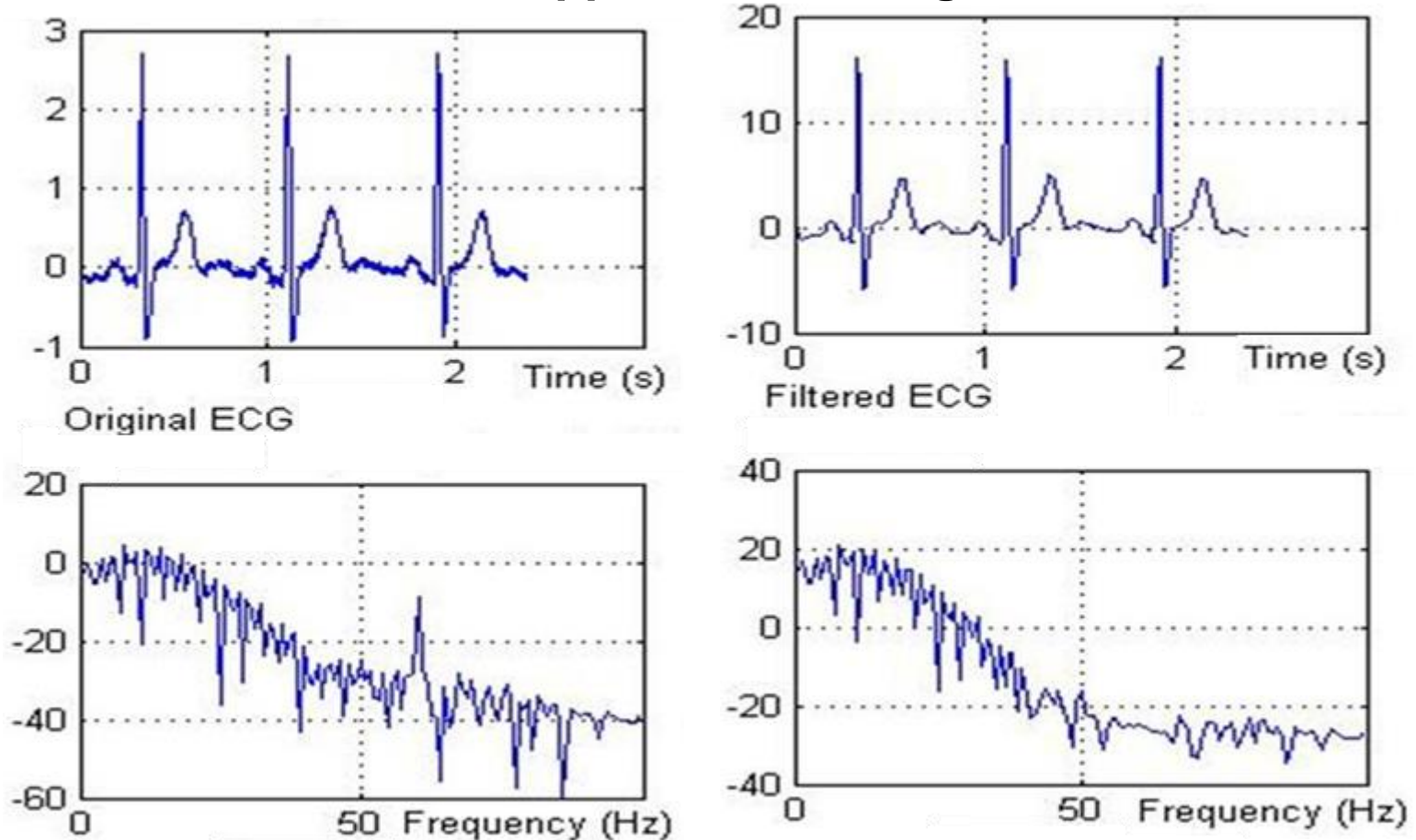


$\arg[Z_1], \arg[Z_2]$

Design digital FIR Filters

60 Hz notch filter - implementation in Matlab

60Hz notch applied to ECG signal



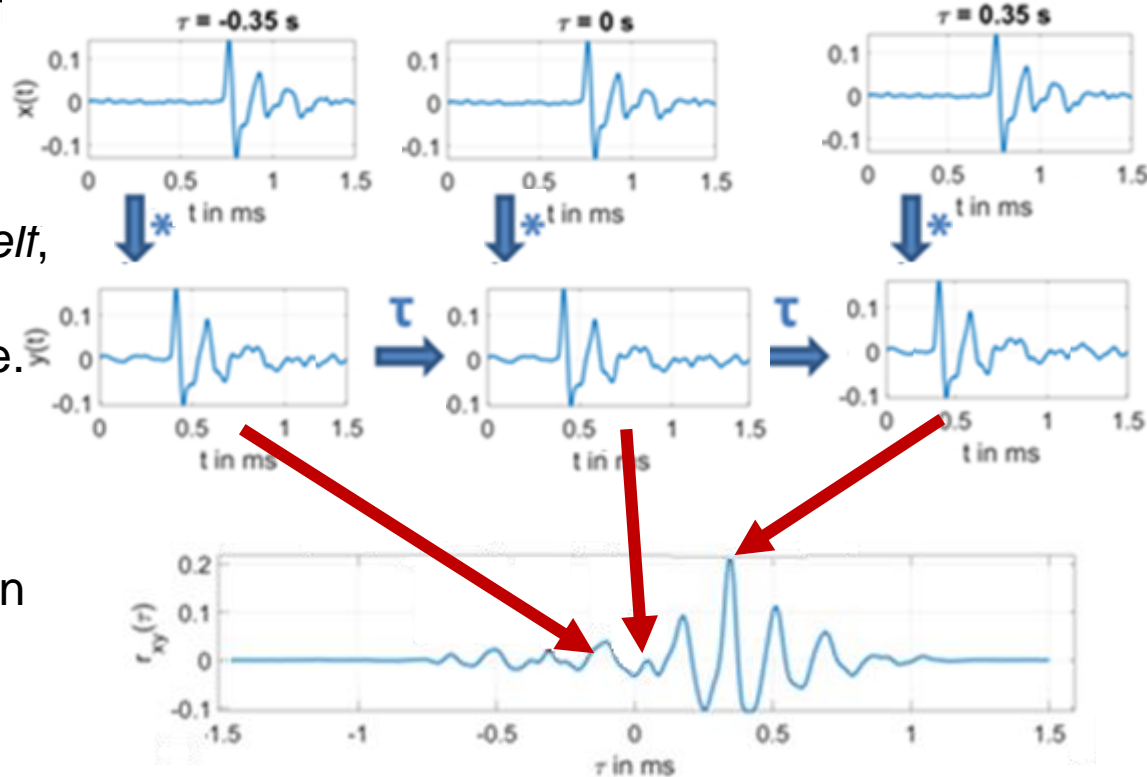
Other Signal processing techniques correlation

- mathematical operation that is very similar to convolution
- uses two signals to produce a third signal. This third signal is called the **cross-correlation** of the two input signals (i.e. finds similar signals in a signal)
- if a signal is correlated with *itself*, the resulting signal is instead called the **auto-correlation** (i.e. finds periodic parts of a signal)
- Correlation is the *optimal* technique for detecting a known waveform in random noise.

[Watch this video](#)

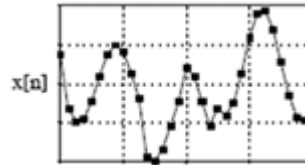
$$R_{xx}(\tau) = \int_{-\infty}^{\infty} x(t) x^*(t - \tau) dt$$

$$R_{xx}[m] = \sum_{n=-\infty}^{\infty} x[n] x^*[n - m]$$

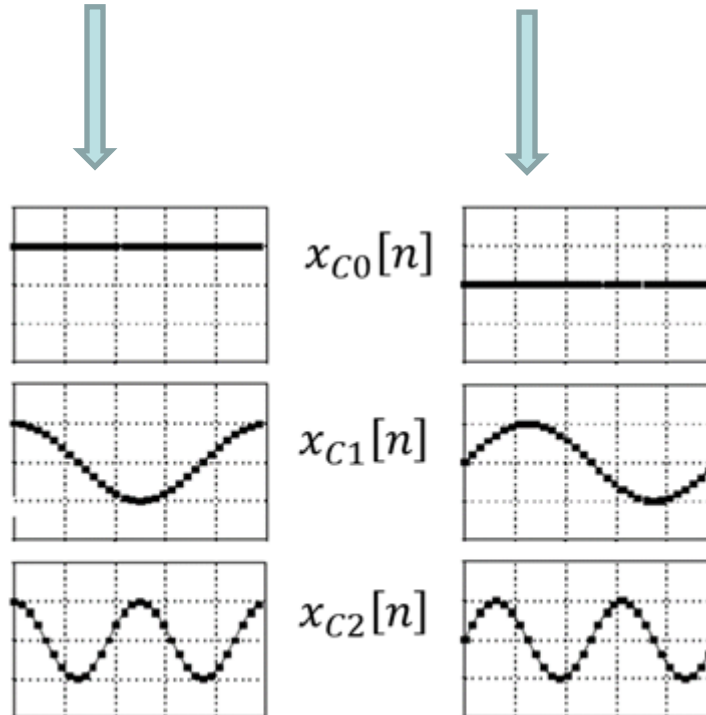


Other signal processing techniques discrete Fourier transform (DFT)

- Decomposition of a signal into



sine and cosine waves



Other signal processing techniques discrete Fourier transform (DFT)

Fourier Analysis of Discrete Time Signals mathematical concept

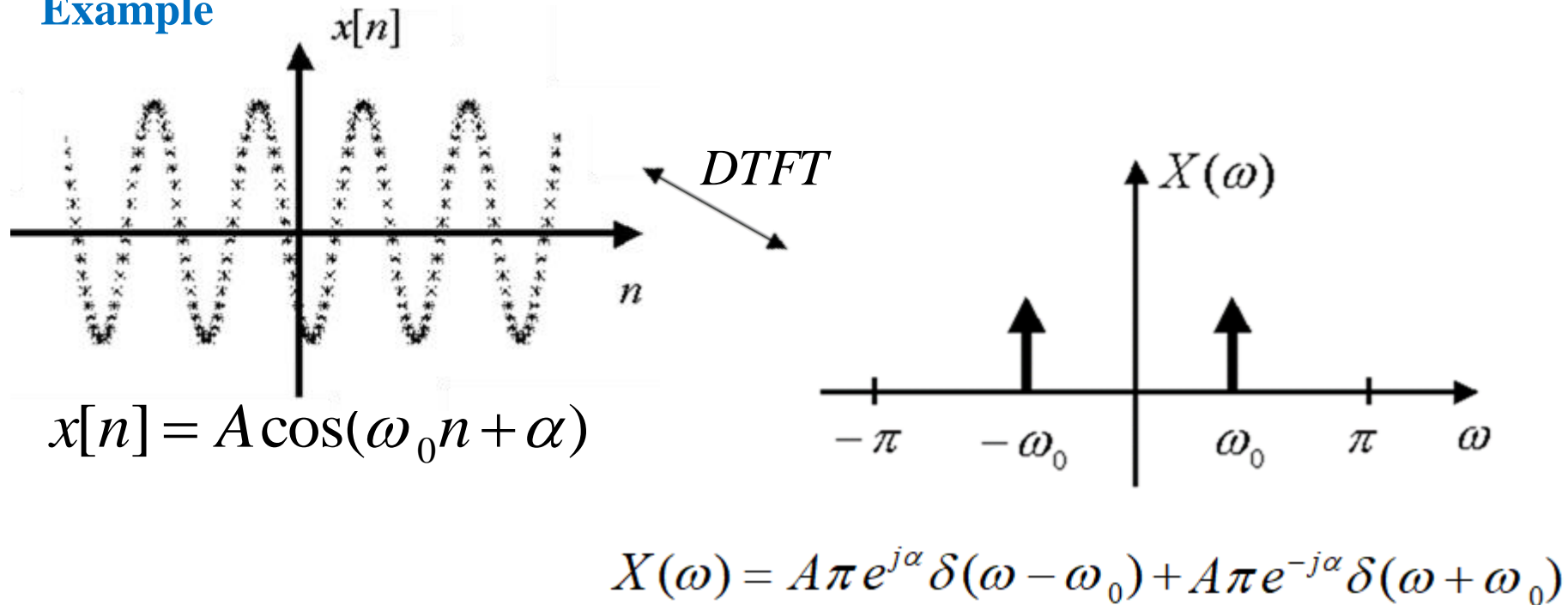
For a discrete time sequence we define two classes of Fourier Transforms:

- DTFT (Discrete Time FT) for sequences having **infinite** duration,
- DFT (Discrete FT) for sequences having **finite** duration.

Other signal processing techniques discrete Fourier transform (DFT)

Fourier Analysis of Discrete Time Signals mathematical concept

Example



Other signal processing techniques discrete Fourier transform (DFT)

Fourier Analysis of Discrete Time Signals mathematical concept *Discrete Fourier Transform (DFT)*

Consider the finite discrete sequence

$$x = [x(0), x(1), \dots, x(N-1)]$$

its Discrete Fourier Transform (DFT) is a finite sequence

$$X = DFT(x) = [X(0), X(1), \dots, X(N-1)]$$



where

$$X(k) = \sum_{n=0}^{N-1} x(n) w_N^{kn} \quad w_N = e^{-j2\pi / N}$$

Other signal processing techniques discrete Fourier transform (DFT)

Fourier Analysis of Discrete Time Signals mathematical concept

Inverse Discrete Fourier Transform (IDFT)

Consider the frequency series

$$X = [X(0), X(1), \dots, X(N-1)]$$

its Inverse Discrete Fourier Transform (IDFT) is a finite sequence



$$x = IDFT(X) = [x(0), x(1), \dots, x(N-1)]$$

where

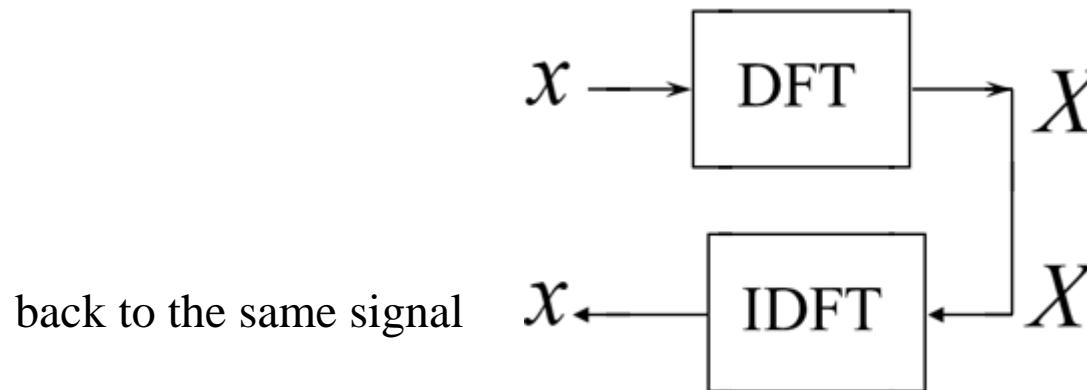
$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) w_N^{-kn}$$
$$w_N = e^{-j2\pi/N}$$

Other signal processing techniques discrete Fourier transform (DFT)

Fourier Analysis of Discrete Time Signals mathematical concept

Note that:

The DFT and the IDFT form a transform pair.



The DFT is a numerical algorithm, and it can be computed by a digital computer.

Other signal processing techniques discrete Fourier transform (DFT)

DFT as vector operation

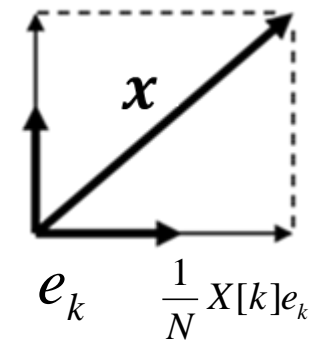
Let consider a discrete sequence as a vector $x = \begin{bmatrix} x[0] \\ x[1] \\ \vdots \\ x[N-1] \end{bmatrix},$

Let consider as well the vector base: $e_k = \begin{bmatrix} 1 \\ w_N^{-k} \\ \vdots \\ w_N^{-k(N-1)} \end{bmatrix},$

$$x = \frac{1}{N} (X[0]e_0 + X[1]e_1 + \dots + X[N-1]e_{N-1})$$

DFT of this discrete sequence is also as vector

$$X = DFT\{x\} = \begin{bmatrix} X[0] \\ X[1] \\ \vdots \\ X[N-1] \end{bmatrix} \quad X[k] = e_k^{*T} x$$



Other signal processing techniques discrete Fourier transform (DFT)

DFT as vector operation

$$X = DFT\{x\} = \begin{bmatrix} X[0] \\ X[1] \\ \vdots \\ X[N-1] \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 & w_N & \cdots & w_N^{N-1} \\ \vdots & & \ddots & \\ 1 & w_N^{N-1} & & w_N^{(N-1)(N-1)} \end{bmatrix}}_{W_N} \begin{bmatrix} x[0] \\ x[1] \\ \vdots \\ x[N-1] \end{bmatrix}$$

$$\Rightarrow X = W_N x$$

$$x = \underbrace{\frac{1}{N} W_N^{*T}}_{W_N^{-1}} X$$

Other signal processing techniques discrete Fourier transform (DFT)

Periodicity

IDFT expression, shows that the sequence $x(n)$ is interpreted as one period sequence $x_p(n)$

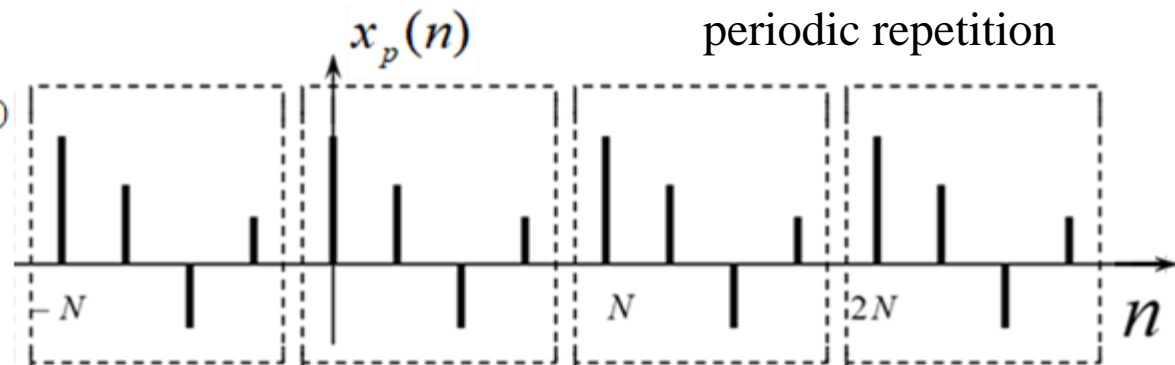
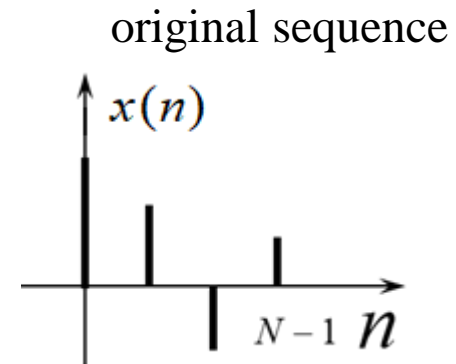
$$x_p(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) w_N^{-kn}$$

We can multiply by w_N^{-kN} since $w_N^{-kN} = e^{-j2\pi kN/N} = e^{-j2\pi} = 1$

$$x_p(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) w_N^{-kn} w_N^{-kN}$$

$$= \frac{1}{N} \sum_{k=0}^{N-1} X(k) w_N^{-k(n+N)}$$

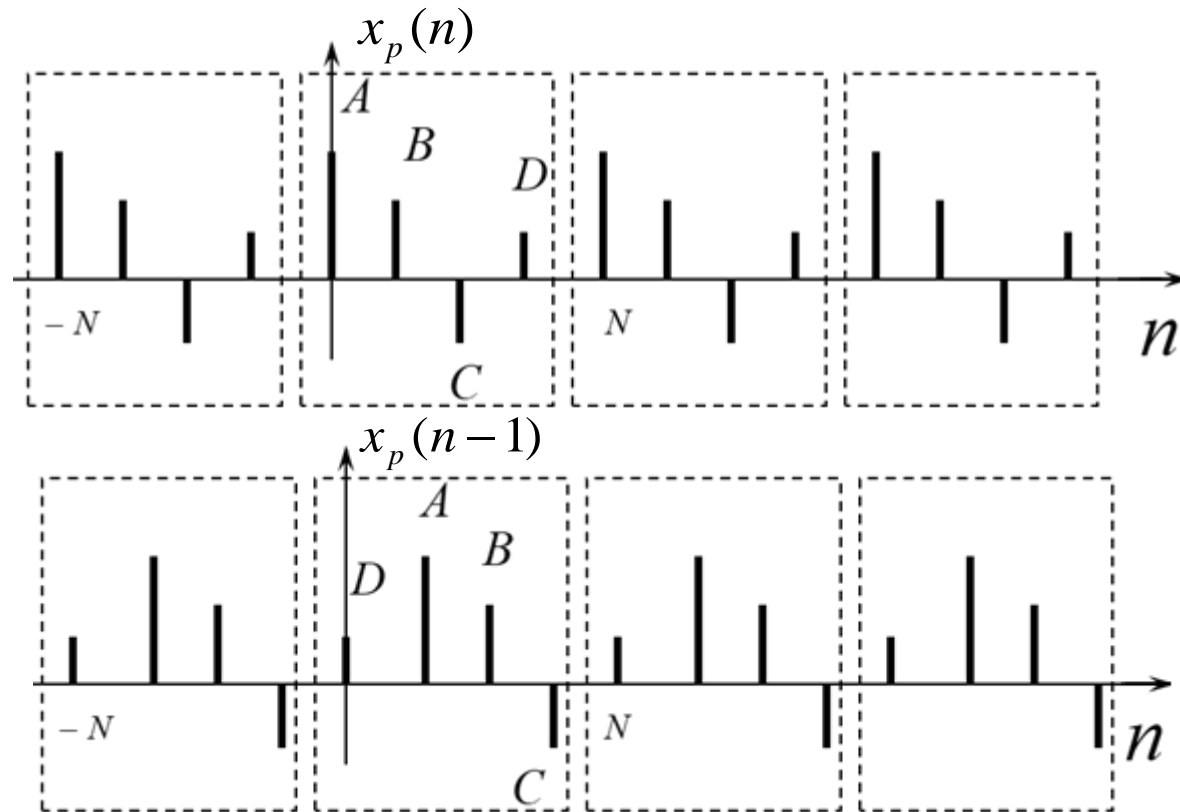
$$= x_p(n+N)$$



Other signal processing techniques discrete Fourier transform (DFT)

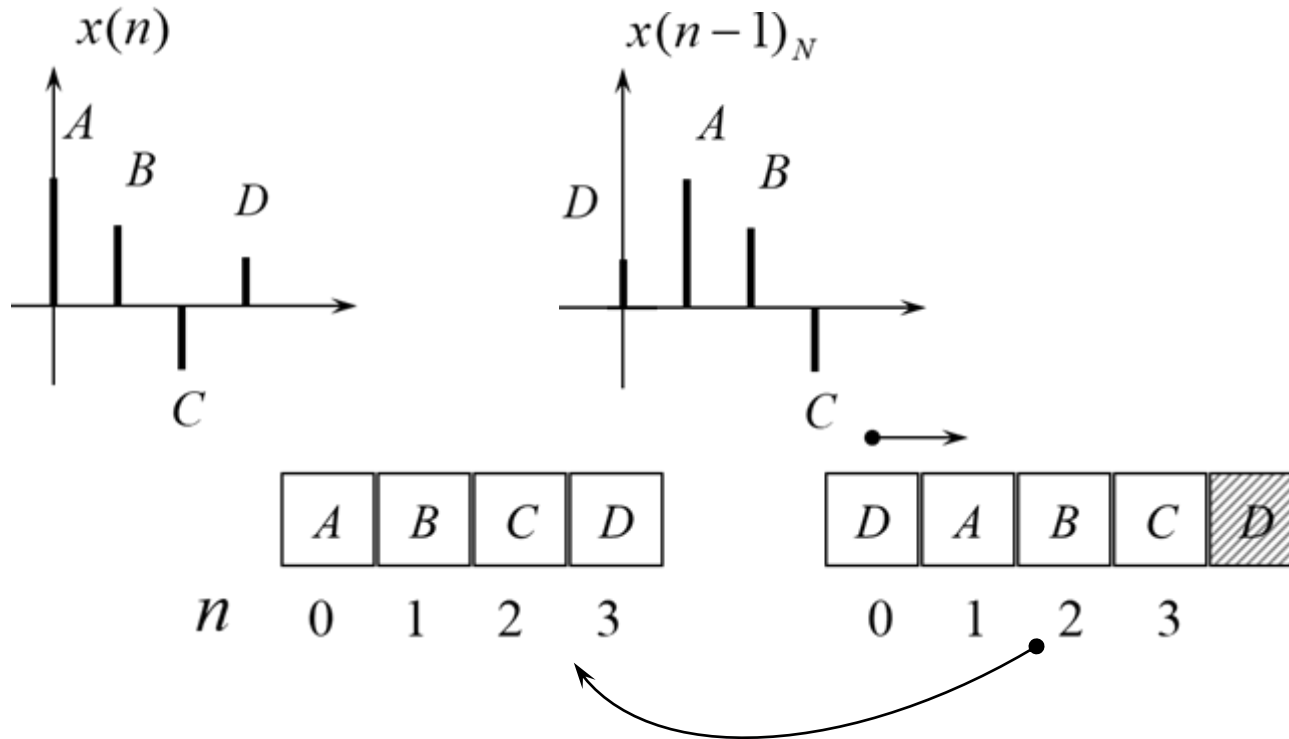
Time shift of the sequence.

For example see what we mean with $x(n-1)$. Start with the periodic extension $x_p(n)$



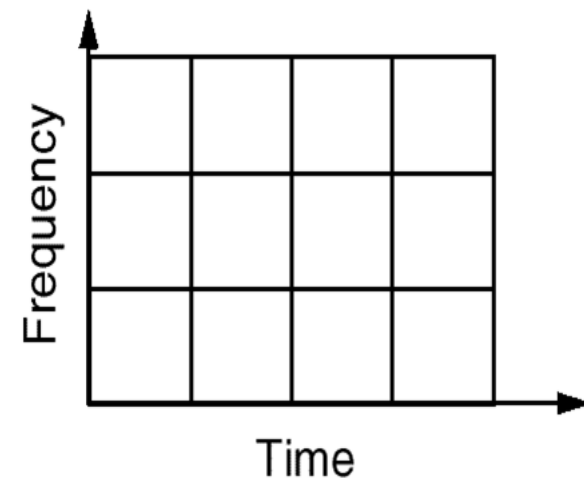
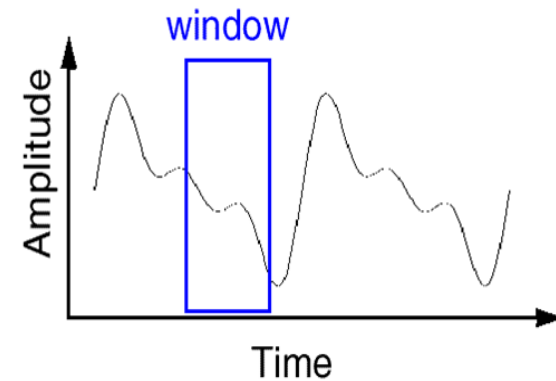
Other signal processing techniques discrete Fourier transform (DFT)

Circular shift of the sequence at time period



Short time Fourier Analysis

- In order to analyze small section of a signal, Denis Gabor (1946), developed a technique, based on the FT and using *windowing* : STFT (Short time Fourier transform)
- A compromise between time-based and frequency-based views of a signal.
- both time and frequency are represented in limited precision.
- The precision is determined by the size of the window.
- Once you choose a particular size for the time window - it will be the same for all frequencies.
- Many signals require a more flexible approach
- We can vary the window size to determine more accurately either time or frequency.

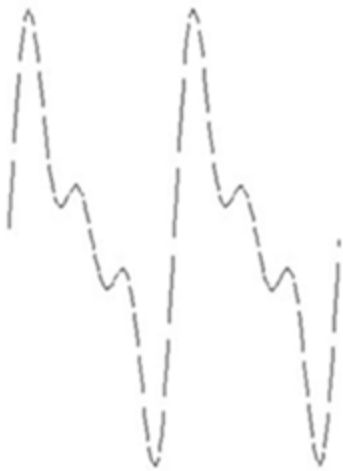


The Continuous Wavelet Transform (CWT)

- The Fourier transform for a continuous data or a signal given by the function $f(t)$ is:

$$F(\omega) = \int_{-\infty}^{+\infty} f(t)e^{-j\omega}dt$$

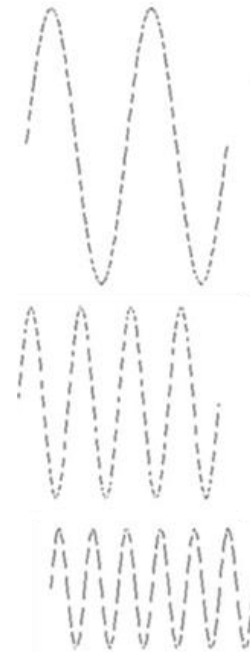
- is composed of multiple sinusoids with different frequencies and amplitudes



Signal $f(t)$



Fourier transform $F(\omega)$



Signal $F(\omega)$

Wavelet Transformation- Equations

➤ Wavelet Transform

$$\gamma(s, \tau) = \int f(t) \psi_{s,T}^*(t) dt$$

➤ Inverse Wavelet Transform

$$f(t) = \iint \gamma(s, \tau) \psi_{s,T}(t) d\tau ds$$

➤ Mother wavelet

$$\psi_{s,T}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t - \tau}{s}\right)$$

Wavelet Transformation- Scaling

Proprieties

$$\psi_{s,T}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t - \tau}{s}\right)$$

Diagram illustrating the properties of the wavelet transformation equation:

- $\psi_{s,T}(t)$: wavelet with scale, s and time, τ
- $\frac{1}{\sqrt{s}}$: normalization
- ψ : Mother wavelet
- $\frac{t - \tau}{s}$: shift in time (indicated by τ) and change in scale: big s means long wavelength (indicated by s)

Wavelet transform

Proprieties

The diagram shows the wavelet transform equation $\gamma(s, \tau) = \int f(t) \psi_{s, \tau}^*(t) dt$. Annotations include: an arrow from 'time-series' to $f(t)$; an arrow from 'conjugate from now on, assuming that we're using real wavelets' to the asterisk on ψ ; an arrow from 'coefficient of wavelet with scale, s and time, τ ' to $\gamma(s, \tau)$; and an arrow from 'complex conjugate of wavelet with scale, s and time, τ ' to $\psi_{s, \tau}$.

$$\gamma(s, \tau) = \int f(t) \psi_{s, \tau}^*(t) dt$$

time-series

conjugate from now on, assuming that we're using real wavelets

coefficient of wavelet with scale, s and time, τ

complex conjugate of wavelet with scale, s and time, τ

Inverse Wavelet Transform

$$f(t) = \iint \gamma(s, \tau) \psi_{s, \tau}(t) d\tau ds$$

The diagram illustrates the components of the inverse wavelet transform equation. Three arrows point from labels below to specific parts of the equation: one from 'time-series' to $f(t)$, one from 'coefficients of wavelets' to $\gamma(s, \tau)$, and one from 'wavelet with scale, s and time, τ ' to $\psi_{s, \tau}(t)$.

time-series

coefficients of wavelets

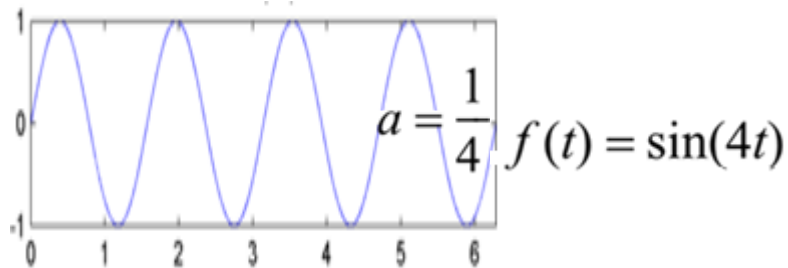
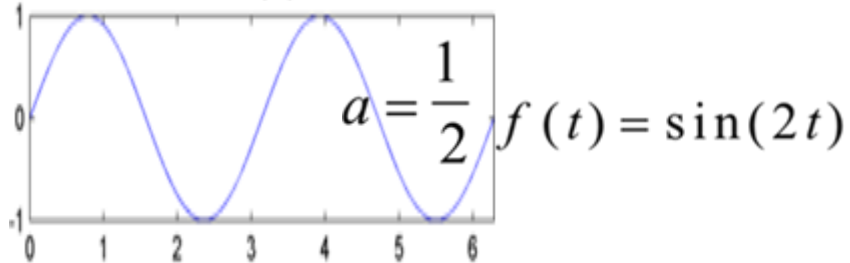
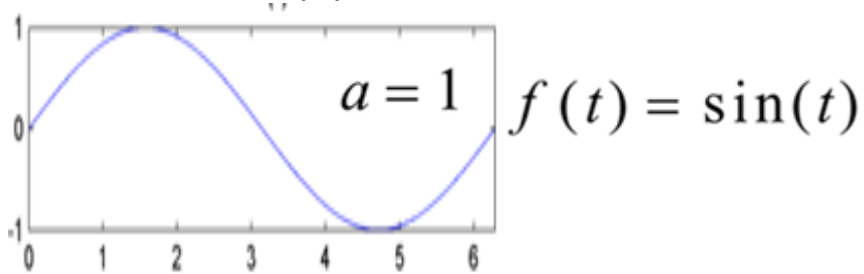
wavelet with scale, s and time, τ

[Watch this video](#)

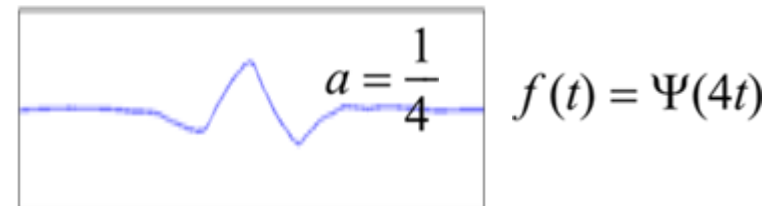
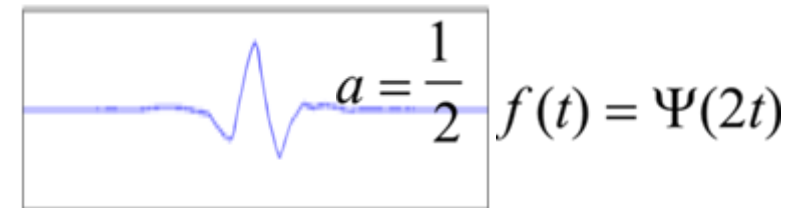
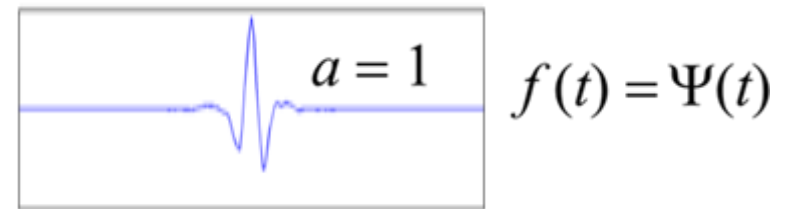
Wavelet Transformation- Scaling

- Wavelet analysis produces a time-scale view of the signal.
- *Scaling* means stretching or compressing of the signal.

Scale factor (a) for sine waves:



Scale factor (a) with wavelets:



END