

Signal Processing for Communication

Ch. Bollinger

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Part I.

Week 1 Module 1:

1. Basics of Digital Signal Processing

1.1. Introduction to digital signal processing

1.1.1. Signal

- Description of the evolution of a physical phenomenon

phenomenon	signal
weather	temperature
sound	pressure
sound	magnetic deviation
light intensity	gray level on paper

1.1.2. Processing

- **Analysis:** Understanding the information carried by the signal
- **Synthesis:** Creating a signal to contain the given information

1.1.3. Digital

- Discrete Time
 - Splice up time into a series of discrete instances without losing information
 - Harry Nyquist and Claude Shannon state with the [Sampling Theorem](#) that continuous time representation and discrete time representation are equivalent.
 - The Sampling Theorem: Under appropriate "slowness" conditions for $x(t)$ we have

$$x(t) = \sum_{n=-\infty}^{\infty} x[n] \operatorname{sinc}\left(\frac{t - nT_s}{T_s}\right) \quad (1.1)$$

- The condition under which the Sampling Theorem holds was given by Fourier and it's [Fourier Analysis](#).
 - The Fourier transform will give us a quantitative measure how fast a signal moves
- Discrete Amplitude
 - Through discretisation of amplitudes only a set of predefined values are possible.
 - The set of levels is countable i.e. we can always map the level of a sample to an integer. If our data is represented by integer it becomes complete abstract and general which has very important consequences in the following three domains:
 - * **Storage** special devices for recoding needed
 - * **Processing** General purpose microprocessor is sufficient
 - * **Transmission** Reproduction of the original signal and therefore eliminating noise is easy

1.1.4. From Analog to Digital Signal Processing

- Analog asks for $f_{(t)} = ?$
- Digital represents data as a sequence of numbers (scaled with a factor of 1000)

-12 -12 -12 -11 -11 -12 -12 -11 -11 -10
 -10 -10 -9 -10 -10 -9 -9 -9 -9 -9
 -8 -8 -7 -7 -8 -8 -8 -7 -7 -7

1.2. Discrete-Time Signals

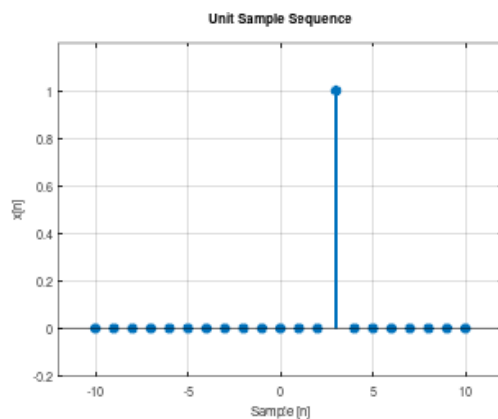
1.2.1. Basic Definitions

- Sequence: defined as [complex-valued function](#)
- Discrete-Time Signal: a sequence of complex numbers
 - one dimension (for now)
 - notation: $x[n]$
 - two-sides sequences: $x: \mathbb{Z} \rightarrow \mathbb{C}$
 - n is *a-dimensional* "time", sets an order on the sequence of samples
 - analysis: periodic measurement
 - synthesis: stream of generated samples, reproduce a physical phenomenon

1.2.2. Octave Algorithm for some basic Signals

Unit Impulse

```
function [x,n] = impseq(n0,n1,n2)
% Generates  $x(n) = \delta(n-n0)$ ;  $n1 \leq n \leq n2$ 
% -----
% [x,n] = impseq(n0,n1,n2)
%
n = [n1:n2]; x = [(n-n0) == 0];
end
```



$$x[n] = \delta[n] = \begin{cases} 1 & n = 0 \\ 0 & n \neq 0 \end{cases}$$

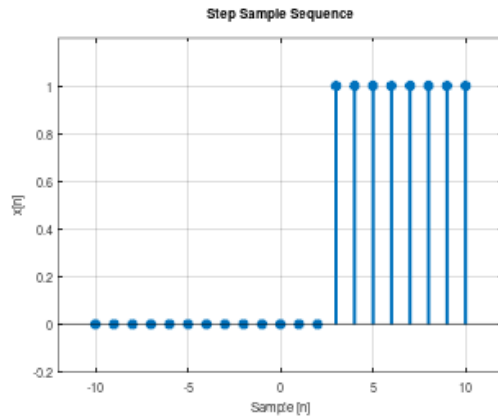
Unit Step

```

function [x,n] = stepseq(n0,n1,n2)
% Generates x(n) = delta(n-n0); n1 <= n0 <= n2
% -----
% [x,n] = stepseq(n0,n1,n2)
%
n = [n1:n2]; x = [(n-n0) >= 0];
end

```

$$x[n] = u[n] = \begin{cases} 1 & n \geq 0 \\ 0 & n < 0 \end{cases}$$



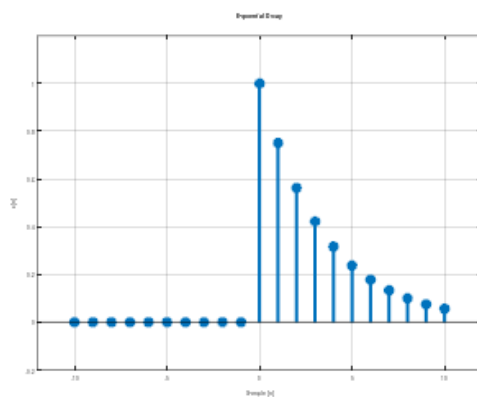
Real-valued exponential Sequence

```

function [x,n] = expseq(n1,n2,a)
% Generates x(n) = a^n
% -----
% [x,n] = expseq(n1,n2,A,omega,phi)
%
n = [n1:n2];
for (i = 1 : length(n))
    if (n(i) >= 0)
        x(i) = (a).^n(i);
    else
        x(i) = 0;
    end
end
end

```

$$x[n] = a^n, \forall n \in \mathbb{R}$$



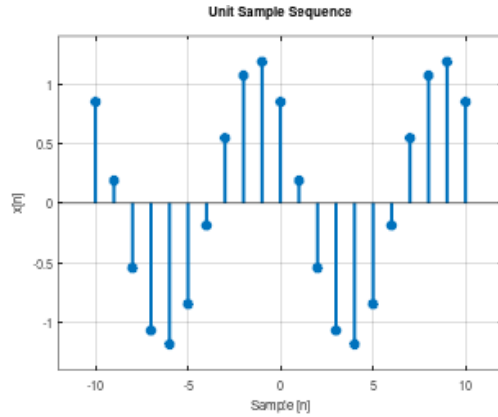
Sinusoidal Sequence

```

function [x,n] = cosseq(n1,n2,A, omega, phi)
% Generates x(n) = A*cos(2*pi*omega*n + phi); n1 <= n2
% -----
% [x,n] = cosseq(n1,n2,A,omega,phi)
%
n = [n1:n2]; x = A*cos(2*pi*omega*n + phi);
end

```

$$x[n] = A \cos(\omega_0 n + \Phi)$$



1.2.3. Classes of Discrete-Time signals

1.2.3.1. Finite-Length

- indicate notation: $x[n]$, $n = 0, 1, 2, \dots, N-1$
- vector notation: $x = [x_0, x_1, \dots, x_{N-1}]^T$
- practical entities, good for numerical packages (e.g. numpy)

1.2.3.2. Infinite-Length

- sequence notation: $x[n]$, $n \in \mathbb{Z}$
- abstraction, good for theorems

1.2.3.3. Periodic

- N-periodic sequence: $\tilde{x}[n] = \tilde{x}[n + kN]$, $n, k, N \in \mathbb{Z}$
- same information as in finite-length of length N
- [natural bridge](#) between finite and infinite length

1.2.3.4. Finite-Support

[Finite-support sequence](#)

$$\bar{x}[n] = \begin{cases} x[n] & \text{if } 0 \leq n < N, n \in \mathbb{Z} \\ 0 & \text{otherwise} \end{cases} \quad (1.2)$$

- same information as in finite-length of length N
- another bridge between finite and infinite lengths

1.2.3.5. Elementary Operations

Scaling

$$y[n] = ax[n] \rightarrow \begin{cases} a > 0 & \text{amplification} \\ a < 0 & \text{attenuation} \end{cases} \quad (1.3)$$

Sum

$$y[n] = x[n] + z[n] \quad (1.4)$$

Product

$$y[n] = x[n] * z[n] \quad (1.5)$$

Shift

$$y[n] = x[n - k] \rightarrow \begin{cases} k > 0 & \text{delay} \\ k < 0 & \text{anticipate} \end{cases} \quad (1.6)$$

Integration

$$y[n] = \sum_{k=-\infty}^n x[k] \quad (1.7)$$

Differentiation

$$y[n] = x[n] - x[n - 1] \quad (1.8)$$



Relation Operator and Signals

- The **unit step** can be obtained by applying the **integration** operator to the **discrete time pulse**.
- The **unit impulse** can be obtained by applying the **differentiation** operator to the **unit step**.

1.2.4. Energy and Power

Energy Many sequences have an infinity amount of energy e.g. the unit step $u[n]$,

$$E_x = \|x\|_2^2 = \sum_{k=-\infty}^{\infty} |x[k]|^2 \quad (1.9)$$

Power To describe the energetic properties of the sequences we use the concept of power

$$P_x = \|x\|_2^2 = \frac{1}{N} \sum_{n=0}^{N-1} |x[n]|^2 \quad (1.10)$$

Many signals have infi

1.3. Basic signal processing

1.3.1. How a PC plays discrete-time sounds

1.3.1.1. The discrete-time sinusoid

$$x[n] = \sin(\omega_0 t + \Theta)$$

```

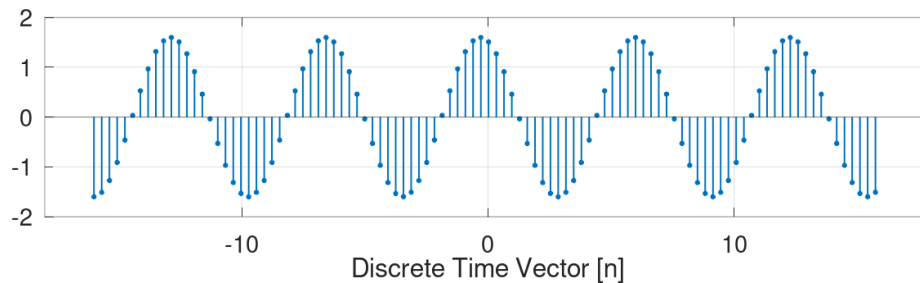
N=33                                # Vector lenght
n=-(N-1)/2:pi/10:(N-1)/2; # Discrete Time Vector
omega0 = pi/10;
theta = pi/2

f = 1.6*sin(omega0+n + theta); # The sinusoid

# Do not open the graphic window in org
figure( 1, "visible", "off");

stem(n,f, "filled", "linewidth", 2, "markersize", 6);
axis([- (N-1+4)/2 (N-1+4)/2 -2 2])
set(gca, "fontsize", 24);
grid on ;
xlabel("Discrete Time Vector [n]");
print -dpng "-S1400,350" ./image/sin.png;
# Org-Mode specific output
ans = "./image/sin.png";

```



1.3.1.2. Digital vs physical frequency

- Discrete Time:
 - Periodicity: how many samples before the pattern repeats (M)
 - n: no physical dimension
- Physical World:
 - Periodicity: how many seconds before the pattern repeats
 - frequency measured in Hz
- Soundcard T_s System Clock
 - A sound card takes every T_s a new sample from the discrete-time sequence.
 - periodicity of M samples \rightarrow periodicity of $M T_s$ seconds
 - real world frequency

$$f = \frac{1}{M T_s} \text{ Hz} \quad (1.11)$$

- Example
 - usually we choose F_s the number of samples per seconds
 - $T_s = 1/F_s$

$F_s = 48000$ e.g. a typical value

$T_s = 20.8 \mu s$

$f = 440 \text{ Hz}$, with $M = 110$

1.3.2. The Karplus Strong Algorithm

1.3.2.1. The Moving Average

- simple average (2 point average)

$$m = \frac{a + b}{2} \quad (1.12)$$

- moving average: take a "local" average

$$y[n] = \frac{x[n] + x[n-1]}{2} \quad (1.13)$$

- Average a sinusoid

$$\begin{aligned} x[n] &= \cos(\omega n) \\ y[n] &= \frac{\cos(\omega n) - \cos(\omega (n-1))}{2} \\ y[n] &= \cos(\omega n + \theta) \end{aligned}$$



Linear Transformation



Applying a linear transformation to a sinusoidal input results in a sinusoidal output of the same frequency with a phase shift.

1.3.2.2. Reversing the loop

$$y[n] = x[n] + \alpha y[n-1] \rightarrow \text{The Karplus Strong Algorithm} \quad (1.14)$$

- **Zero Initial Conditions:**
 - set a start time (usually $n_0 = 0$)
 - assume input and output are zero for all time before N_0

1.4. Digital Frequency



Digital Frequency



$$\begin{aligned} \sin(n(\omega + 2k\pi)) &= \sin(n\omega + \phi), \text{ k in } \mathbb{Z} \\ &= e^{i(\phi + n*2\pi\omega)} \end{aligned} \quad (1.15)$$



Complex Exponential



$$\omega = \frac{M}{N} \times 2 \times \pi \quad (1.16)$$

1.5. The Reproduction Formula

**Reproduction Formula**

$$x[n] = \sum_{k=-\infty}^{\infty} x[k]\delta[n-k] \quad (1.17)$$

Any [signal](#) can be expressed as a linear combination of wighted and shifted pulses.

Part II.

Week 2 Module 2:

2. Vector Spaces



Vector Space

Vector spaces build among others a common framework to work with the four classes of signals:

- Finite Length Signal
- Infinte Length Signal
- Periodic Signal
- Finite Support Signal

Finite length and periodic signal, i.e. the "practical signal processing" live in the \mathbb{C}^N Space. To represent infinite length signals we need something more. We require sequeces to be square-summabe $\sum_{n=-\infty}^{\infty} |x[n]|^2$

$\mathbb{R}^2, \mathbb{R}^3$

Euclidean space, geomtery

$\mathbb{R}^n, \mathbb{C}^n$

Linear algebra

$\ell_2(\mathbb{Z})$

Square-Summable infinite sequences

$L_2([a, b])$

Square-integrable functions over an interval

2.1. Operationl Definitions



Inner Product

↗ Measure of similarity between vectors

Inner Product

$$\langle \mathbf{x}, \mathbf{y} \rangle := \sum_{n=0}^{N-1} x_n y_n$$

A vector space with an inner product is called an **inner product space**

Inner Product in \mathbb{R}^2

$$\langle \mathbf{x}, \mathbf{y} \rangle = x_0 y_0 + x_1 y_1 = \mathbf{x} + \mathbf{y} \cos(\alpha)$$

Inner Product in $\mathbb{L}_{[-1,1]}$

$$\langle \mathbf{x}, \mathbf{y} \rangle = \int_{-1}^1 x(t) y(t) dt$$

Norm of a Vector

$$\mathbf{v} := \langle \mathbf{v}, \mathbf{v} \rangle = \|\mathbf{v}\|^2$$

self inner product

Orthogonal

$$\langle \mathbf{p}, \mathbf{q} \rangle = 0$$

maximal different vectors
inner product = 0

Distance

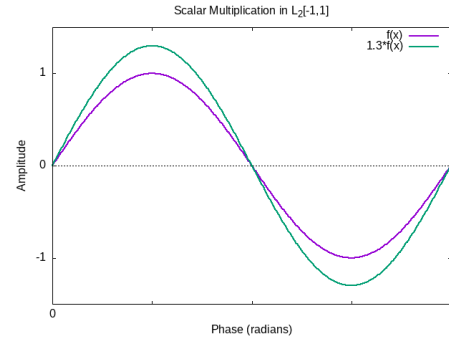
$$d(x, y) = \mathbf{x} - \mathbf{y}_2$$

2.2. Some Examples

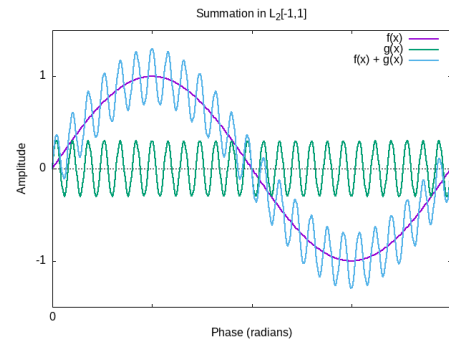
Not all vector spaces have got a graphical representation. The following table shows the graphical representation of vector spaces

graphical representation	no graphical representation
\mathbb{R}^2	\mathbb{C}^N for $N > 1$
\mathbb{R}^3	\mathbb{R}^N for $N > 3$
$\mathbb{L}_{[-1,1]}$	

Scalar Multiplication in $\mathbb{L}_2[-1, 1]$

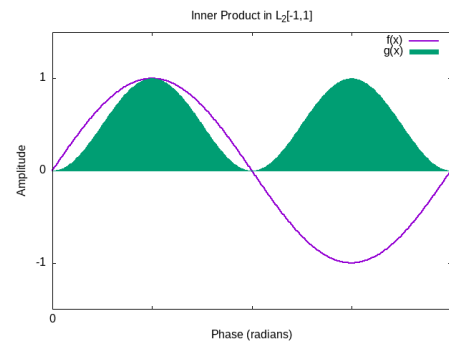


Summation of two Vectors in $\mathbb{L}_2[-1, 1]$



Inner Product in $\mathbb{L}_2[-1, 1]$ - The Norm:
with $x = \sin(\pi \cdot t)$

$$\begin{aligned}\langle \mathbf{x}, \mathbf{x} \rangle &= \|\mathbf{x}\|^2 \\ &= \int_{-1}^1 \sin^2(\pi t) dt = 1\end{aligned}$$



2.3. Hilbert Space

A hilbert space is an **inner product space** which fulfills completeness.

2.4. Signal Spaces

Finite length signal live in \mathbb{C}^N

- all operations well defined and intuitive
- space of N-periodic signals sometimes indicated by $\tilde{\mathbb{C}}^N$

2.5. TODO Vecotor Bases

2.6. TODO Subspace Approximations

2.6.1. Least-Square Approximation

Consider a orthonormal basis for subspace S, called S of K

$s - (k)_{k=0,1\ldots,k-1}$ orthonormal basis for S

orthonormal projection is defined as follows:

$$\hat{x} = \sum_{k=0}^{k-1} \langle s^{(k)}, x \rangle s^{(k)}$$

- orthogonal projection has minimum-norm error:

$$\arg \min ||x - y|| = \hat{x}$$

- :

$$\langle x - \hat{x}, \hat{x} \rangle = 0$$

Part III.

Week 3 Module 3:

3. Part 1 - Introduction to Fourier Analysis

3.1. Introduction to Fourier Analysis

3.1.1. The Frequency Domain

3.1.1.1. Oscillations are every where

- A train has got an engine which makes the wheels turn in circular motion
- Waves, ebb and flow can be modeled as sinusoidal fashion
- Musical instruments generates sound by vibrating at a certain fundamental frequency
- Intuitively: things that don't move in circles can't last
 - bombs
 - rockets
 - human beings

3.1.1.2. Descriptin of the oscillations in the plane

Period P

Frequency $f = \frac{1}{P}$

Ordinate $\sin(ft)$

Abscissa $\cos(ft)$

3.1.1.3. Example Sinusoidal Detectors in our Body:

cochlea In the inner ear that detects air pressure sinusoids at frequencies from 20 to 20kHz

retina In the eye to detect electromagnetic sinusoids with frequency 430THz to 790THz. This is the frequency of lights in the visible spectrum

Humans anlayze complex signals (audio, images) in terms of their sinusoidal components

Frequency Domain semms to be as good a the time domain

3.1.1.4. Fundamental Questions: Can we decompse any signal into sinusoidal elements?

- Yes, Fourier showed us how to do it exactly
- Analysis
 - From time domain to frequency domain
 - Find the contribution of different frequencies
 - Discover "hidden" signal properties
- Synthesis
 - From frequency domain to time domain
 - Create signals with known frequency content
 - Fit signals to specific frequency regions

3.1.2. The DFT as a change of basis

- let's start with finite-length signals (i.e. vectors in \mathbb{C}^N)
- **Fourier analysis is a simple change of basis**
- a change of basis is a change of perspective
- a change of perspective can reveal things (if the basis is good)

3.1.2.1. The Fourier Basis for \mathbb{C}^N

Claim: the set of N signals in \mathbb{C}^N

$$w_k[n] = e^{j\frac{2\pi}{N}nk} \text{ with } n, k = 0, 1, \dots, N-1$$

is an orthogonal basis in \mathbb{C}^N .

- \mathbb{C}^N : N different vectors all with length N
- k : is the index that indicates different vectors (signals), $k = 0, \dots, N-1$
- n : is the index that indicates different elements within the vector, $n = 0, \dots, N-1$
- $w_k[n] = e^{j\frac{2\pi}{N}nk}$: Form of the N -Signals
- $\omega = \frac{2\pi}{N}nk$: The index of the signal makes up the **Fundamental Frequency** of the complex exponential.

In Vector Notation:

$$\left\{ \mathbf{w}^{(k)} \right\}_{k=0,1,\dots,N-1}$$

with

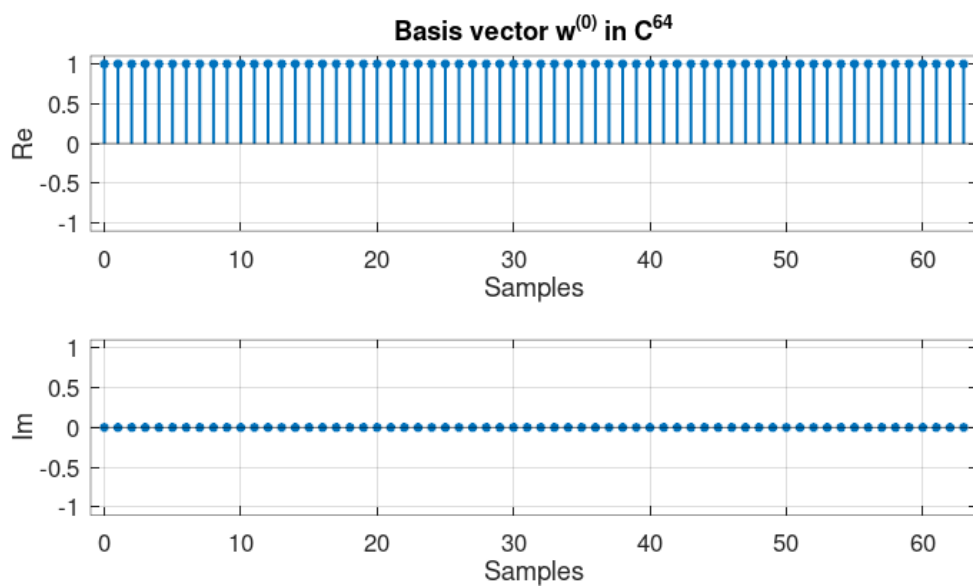
$$w_n^{(k)} = e^{j\frac{2\pi}{N}nk}$$

is an orthogonal basis in \mathbb{C}^N

Fundamental Frequency

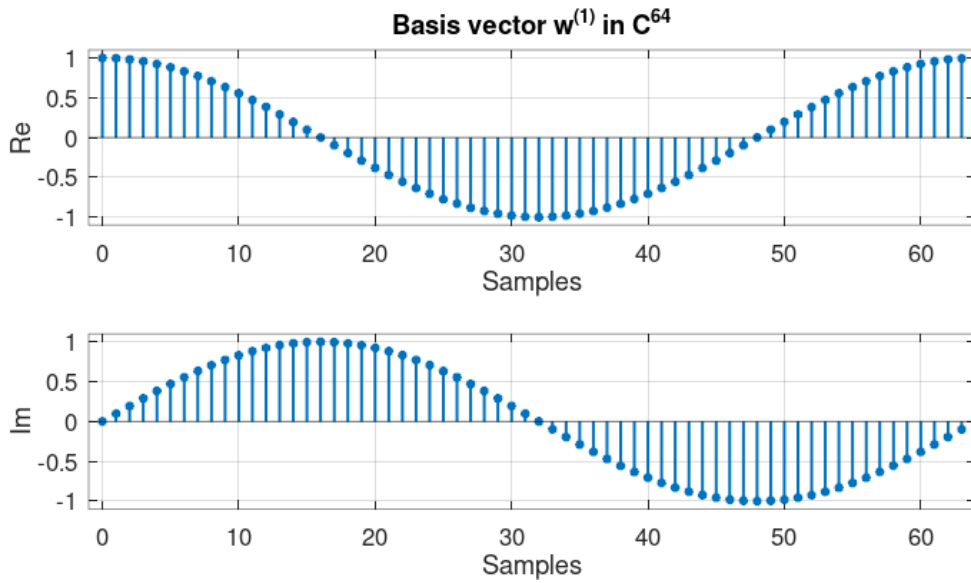
$$\omega = \frac{2\pi}{N}0 = 0$$

3.1.2.1.1. Basis vector $\mathbf{w}^{(0)} \in \mathbb{C}^{64}$



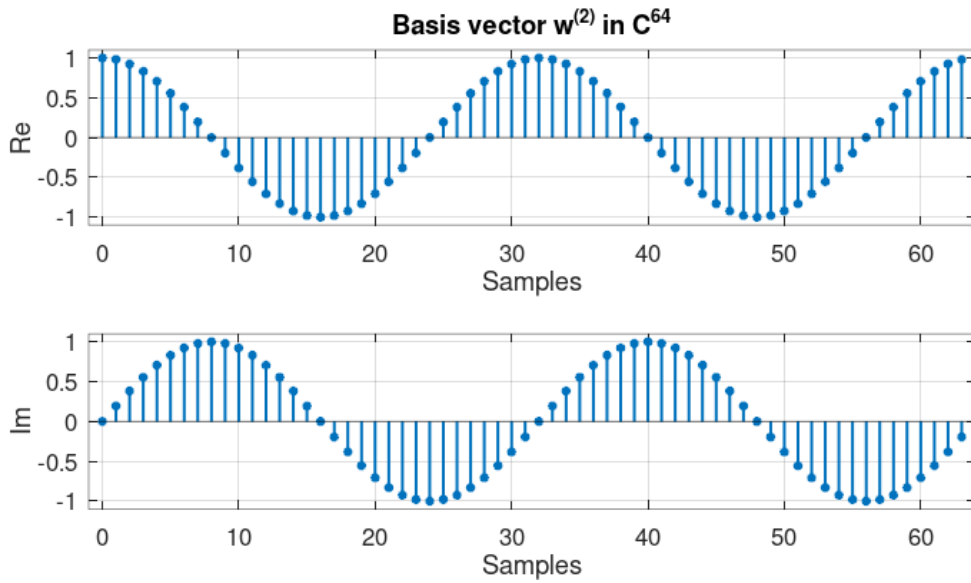
Fundamental Frequency

$$\omega = \frac{2\pi}{N} 1 = \frac{2\pi}{N}$$

3.1.2.1.2. Basis vector $\mathbf{w}^{(1)} \in \mathbb{C}^{64}$ 

Fundamental Frequency

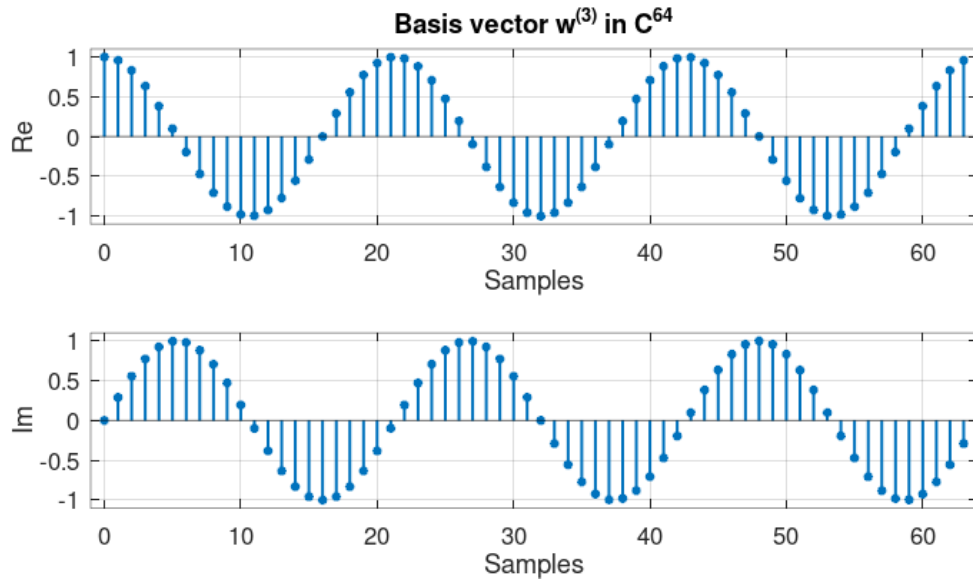
$$\omega = \frac{2\pi}{N} 2$$

3.1.2.1.3. Basis vector $\mathbf{w}^{(2)} \in \mathbb{C}^{64}$ 

Fundamental Frequency

$$\omega = \frac{2\pi}{N} 3$$

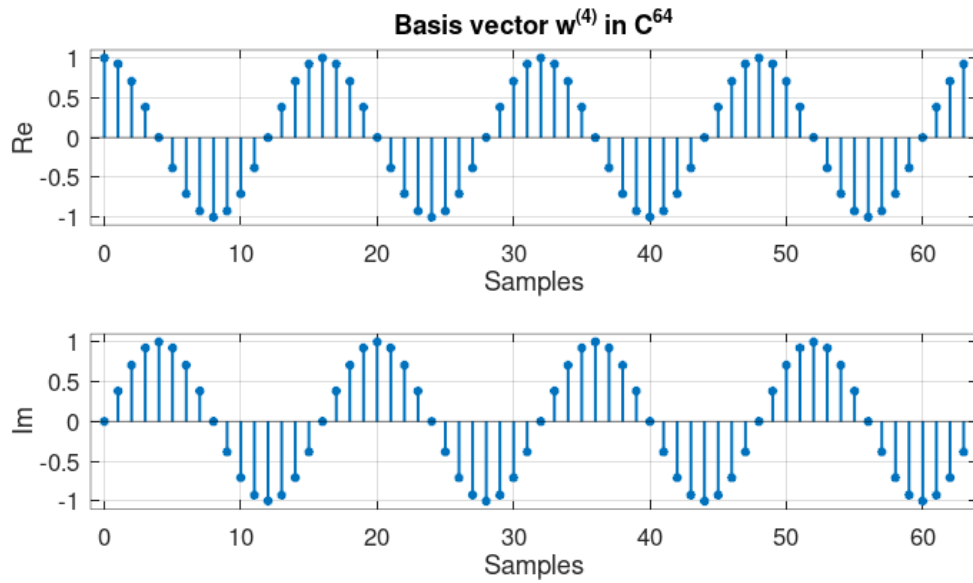
3.1.2.1.4. Basis vector $\mathbf{w}^{(3)} \in \mathbb{C}^{64}$



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 4$$

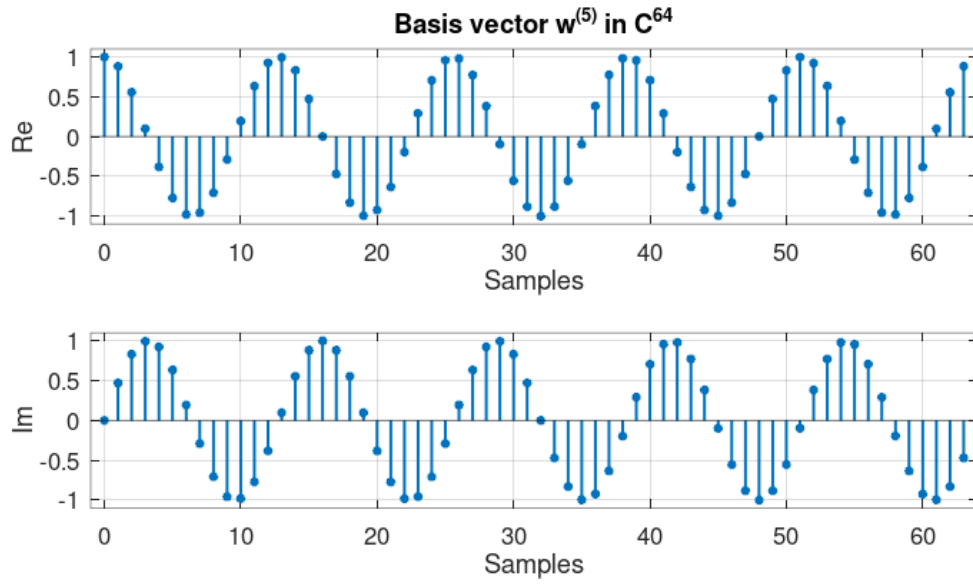
3.1.2.1.5. Basis vector $w^{(4)} \in \mathbb{C}^{64}$



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 5$$

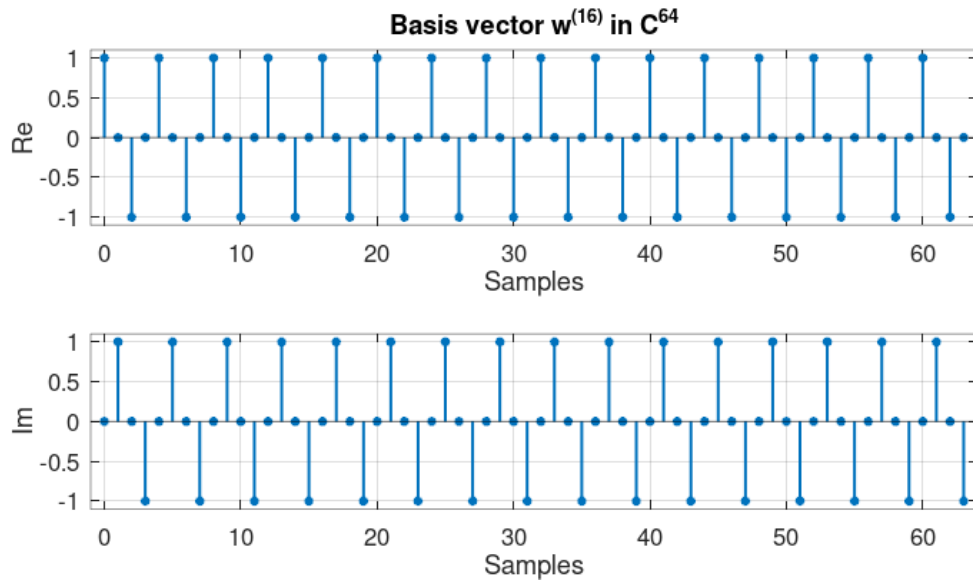
3.1.2.1.6. Basis vector $w^{(5)} \in \mathbb{C}^{64}$



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 2 = \frac{\pi}{2}$$

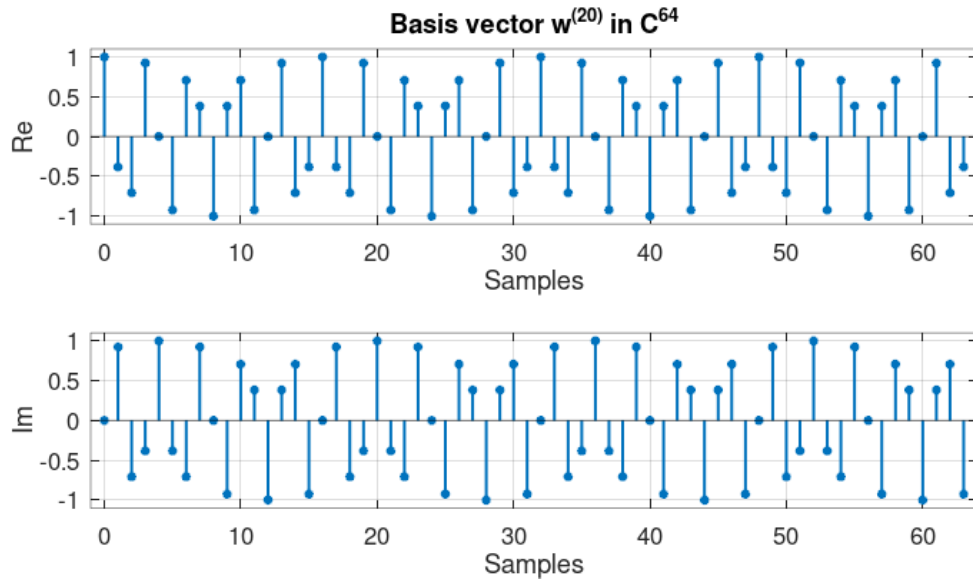
3.1.2.1.7. Basis vector $w^{(16)} \in \mathbb{C}^{64}$



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 20$$

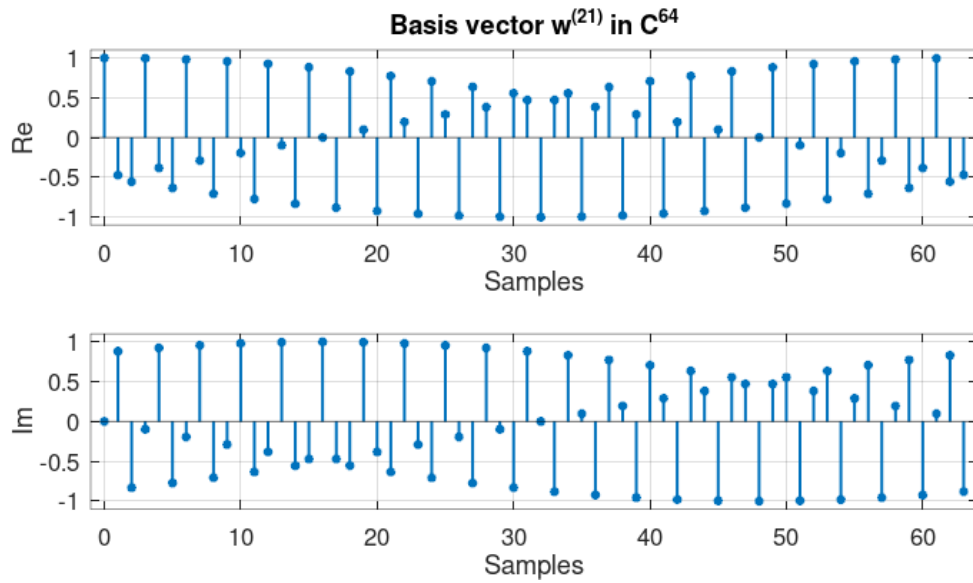
3.1.2.1.8. Basis vector $w^{(20)} \in \mathbb{C}^{64}$



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 21$$

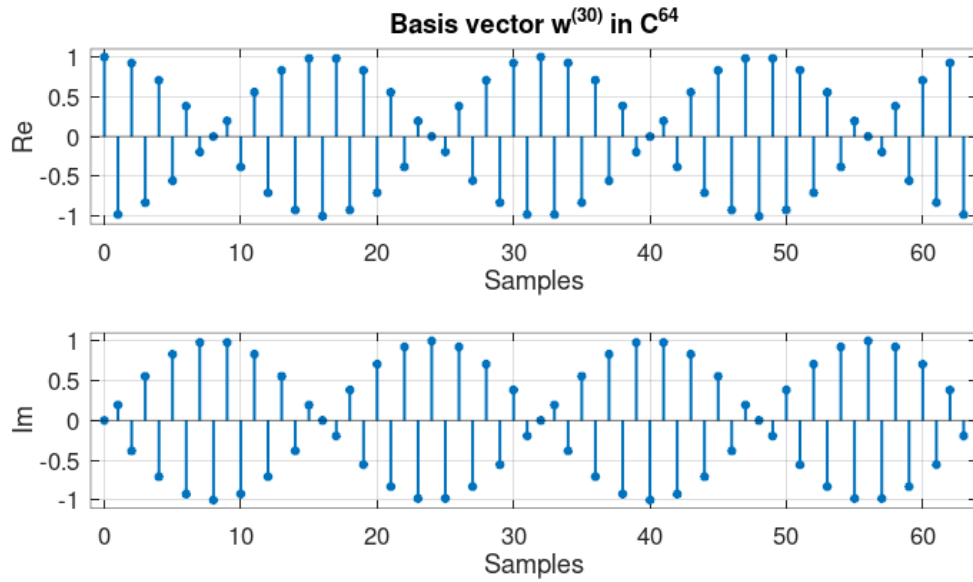
3.1.2.1.9. Basis vector $w^{(21)} \in \mathbb{C}^{64}$



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 30$$

3.1.2.1.10. Basis vector $w^{(30)} \in \mathbb{C}^{64}$

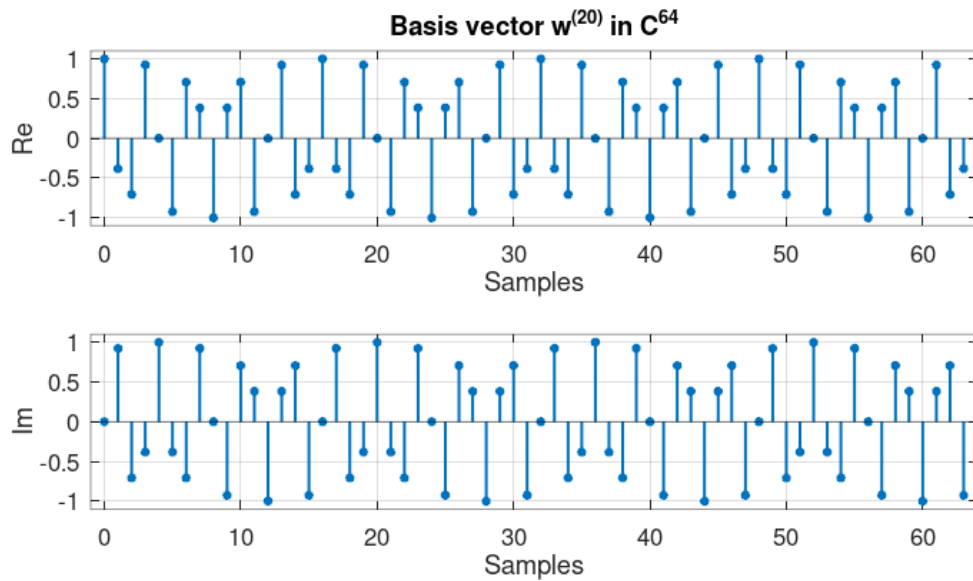


Fundamental Frequency

$$\omega = \frac{2\pi}{N} 20$$

3.1.2.1.11. Basis vector $w^{(31)} \in \mathbb{C}^{64}$

The sign alternation is a tell tale sign of a high frequency sinusoid.

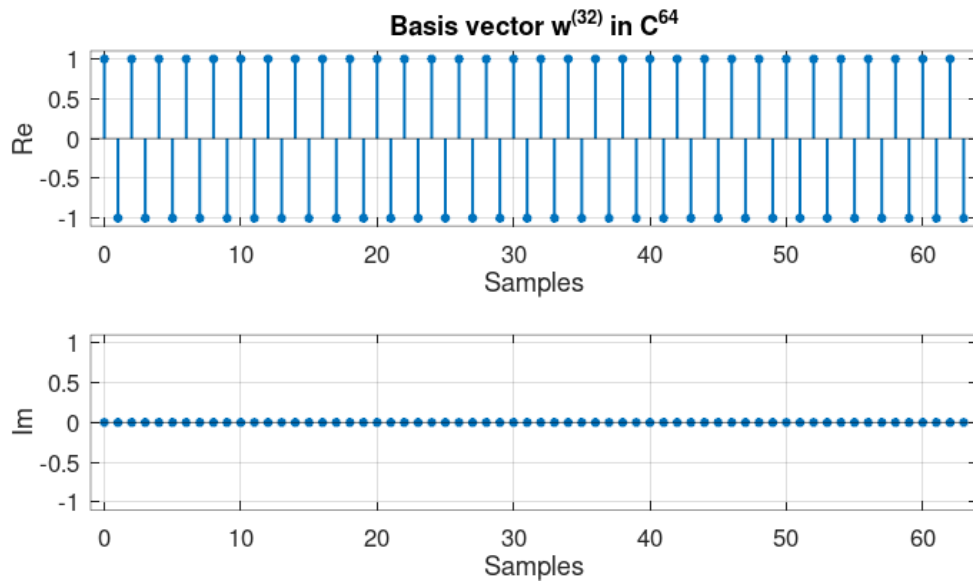


Fundamental Frequency

$$\omega = \frac{2\pi}{N} 32 = \frac{2\pi}{64} 32 = \pi$$

3.1.2.1.12. Basis vector $w^{(32)} \in \mathbb{C}^{64}$

At k equal to 32 the highest fundamental frequency is reached.

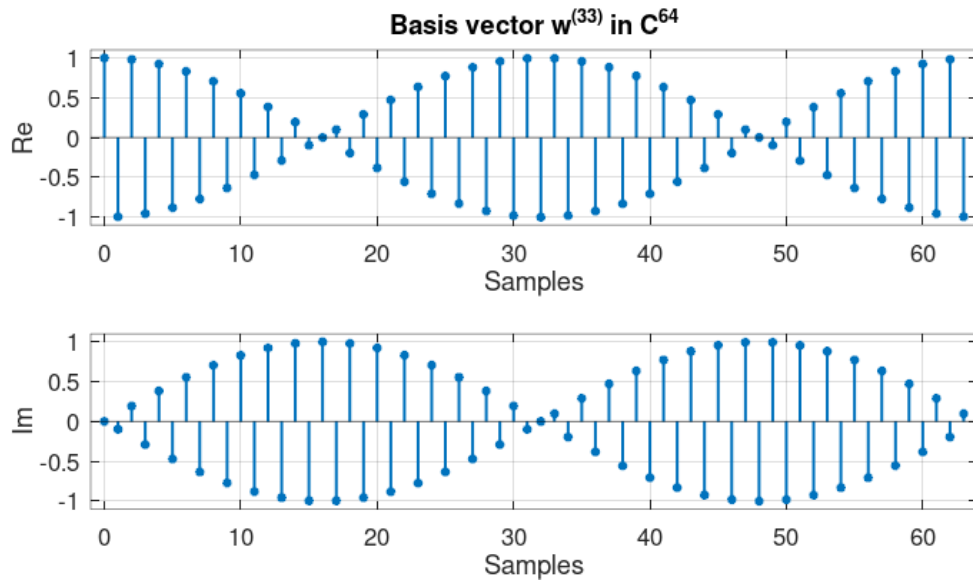


Fundamental Frequency

$$\omega = \frac{2\pi}{N} 33$$

3.1.2.1.13. Basis vector $w^{(33)} \in \mathbb{C}^{64}$

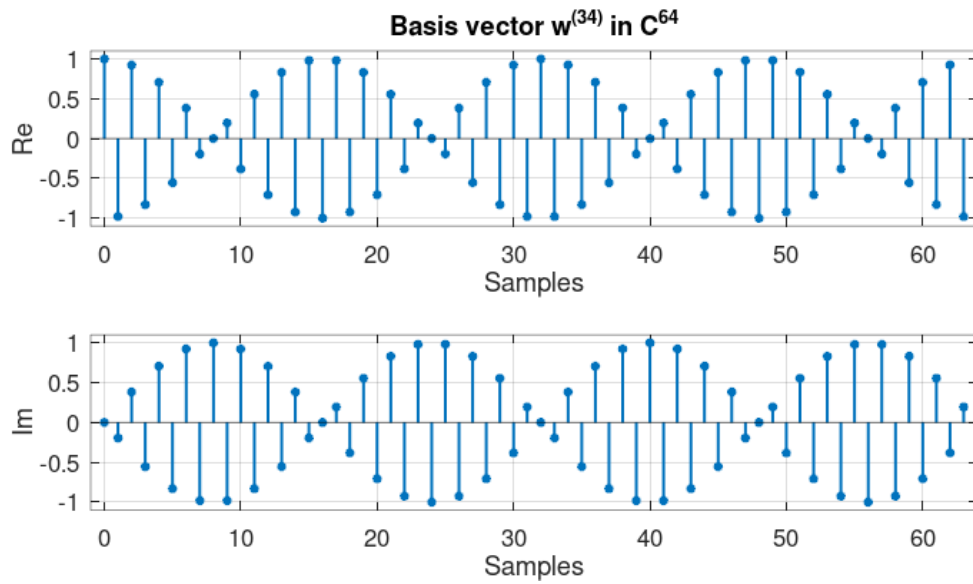
If we go forward with the index the apparent speed of the point decreases and the direction of the rotation changes from counter clockwise to clockwise.



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 34$$

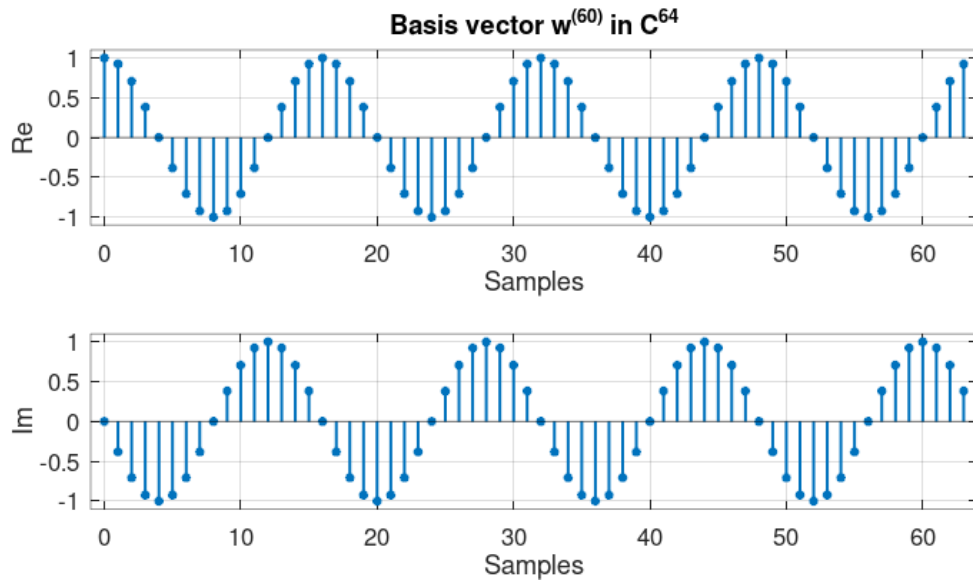
3.1.2.1.14. Basis vector $w^{(34)} \in \mathbb{C}^{64}$



Fundamental Frequency

$$\omega = \frac{2\pi}{N}60$$

3.1.2.1.15. Basis vector $\mathbf{w}^{(60)} \in \mathbb{C}^{64}$

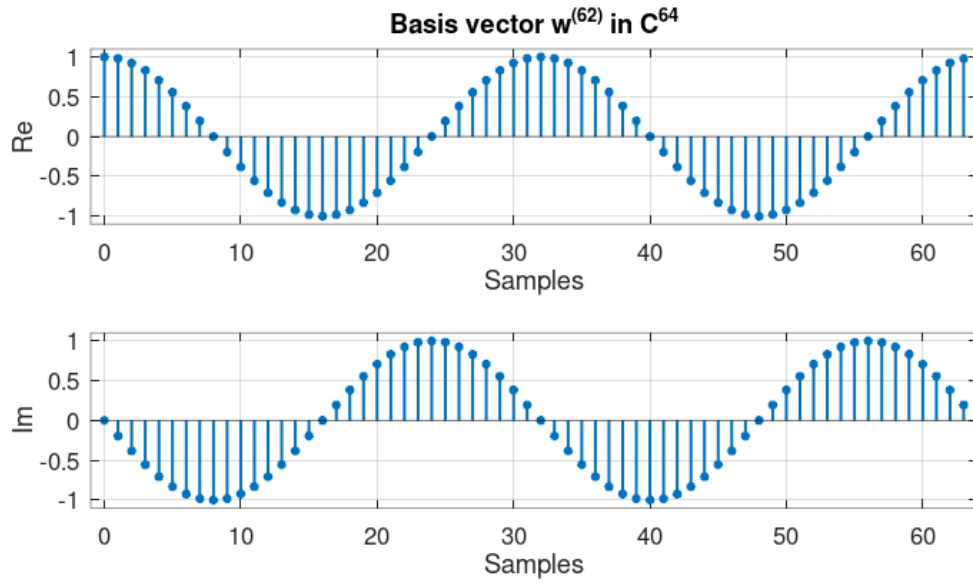


Fundamental Frequency

$$\omega = \frac{2\pi}{N}62$$

3.1.2.1.16. Basis vector $\mathbf{w}^{(62)} \in \mathbb{C}^{64}$

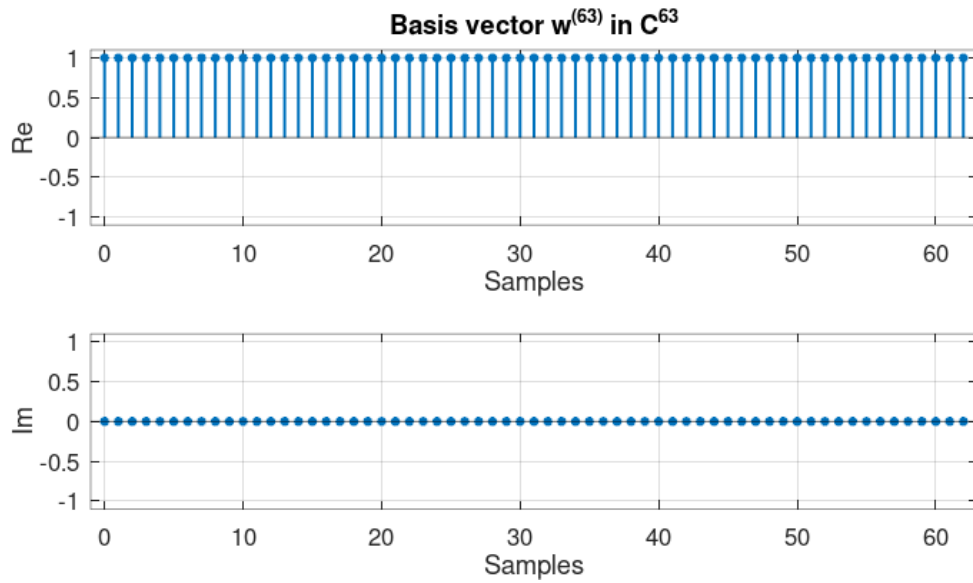
So here, for instance, if you compare this basis vector to $\mathbf{w}^{(2)}$, you would see that the real part is the same, but the imaginary part has a sign inversion.



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 63$$

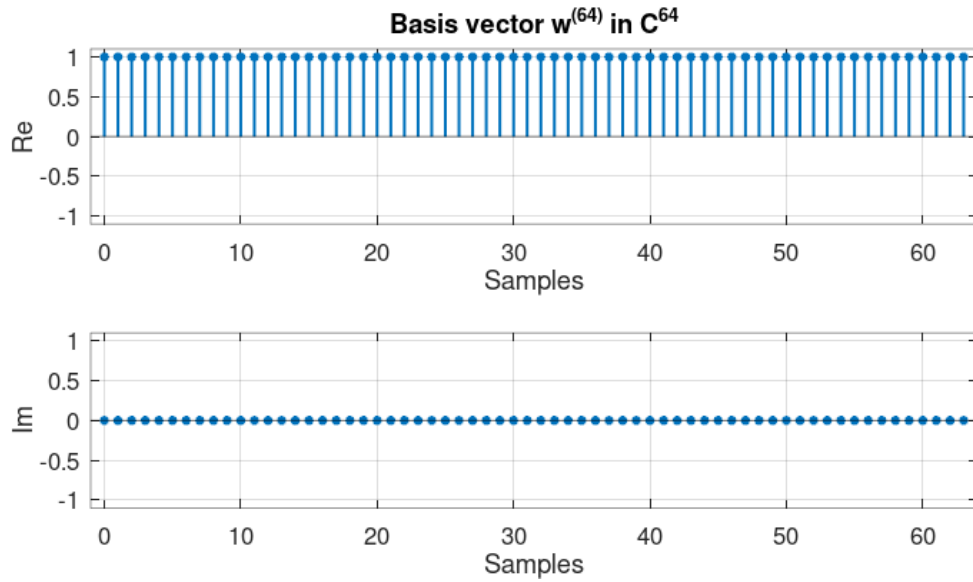
3.1.2.1.17. Basis vector $w^{(63)} \in \mathbb{C}^{64}$



Fundamental Frequency

$$\omega = \frac{2\pi}{N} 64$$

3.1.2.1.18. Basis vector $w^{(64)} \in \mathbb{C}^{64}$



3.2. The Discrete Fourier Transform (DFT)

3.2.1. DFT definition

3.2.1.1. The Fourier Basis for \mathbb{C}^N in "Signal" Notation

$$w_k[n] = e^{j\frac{2\pi}{N}nk} \text{ with } n, k = 0, 1, \dots, N-1 \quad (3.1)$$

3.2.1.2. The Fourier Basis in Vector Notation

$$\{\mathbf{w}^{(k)}\}_{k=0,1,\dots,N-1} \text{ with } w_n^{(k)} = e^{j\frac{2\pi}{N}nk}, n = 0, 1, \dots, N-1 \quad (3.2)$$

N N Dimension of vector space

k Index for different vectors and goes from 0..N-1

n Index of element in each vector goes from 0..N-1

3.2.1.3. Basis Expansion Vector Notation

3.2.1.3.1. Analysis Formula

$$X_k = \langle \mathbf{w}^{(k)}, \mathbf{x} \rangle \quad k = 0, \dots, N-1 \quad (3.3)$$

X_k Coefficient for the new basis. Inner Product of \mathbf{x} with each vector $\mathbf{w}^{(k)}$

\mathbf{x} An arbitrary vector of \mathbb{C}^N

$\mathbf{w}^{(k)}$ New basis

3.2.1.3.2. Synthesis Formula

$$\mathbf{x} = \frac{1}{N} \sum_{k=0}^{N-1} X_k \mathbf{w}^{(k)} \quad k = 0, \dots, N-1 \quad (3.4)$$

3.2.1.4. TODO Change of basis in matrix form

3.2.1.5. Basis Expansion Signal Notation

- Consider explicitly the operations involved in the transformation
- This notion is particularly useful if you want to consider the algorithmic nature of the transform

3.2.1.5.1. Analysis Formula N-point signal in the frequency domain

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j \frac{2\pi}{N} nk}, \quad k = 0, 1, \dots, N-1$$

$X[k]$ Signal vector in the frequency domain

$x[n]$ Signal vector in the (discrete) time domain

Reminder This is the inner Product in explicit form

3.2.1.5.2. Synthesis Formula N-point signal in the time domain

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] e^{j \frac{2\pi}{N} nk}, \quad k = 0, 1, \dots, N-1$$

$X[k]$ Signal vector in the frequency domain

$\frac{1}{N}$ Normalisation coefficient

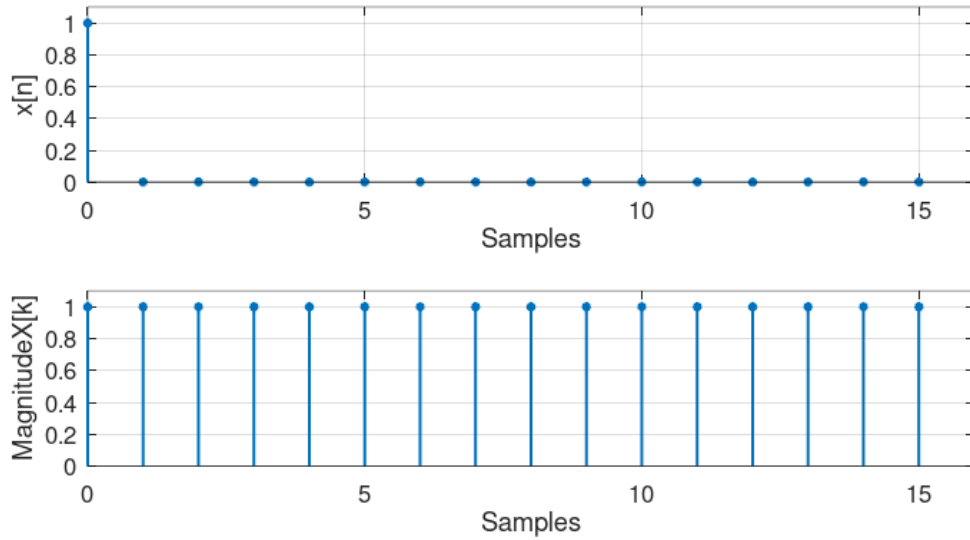
Reminder This is the inner Product in explicit fashion

3.2.2. Examples of DFT Calculation

3.2.2.1. DFT of the impulse function

$$x[n] = \delta[n]$$

$$X[k] = \sum_{n=0}^{N-1} \delta[n] e^{-j \frac{2\pi}{N} nk} = 1$$

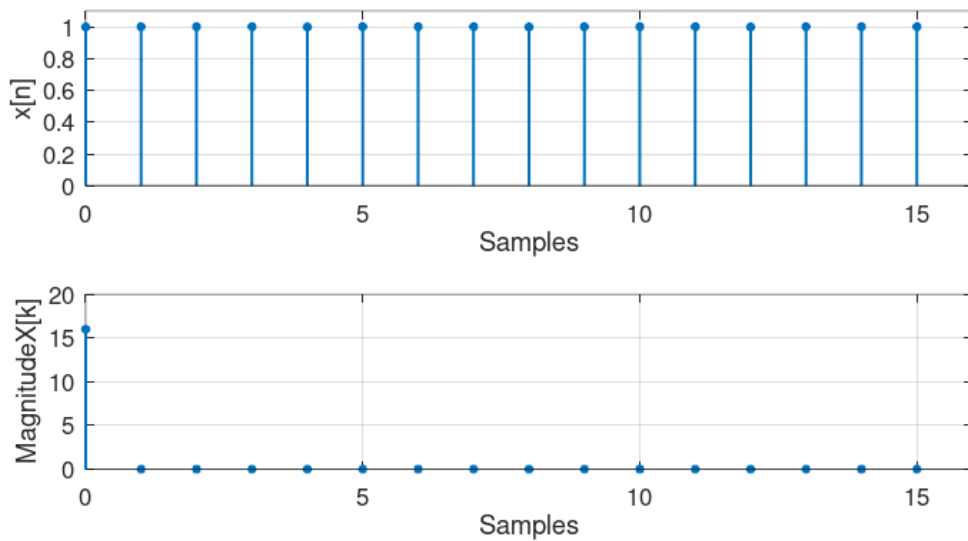


- The delata contains all frequencies over the range of all possible frequencies

3.2.2.2. DFT of the unit step

$$x[n] = 1$$

$$X[k] = \sum_{n=0}^{N-1} e^{-j\frac{2\pi}{N}nk} = N\delta[k]$$



3.2.2.3. DFT Cosine Calculation Problem 1

$$x[n] = 3 \cos(2\pi/16 \times n), \quad x[n] = \mathbb{C}^{64}$$

1. Determine dimension and fundamental frequency of the signal

- Dimension of space $N = 64$
- Fundamental frequency $\omega = \frac{2\pi}{N} = \frac{2\pi}{64}$

All frequencies in the fourier basis will be a multiple of the fundamental frequency ω . With this in mind we can start by expressing our sinuoid as a multiple of the fundamental frequency in space \mathbb{C}^{64} .

- Express the signal as a multiple of the fundamental frequency in space.

$$\begin{aligned} X[n] &= 3 \cos\left(\frac{2\pi}{16}n\right) \\ &= 3 \cos\left(\frac{2\pi}{64}4n\right) \\ &= \frac{3}{2} \left[e^{j\frac{2\pi}{64}4n} + e^{-j\frac{2\pi}{64}4n} \right], \text{ with Euler: } \cos(\omega) = \frac{e^{j\omega} + e^{-j\omega}}{2} \\ &= \frac{3}{2} \left[e^{j\frac{2\pi}{64}4n} + e^{j\frac{2\pi}{64}60n} \right], \text{ with: } j\frac{2\pi}{64}60n = -j\frac{2\pi}{64}4n + j2\pi n \\ &= \frac{3}{2} \langle w_4[n] + w_{60}[n] \rangle \end{aligned}$$

- $w_4[n]$ Basis vector number 4
- $w_{60}[n]$ Basis vector number 60

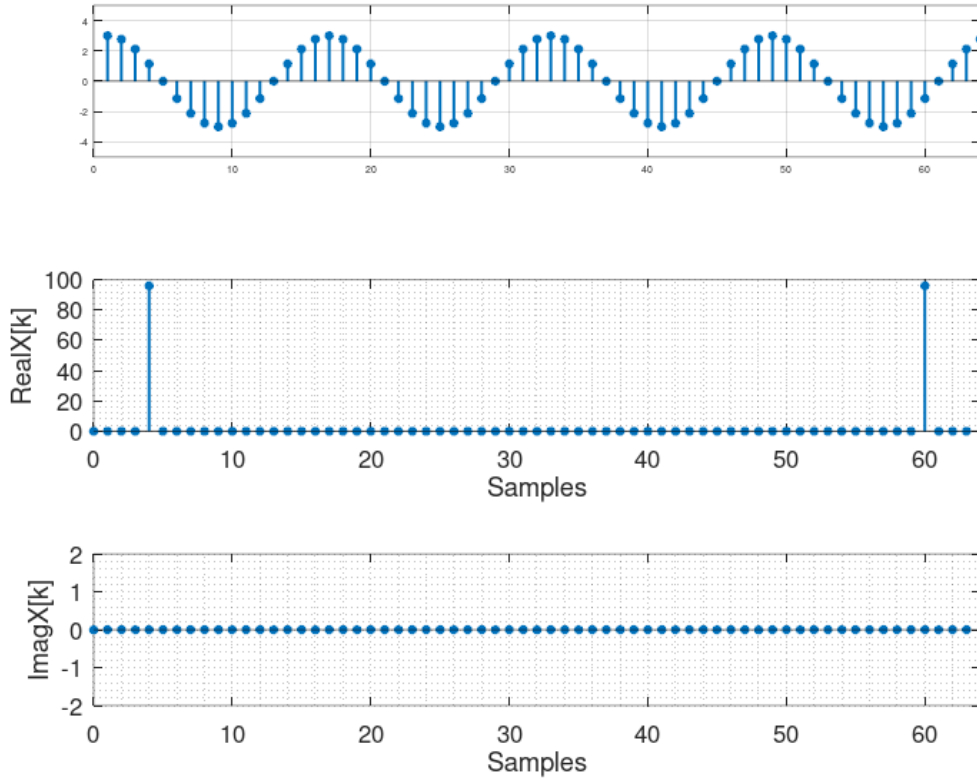
Now we don't like this minus. So what we're going to do is exploit the fact that we can always add an integer multiple of 2π to the exponent of the complex exponential. And the point will not change on the complex plane.

- The original signal is now expressed as the sum of two fourier basis vectors**

- Calculate the DFT with the analysis formula

$$\begin{aligned} X[k] &= \langle w_k[n], x[n] \rangle, \text{ with: } k = 0, 1, \dots, N-1 \\ &= \begin{cases} 96 & \text{for } k = 4, 60 \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

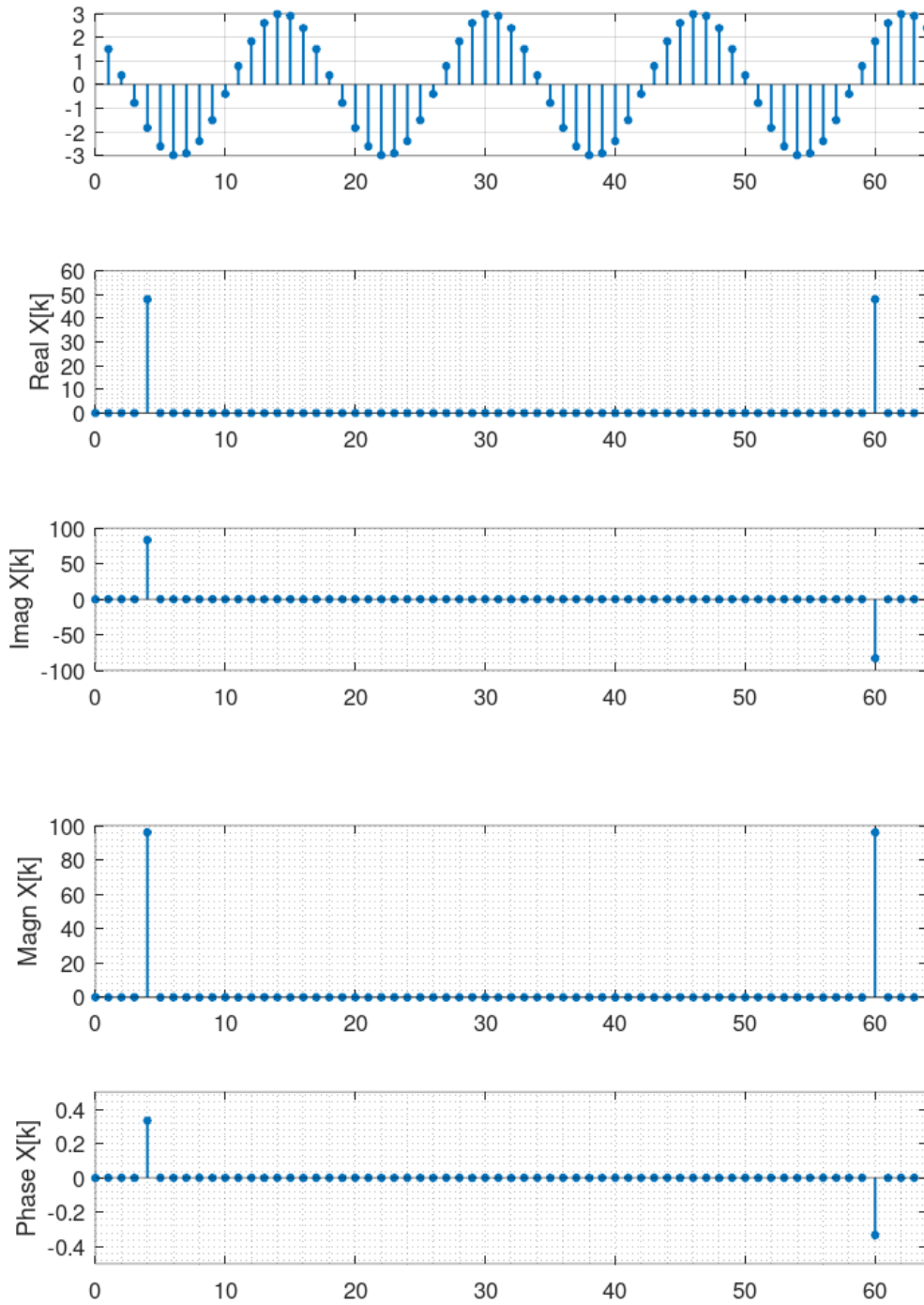
- $w_k[n]$ Canonical basis vector number k



3.2.2.4. DFT Cosine Calculation Problem 2

$$x[n] = 3 \cos(2\pi n/16 + \pi/3), x[n] \in \mathbb{C}^{64}$$

$$X[k] = \begin{cases} 96e^{j\frac{\pi}{3}} & \text{for } k = 4 \\ 96e^{-j\frac{\pi}{3}} & \text{for } k = 96 \\ 0 & \text{otherwise} \end{cases}$$

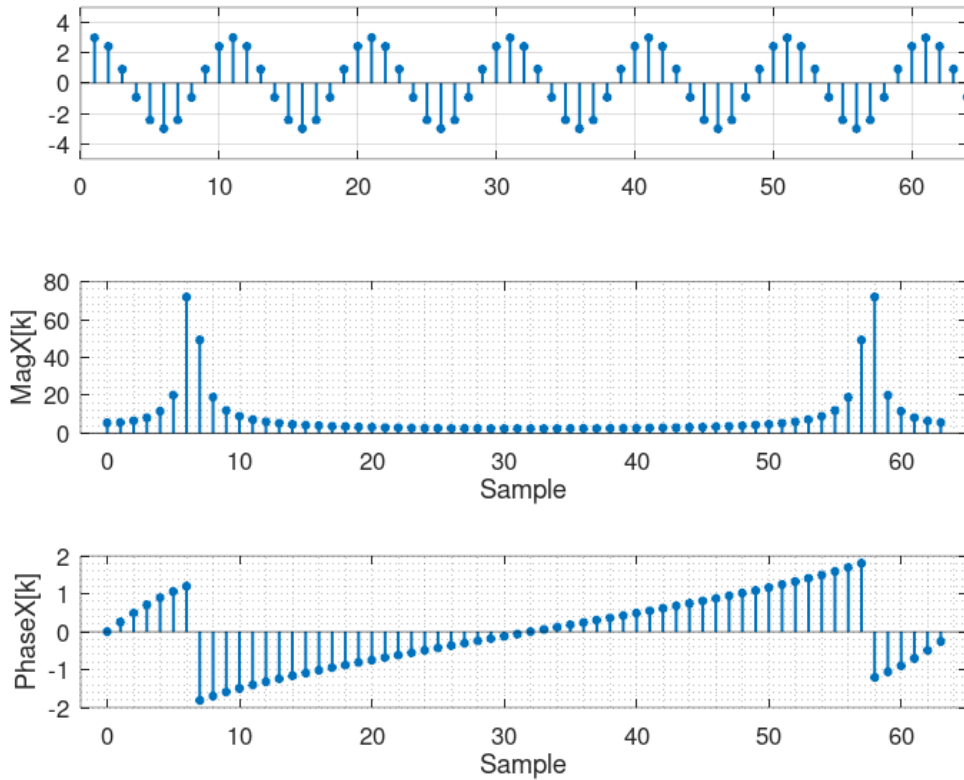


The calculation of the phase just does not work out of the box with octave.

3.2.2.5. DFT Cosine Calculation Problem 3

$$x[n] = 3 \cos(2 \pi / 10 n), x[n] \in \mathbb{C}^{64}$$

$$X[k] = \begin{cases} 96e^{j\frac{\pi}{3}} & \text{for } k = 4 \\ 96e^{-j\frac{\pi}{3}} & \text{for } k = 96 \\ 0 & \text{otherwise} \end{cases}$$



3.2.3. Properties of the DFT

Linearity $DFT\alpha x[n] + \beta y[n] = DFT\alpha x[n] + DFT\beta y[n]$

3.2.4. Interpreting a DFT Plot

- Frequency coefficient $< \pi[0 \dots N/2]$ are interpreted as counter clock wise rotation in the plane
- Frequency coefficient $> \pi[N/2 \dots N-1]$ are interpreted as clock wise rotation in the plane
- The fastest frequency of the signal in the vector space is at $N/2$



Energy of a Signal



The square magnitude of the k -th DFT coefficient is proportional to the signal's energy at frequency

$$\omega = \left(\frac{2\pi}{N}\right)k$$

- Energy concentrated on single frequency (counterclockwise and clockwise combine to give real signal)

$$x1[n] = 3 \cos(2 \pi i/16 n), x[n] \in \mathbb{C}^{64}$$

$$x1[n] = u[n] - u[n-4]$$

- For real signals the DFT is **symmetric** in magnitude
 - $|X[k]| = |X[N-k]|$, for $k = 1, 2, \dots [N/2]$
 - For real signals, magnitude plots need only $[N/2] + 1$ points

3.3. The DFT in Practice

3.3.1. TODO DFT Analysis

3.3.1.1. TODO Mystery Signal revisited

3.3.1.2. TODO Solar Spots

3.3.1.3. TODO Daily Temperature (2920 days)

- The recorded signal
- average value (0-th DFT coefficient: 12.3°)
- DFT main peak for $k = 8$, value 6.4°C
- 8 cycles over 29920 days
- $period = \frac{2920}{8} = 365\text{days}$
- temperature excursion: $12.3^\circ \pm 12.8^\circ\text{C}$

The fastest positive frequency of a signal is at $\frac{N}{2}$ samples. Since a full revolution of 2π requires N samples, the discrete frequency corresponding with $\frac{N}{2}$ is π .

3.3.1.4. Labeling Frequency Band Axis

- If "clock" of a System is T_s
 - fastest (positive) frequency is $\omega = \pi$
 - sinusoid at $\omega = \pi$ needs two samples to do a full revolution
 - time between samples: $T_s = \frac{1}{F_s}$ seconds
 - real world period for fastest sinusoid: $2T_s$ seconds
 - real world frequency for fastest sinusoid: $F_s/2$ Hz
- The discrete frequency x of a sinusoid component at peak k can be determined as follows:

$$\frac{x}{k} = \frac{N}{2\pi}, \text{ with } k=0\dots N-1 \quad (3.5)$$

- The real world frequency of a sinusoid component at peak k can be determined as follows:

$$\begin{aligned} \frac{x}{k} &= \frac{2\pi}{N}, \text{ with } k=0\dots N-1 \\ \frac{f_s}{2} &\rightarrow \pi, f_s \text{ sampling frequency} \\ \frac{x}{k} &= \frac{f_s}{N} \\ x &= \frac{k f_s}{N} \end{aligned}$$

3.3.1.5. TODO Example: train whistle

3.3.1.6. Example 1

A DFT analysis of a signal with length $N = 4000$ samples at a frequency $f_s = 44.1\text{kHz}$ shows a peak at $k = 500$. What is the corresponding frequency in Hz of this digital frequency in Hz.

- Solution

$$\begin{aligned}
 \frac{x}{k} &= \frac{2\pi}{N} \\
 x &\rightarrow \frac{2\pi k}{N} \\
 \frac{f_s}{2} &\rightarrow \pi \\
 x &= \frac{k}{N} f_s = 55125.5
 \end{aligned}$$

3.3.1.7. Example 2

Calculation of the corresponding frequency vector for a signal for which its spectrum is analysed with the fourier transform

- Sampling Period: $T_s = 1/1000s$
- Sampling Frequency: $f_s = 1/T = 1000Hz$
- Vector Length $N = 2^{10} = 1024$

$$\begin{aligned}
 \frac{X}{k} &= \sum_{n=1}^N x[n] e^{-j2\pi(k-1)(\frac{n-1}{N})} \\
 f(k) &= \frac{k-1}{NT}, \text{ corresponding Frequency in Hz}
 \end{aligned}$$

- [StackOverflow](#)

```

clear all;
close all;
N = 1024;    # vector length
Fs = 1000;   # Sample Frequency Fs = 1000Hz
Ts = 1/Fs;   # Sampling Period Ts = 0.001s
f1 = 60;     # 50Hz
f2 = 120;    # 120Hz

n = 0:Ts:(N-1)*Ts;           # time vector
x = sin(2*pi*f1*n) + sin(2*pi*f2*n); # a sinusoid signal
xr = x + 2*randn(size(n));    # a noisy signal

X = fft(xr);                  # FFT
X2 = 1/N*abs(X);              # FFT magnitude full buffer length
F2 = Fs*(0:(N-1))/N;          # Frequency vector full buffer length

X1 = X2(1:N/2+1)/2;           # FFT magnitude half buffer length
X1(2:end-1) = 2*X1(2:end-1);  # Arranged values
F1 = Fs*(0:(N/2))/N;          # Frequency vector half buffer length

figure( 1, "visible", "off" )

subplot(2,1,1)
plot(Fs*n(1:100),xr(1:100));
title('Zeitbereich')
ylabel('Amplitude');
xlabel('Zeit [ms]')
set(gca, "fontSize", 24);

```

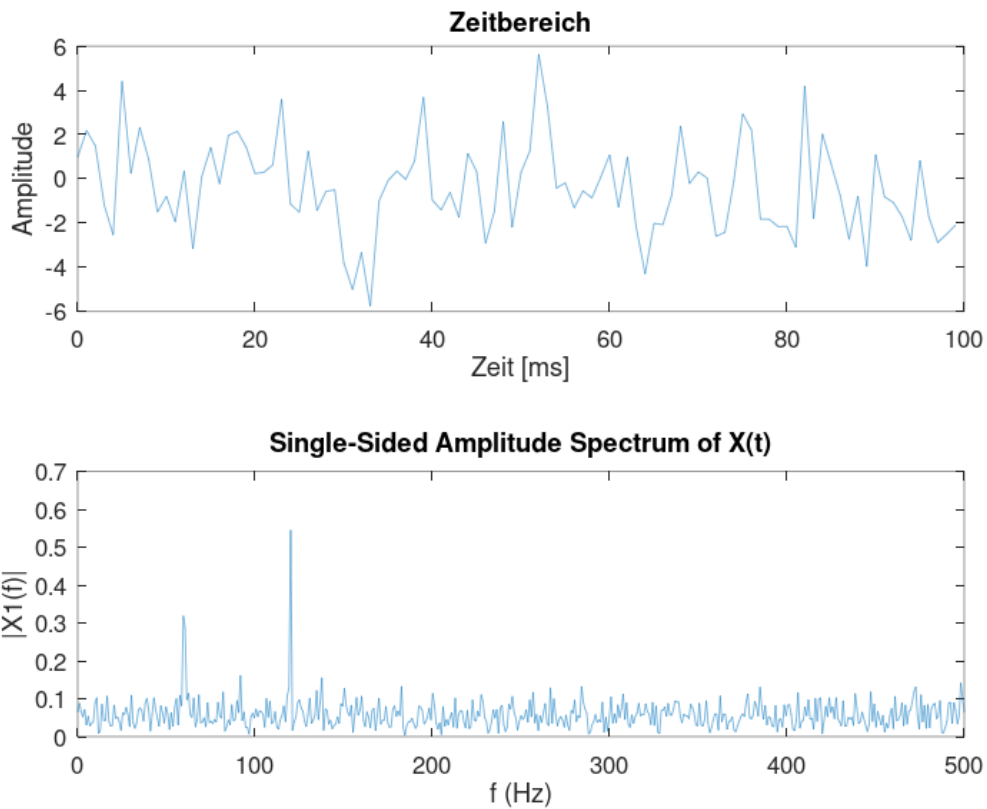
```

subplot(2,1,2)
plot(F1,X1)
title('Single-Sided Amplitude Spectrum of X(t)')
xlabel('f (Hz)')
ylabel('|X1(f)|')
set(gca, "fontsize", 24);

## subplot(2,1,3);
## plot(F2,X2);
## title('Two-Sided Amplitude Spectrum of X(t)')
## ylabel('|X2(f)|')
## xlabel('Frequenz [Hertz]')
## set(gca, "fontsize", 24);

# Org-Mode specific setting
print -dpng "-S800,600" ./image/eth-example.png;
ans = "./image/eth-example.png";

```



3.3.2. TODO DFT Example Analysis of Musical Instruments

- The fundamental note is the [first peak](#) in the spectrum
- The relative size of the harmonics gives the timber or the character of an instrument

3.3.3. TODO DFT Synthesis

3.3.4. TODO DFT Example - Tide Prediction in Venice

3.3.5. TODO DFT Example - MP3 Compression

- MP3 compression approx. factor 20 or more
- Compression introduces noise from approximation error
- [Noise Shaping](#) : Error shaped as the song in the Fourier domain.
- [Perceptual Compression](#) includes the human hearing system properties into compression algorithm

3.3.6. TODO Signal of the Day: The first man-made signal from outer space

$$f = \frac{\omega f_s}{2\pi}$$

- A [multiplication](#) in time domain corresponds to a [convolution](#) in frequency domain

3.4. The Short-Time Fourier Transform STFT

- STFT is a clever way of using DFT
- Spectrogram, is a graphical way to represent the STFT data

3.4.1. The short-time Fourier transform

- DTMF Dual-Tone Multi Frequency dialing
- Time representation obfuscates frequency
- Frequency representation obfuscates time

$$x[m; k] = \sum_{n=0}^{L-1} x[m+n]e^{-j\frac{2\pi}{L}nk}$$

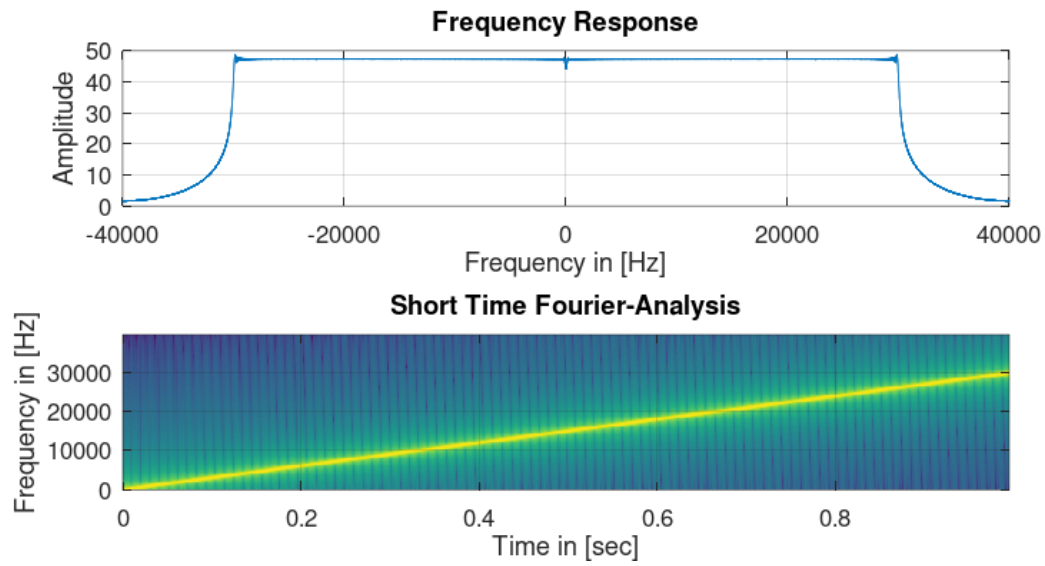
- **m** Starting point of the localized DFT
- **k** Is the DFT index

3.4.2. TODO The spectrogram

- color-code the magnitude: dark is small, white is large
- use $10\log_{10}(|X[m, k]|)$ to see better (power in dBs)
- plot spectral slices one after another

3.4.3. TODO Time-frequency tiling

3.4.4. STFT Example



Part IV.

Week 4 Module 3:

4. Part 2 - Advanced Fourier Analysis

4.1. Discrete Fourier Series DFS

4.1.1. TODO Discrete Fourier series



Discrete Fourier Series

↗ DFS = DFT with periodicity explicit $\tilde{X}[k] = DFS\{x[n]\}$

- The DFS maps an N-Periodic signal onto an N-Periodic sequence of Fourier coefficients
- The inverse DFS maps an N-periodic sequence of Fourier coefficients onto an N-periodic signal
- DFS is an extension of the DFT for periodic sequences
- A circular time-shift is a natural extension of a shift for finite length signals.

4.1.1.1. Finite-length time shifts revisited

- The DFS helps us understand how to define time shifts for finite-length signals.

test

For an N-periodic sequence $\tilde{x}[n]$

$\tilde{x}[n - M]$ is well-defined for all $M \in \mathbb{N}$

$$DFS\{\tilde{x}[n - M]\} = e^{-j\frac{2\pi}{N}Mk} \tilde{X}[k] \text{ delay factor}$$

$$IDFS\left\{e^{-j\frac{2\pi}{N}Mk} \tilde{X}[k]\right\} = \tilde{x}[n - M] \text{ delay factor}$$

For an N-length signal $x[n]$

$\tilde{x}[n - M]$ not well-defined for all $M \in \mathbb{N}$

build $\tilde{x}[n] = x[n \bmod N] \Rightarrow \tilde{X}[k] = X[k]$

$$IDFT\left\{e^{-j\frac{2\pi}{N}Mk} X[k]\right\} = IDFS\left\{e^{-j\frac{2\pi}{N}Mk} \tilde{X}[k]\right\} = \tilde{x}[n - M] = x[(n - M) \bmod N]$$



Periodicity

↗ Shifts for finite-length signals are "naturally" circular

4.1.2. TODO Karplus-Strong revisited and DFS

4.1.2.1. Analysis Formula for a N-Periodic Signal in the frequency domain

$$\tilde{X}[k] = \sum_{n=0}^{N-1} \tilde{x}[n] e^{-j \frac{2\pi}{N} nk}, k \in \mathbb{Z} \quad (4.1)$$

$X[k]$ Signal vector in the frequency domain

$x[n]$ Signal vector in the (discrete) time domain

Reminder This is the inner Product in explicite form

4.1.2.2. Synthesis Formula for a N-Periodic Signal in the time domain

$$\tilde{x}[n] = \frac{1}{N} \sum_{k=0}^{N-1} \tilde{X}[k] e^{j \frac{2\pi}{N} nk}, k \in \mathbb{Z} \quad (4.2)$$

$x[n]$ Signal vector in the (discrete) time domain

$X[k]$ Signal vector in the frequency domain

$\frac{1}{N}$ Normalisation coefficient

Reminder This is the inner Product in explicite fashion

4.2. The Discret-Time Fourier Transform (DTFT)

4.2.1. Overview Fourier Transform

- N-Point finite-length signals: DFT
- N-Point periodic signals: DFS
- Infinite length (non periodic) signals: DTFT

4.2.2. Karplus Strong revisited and the DTFT

4.2.2.1. Plotting the DTFT

- Frequencies go from $-\pi$ to π
- Positive frequencies are on the right hand side of the x-axis
- Negative frequencies are on the left hand side of the x-axis
- Low frequencies are centered around 0
- High frequencies will be on the extreme of the bound

4.3. Existence and properties of the DTFT

4.3.1. Formal Definition of the DTFT

- $x[n] \in \ell_2(\mathbb{Z})$, the space of square summable infinity sequences
- define the function of $\omega \in \mathbb{R}$

$$F(e^{j\omega}) = \sum_{n=-\infty}^{\infty} x[n] e^{-j\omega n}, \text{ with } \omega = \frac{2\pi}{N} \text{ and } N \rightarrow \infty$$

- inversion (when $F(\omega)$ exists):

$$x[n] = \frac{1}{2\pi} \int_{-\pi}^{\pi} F(e^{j\omega}) e^{j\omega n} d\omega, \text{ with } n \in \mathbb{Z}$$

4.3.2. Properties of the DTFT

linearity	$DTFT\{\alpha x[n] + \beta y[n]\} = \alpha X(e^{j\omega}) + \beta Y(e^{j\omega})$
timeshift	$DTFT\{x[n - M]\} = e^{-j\omega M} X(e^{j\omega})$
modulation	$DTFT\{e^{-j\omega_0 M} x[n]\} = X(e^{j(\omega - \omega_0)})$
time reversal	$DTFT\{x[-n]\} = X(e^{-j\omega})$
conjugation	$DTFT\{x^*[n]\} = X^* X(e^{-j\omega})$

4.3.3. Some particular cases

- if $x[n]$ is symmetric, the DTFT is symmetric: $x[n] = x[-n] \iff X(e^{j\omega}) = X(e^{-j\omega})$
- if $x[n]$ is real, the DTFT is Hermitian-symmetric: $x[n] = x^*[n] \iff X(e^{j\omega}) = X^*(e^{-j\omega})$
- if $x[n]$ is real, the magnitude of the DTFT is symmetric $x[n] \in \mathbb{R} \implies |X(e^{j\omega})| = |X(e^{-j\omega})|$
- if $x[n]$ is real and symmetric, $X(e^{j\omega})$ is also real and symmetric

4.3.4. **TODO** The DTFT as a change of basis

4.4. **TODO** Sinusoidal Modulation

4.4.1. **TODO** Sinusoidal modulation

4.4.2. **TODO** Tuning a guitar

4.4.3. **TODO** Signal of the day: Tristan Chord

4.5. **TODO** Notes and Supplementary Material

4.5.1. **TODO** Relation Ship between transforms

4.5.2. **TODO** The fast fourier transform

Part V.

Week 5 Module 4:

5. Part 1 Introduction to Filtering

5.1. Linear Time-Invariant Systems



LTI System



Linearity and Time Invariance taken together: A Linear Time Invariant System is completely characterized by its response to the input in particular by its the Impulse Response .

5.1.1. Linearity

Linearity is expressed by the equivalence

$$\mathfrak{H}\{\alpha x_1[n] + \beta x_2[n]\} = \alpha \mathfrak{H}\{x_1[n]\} + \beta \mathfrak{H}\{x_2[n]\} \quad (5.1)$$

- Fuzz-Box, example for a none linear device

5.1.1.1. TODO Add calculation examples

5.1.2. Time invariance

- The system behaves the same way independently of when a it's switched on

$$y[n] = \mathfrak{H}\{x[n]\} \Leftrightarrow \mathfrak{H}\{x[n - n_o]\} = y[n - n_o] \quad (5.2)$$

- Wah-Pedal, example of a time variant device

5.1.2.1. TODO Add calculation examples

5.1.3. Convolution

The impulse response is the output of a filter when the input is the delta function.

$$h[n] = \mathfrak{H}\{\delta[n]\} \quad (5.3)$$



Impulse Response



Impulse response fully characterize the LTI system!

We can always write

$$x[n] = \sum_{k=-\infty}^{\infty} x[k] \delta[n - k] \quad (5.4)$$

by linearity and time invariance

$$y[n] = \sum_{k=-\infty}^{\infty} x[k] h[n - k] \quad (5.5)$$

$$= x[n] * h[n] \quad (5.6)$$

Performing the convolution algorithmically

$$x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[n-k]$$

- Ingredients**
- a sequence $x[m]$
 - a second sequence $h[m]$
- The Recipe**
- time-reverse $h[m]$
 - at each step n (from $-\infty$ to ∞):
 - center the time-reversed $h[m]$ in n (i.e. by shift $-n$)
 - compute the inner product

Furthermore, the convolution can be defined in terms of the inner product between two sequences.

$$\begin{aligned} (x * y)[n] &= \langle x^*[k], y[n-k] \rangle \\ &= \sum_{k=-\infty}^{\infty} x[k] y[n-k] \end{aligned}$$

5.2. Filtering in the Time Domain

For the convolution of two sequences to exist, the convolution sum must be finite i.e. the both sequences must be [absolutely summable](#)

5.2.1. The convolution operator

Linearity

$$\begin{aligned} x[n] * (\alpha \cdot y[n] + \beta \cdot w[n]) &= \alpha \cdot x[n] * y[n] + \beta \cdot x[n] * w[n] \\ w[n] = x[n] * y[n] &\iff x[n] * y[n-k] = w[n-k] \end{aligned}$$

Commutative

$$x[n] * y[n] = y[n] * x[n]$$

Associative

$$(x[n] * y[n]) * w[n] = x[n] * (y[n] * w[n])$$

5.2.2. Convolution and inner Product

$$x[n] * h[n] = \langle h^*[n-k], x[k] \rangle$$

Filtering measures the time-localized similarity between the input sequence and a prototype sequence - the time reversed impulse response.

In general the convolution operator for a signal is defined with respect to the inner product of its underlying Hilbert space:

Square Summable Sequence $\ell_2(\mathbb{Z})$ $x[n] * h[n] = \langle h^*[n-k], x[k] \rangle$

N-Periodic Sequence

$$\tilde{x}[n] * \tilde{y}[n] = \sum_{k=0}^{N-1} \tilde{x}[n-k] \tilde{y}[k]$$

Square Integrable Function $L_2([-\pi, \pi])$ $X(e^{j\omega}) * Y(e^{\omega}) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(e^{j\sigma}) \cdot Y(e^{j(\omega-\sigma)})$

5.2.3. Properties of the Impulse Response

Causality A system is called causal if its output does not depend on future values of the input. In practice a causal system is the only type of "real-time" system we can actually implement.

Stability A system is called bounded-input bounded-output stable (BIBO stable) if its output is bounded for all bounded input sequences. **FIR** Filter are always stable, since only in the convolution sum only a finite number of terms are involved.

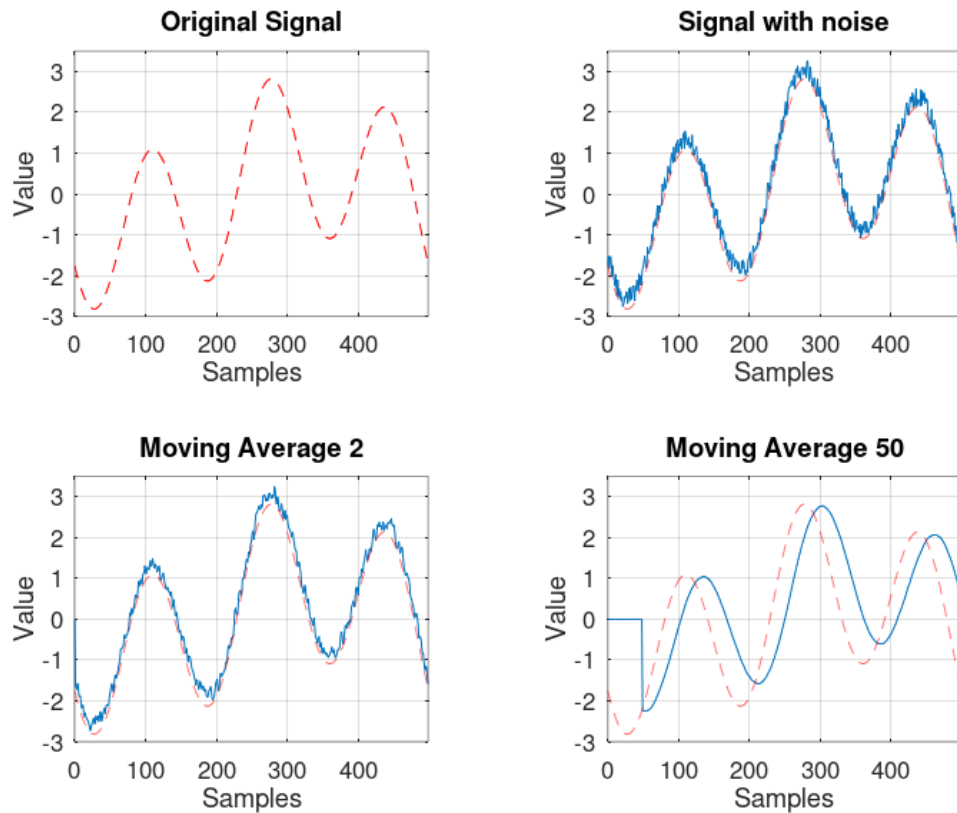
5.2.4. Filtering by Example

5.2.4.1. FIR Filter: Moving Average

Typical filtering scenario: denoising

- idea: replace each sample by the local average. Average are usually good to eliminate random variation from which you don't know much about it.
- for instance: $y[n] = (x[n] + x[n-1])/2$
- more generally:

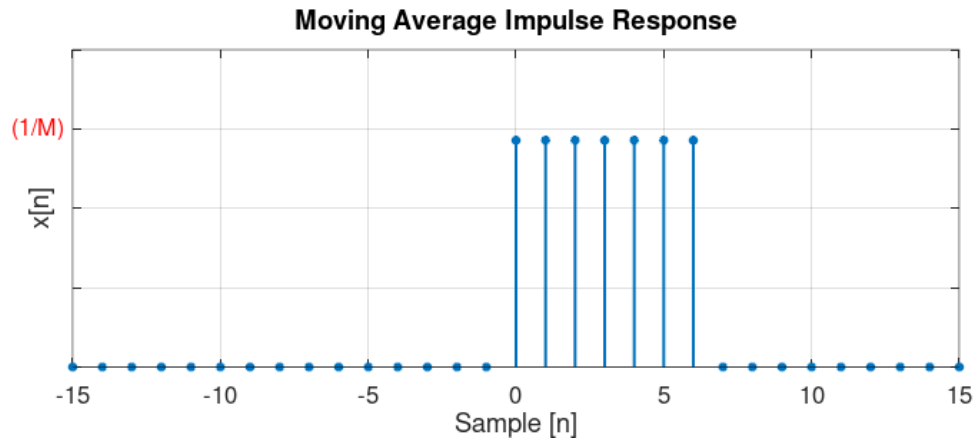
$$y[n] = \frac{1}{M} \sum_{k=0}^{M-1} x[n-k]$$



5.2.4.1.1. Impulse Response

$$h[n] = \frac{1}{M} \sum_{k=0}^{M-1} \delta[n-k] \begin{cases} \frac{1}{M} & \text{for } 0 \leq n < M \\ 0 & \text{otherwise} \end{cases}$$

```
function [x,n] = ma_impresp(M,n1,n2)
% Generates x(n) = delta(n); 0 <= n < M
% -----
% [x,n] = stepseq(n0,n1,n2)
%
n = [n1:n2]; x = [(n >= 0) & !((n-M) >= 0)] ./ M;
end
```



5.2.4.1.2. MA Analysis

- soomthin effect is proportional to M
- number of operations and storage also proportional to M

5.2.4.1.3. From the MA to first-order recursion

$$y_M[n] = \sum_{k=0}^{M-1} x[n-k] = x[n] + \sum_{k=1}^{M-1} x[n-k]$$

$$M y_M[n] = x[n] + (M-1) y_{M-1}[n-1]$$

$$y_M[n] = \frac{M-1}{M} y_{M-1}[n-1] + \frac{1}{M} x[n]$$

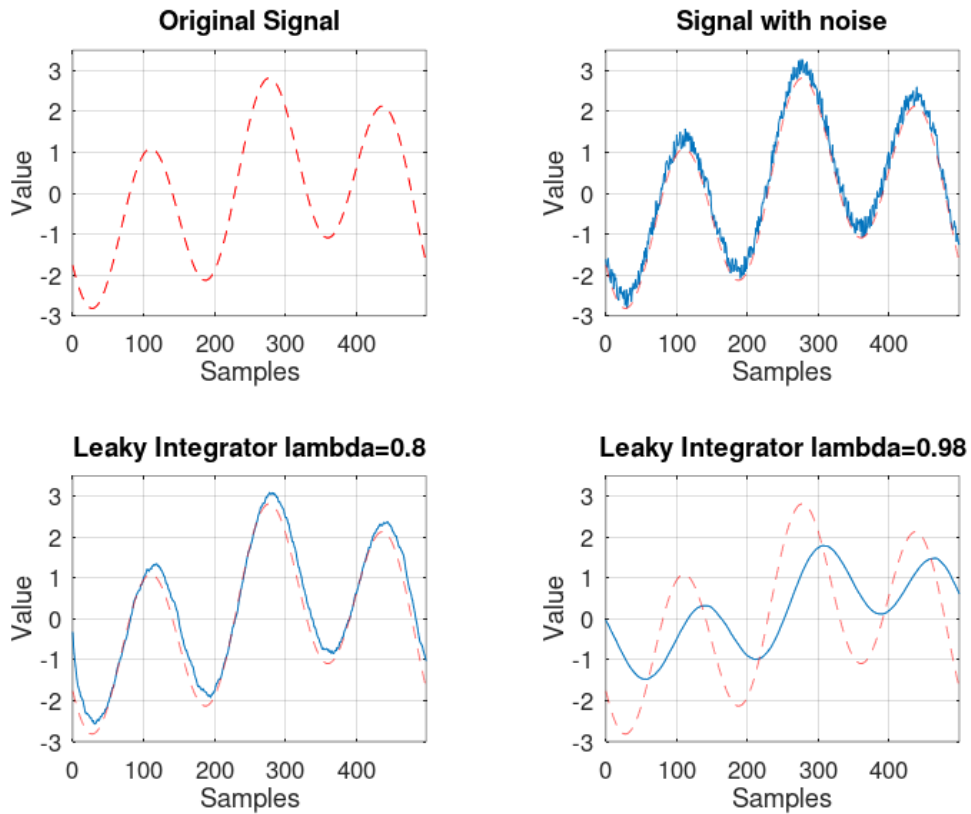
$$y_M[n] = \lambda y_{M-1}[n-1] + (1-\lambda) x[n], \lambda = \frac{M-1}{M}$$

5.2.4.2. IIR Filter: The Leaky Integrator

- when M is large, $y_{M-1}[n] \approx y_M[n]$ and $(\lambda \approx 1)$
- the filter becomes: $y[n] = \lambda y[n-1] + (1-\lambda)x[n]$
- the filter is now recursive, since it uses its previous output value

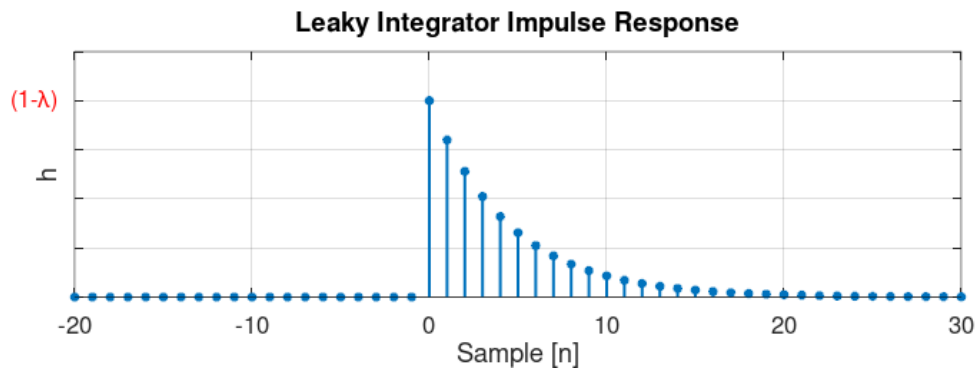
```
function y = lky_impresp(a,b,lambda,x)
% Generates x(n) = a^n
% -----
% [x,n] = lky_impresp(a,b, lambda, x)
% y[n] -lambda y[n-1] = (1-lambda) x[n]
% a = [1, -lambda];
% b = [(1-lambda)];

b = [1-lambda];
a = [1, -lambda];
y = filter(b,a,x);
end
```



5.2.4.2.1. Impulse Response For the impulse we just need to plug the delta function

$$\begin{aligned} h[n] &= (\lambda y[n-1] + (1-\lambda))\delta[n] \\ &= (1-\lambda)\lambda^n u[n] \end{aligned}$$



The peak at $n=0$ is $1 - \lambda$.

5.2.4.2.2. The leaky integrator why the name

- Discrete Time integrator is a boundless accumulator

$$\begin{aligned} y[n] &= \sum_{k=-\infty}^n x[k] \\ &= y[n-1] + x[n] \Rightarrow \text{almost leaky integrator} \end{aligned}$$

To prevent "exploding" we scale the accumulator with λ :

$\lambda y[n-1]$ keep only a fraction λ of the accumulated value so far and forget ("leak") a fraction $\lambda - 1$
 $(1 - \lambda)x[n]$ add only a fraction $1 - \lambda$ of the current value to the accumulator.
 So we get the leaky integrator from the accumulator

$$y[n] = \lambda \cdot y[n-1] + (1 - \lambda) \cdot x[n] \Rightarrow \text{almost leaky integrator}$$

5.3. Classification of Filters

FIR

Finite Impulse Response Filter

- Impulse response has finite support
- only a finite number of samples are involved in the computation of each output
- Example: Moving Average Filter

IIR

Infinite Impulse Response Filter

- Impulse response has infinite support
- a potentially infinite number of samples are involved in the computation of each output sample
- surprisingly, in many cases the computation can still be performed in a finite amount of steps
- Example: The Leaky Integrator

Casual

- impulse response is zero for $n < 0$
- only past samples are involved in the computation of each output sample
- casual filters can work "on line" since they only need the past

Noncasual

- impulse response is nonzero for some (or all) $n < 0$
- can still be implemented in an offline fashion (e.g. image processing)

5.4. Filter Stability



FIR Filter

↪ FIR filters are always stable

because their impulse response only contains a finite number of non-zero values, and therefore the sum of their absolute values will always be finite.

5.5. Frequency Response

5.5.1. References

- [Signal and System for Dummies: Frequency Response](#)

5.5.2. Eigensequence

If a complex exponential is applied to a LTI filter its response is the DTFT of the impulse response of the LTI filter times the complex exponential.

$$\begin{aligned}
 x[n] &= e^{j\omega_0 n} \\
 y[n] &= \mathfrak{H}\{x[n]\} \\
 y[n] &= x[n] * h[n] \\
 y[n] &= e^{j\omega_0 n} * h[n] \\
 y[n] &= H(e^{j\omega_0})e^{j\omega_0 n}
 \end{aligned}$$

- DTFT of impulse response determine the frequency characteristic of a filter
- Complex exponential are [eigensequences](#) of LTI systems, i.e. linear filters cannot change the frequency of a sinusoid.

5.5.3. Magnitude and phase

$$\begin{aligned}
 \text{if } H(e^{j\omega_0}) &= Ae^{j\theta}, \text{ then} \\
 \mathfrak{H}\{e^{j\omega_0 n}\} &= Ae^{j(\omega_0 n + \theta)}
 \end{aligned}$$

amplitude	A	phase shift	θ
amplification	> 1	delay	< 0
attenuation	$0 \leq A < 1$	advancement	> 0

5.5.4. The convolution theorem

The convolution theorem summarizes this result in

$$DTFT\{x[n] * h[n]\} = X(e^{j\omega})H(e^{j\omega})$$

5.5.5. Frequency response

The DTFT of the impulse response is called the frequency response

$$H(e^{j\omega}) = DTFT\{h[n]\}$$

magnitude	$ H(e^{j\omega}) $	phase
amplification	> 1	overall shape and
attenuation	< 1	phase changes

5.5.6. Example of Frequency Response: Moving Average Filter

The difference equation from M-point averager is

$$y[n] = \frac{1}{M} \sum_{k=0}^{M-1} x[n-k]$$

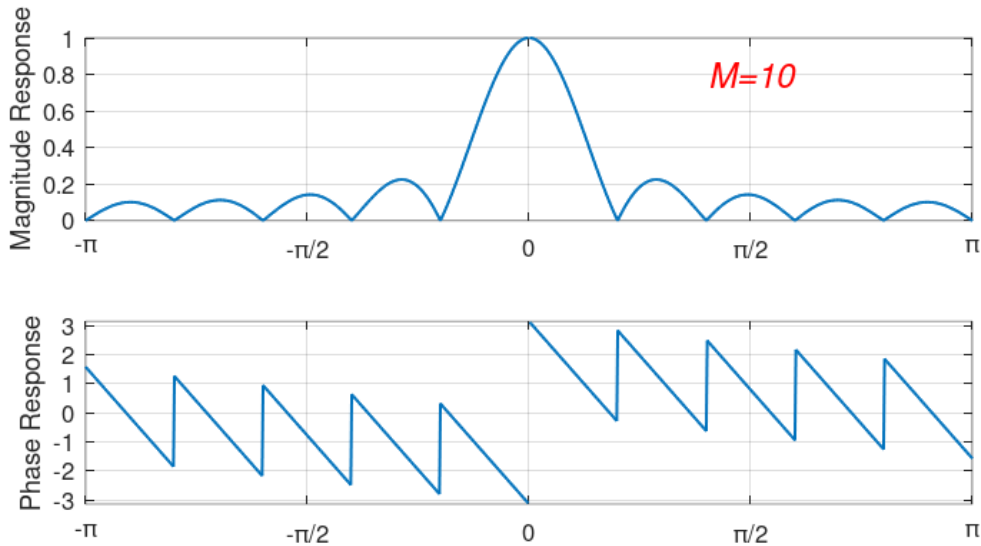
The Frequency response of the moving average filter

$$\begin{aligned} H(e^{j\omega}) &= \frac{1}{M} \sum_{k=0}^{M-1} e^{-j\omega k} = \frac{1}{M} \sum_{k=0}^{M-1} (e^{-j\omega})^k \\ &= \frac{1}{M} \frac{(1 - e^{-j\omega M})}{(1 - e^{-j\omega})} \end{aligned}$$

- The frequency response is composed of a linear term $e^{-j\omega \frac{M-1}{2}}$ and $\pm\pi$ due to the sign changes of $\frac{\sin(\frac{\omega}{2}M)}{\sin(\frac{\omega}{2})}$

The Magnitude response of the moving average filter

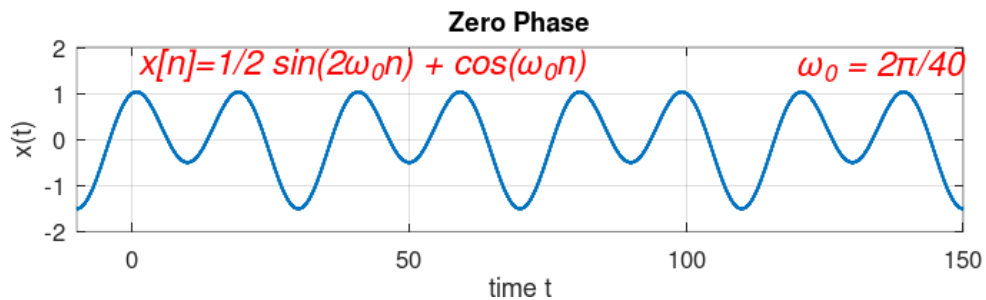
$$H(e^{j\omega}) = \frac{1}{M} \left| \frac{\sin(\frac{\omega}{2}M)}{\sin(\frac{\omega}{2})} \right|$$

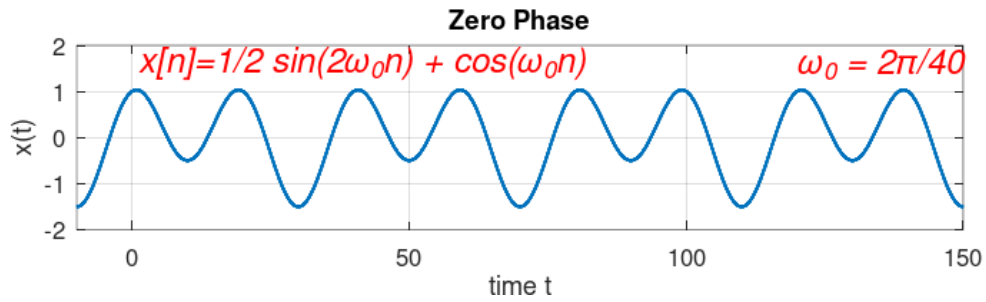


5.5.7. Phase and signal shape

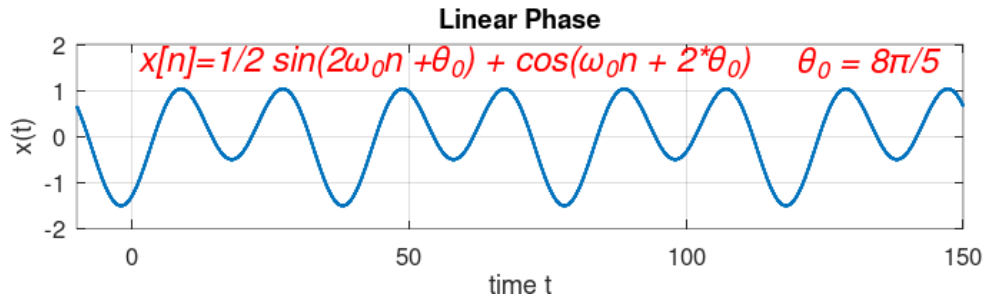
To understand the effects of the phase on a signal is to distinguish three different cases

- zero phase: the spectrum is real: $\angle H(e^{j\omega}) = 0$

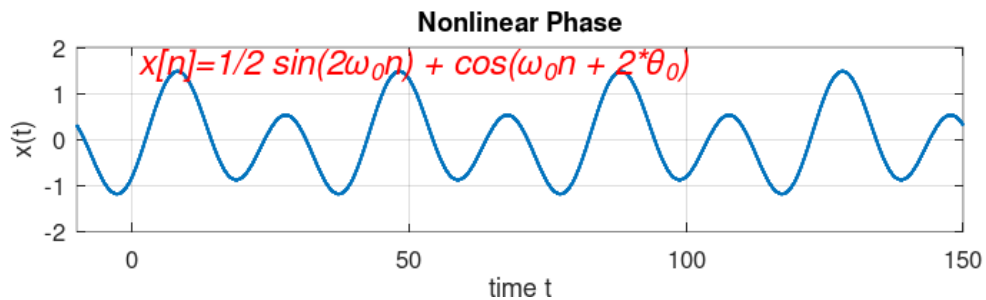




- linear phase: the phase is proportional to the frequency via a real factor, d : $\angle H(e^{j\omega}) = d\omega$ the phase is proportional to the frequency of the sinusoid. The net effect is a shift of the signal if the phase component is proportional to the frequency.



- non linear phase: which covers all the other properties now the shape of the signal in the time domain changes.



Spectrum

↗ The spectrum of all three signals $x[n]$ remains exactly the same in magnitude.

5.5.8. Linear Phase

$$\begin{aligned}
 y[n] &= x[n - d] \\
 Y(e^{j\omega}) &= e^{-j\omega d} X(e^{j\omega}) \\
 H(e^{j\omega}) &= e^{-j\omega d} \Rightarrow \text{linear phase term}
 \end{aligned}$$

5.5.9. Moving Average is linear Phase

$$\begin{aligned}
 H(e^{j\omega}) &= A(e^{j\omega}) e^{-j\omega d} \\
 &\Rightarrow A(e^{j\omega}): \text{pure real term} \\
 &\Rightarrow e^{-j\omega d}: \text{pure phase term} \\
 &= \frac{1}{M} \frac{\sin(\frac{\omega}{2} M)}{\sin(\frac{\omega}{2})} e^{-j\omega \frac{M-1}{2}} \Rightarrow \frac{M-1}{2} = d
 \end{aligned}$$

5.5.10. Example of Frequency Response: Leaky Integrator

The Frequency response of the leaky integrator

$$H(e^{j\omega}) = \frac{1 - \lambda}{1 - \lambda e^{j\omega}}$$

Finding the magnitude and phaser requires a little algebra

From Complex Algebra

$$\frac{1}{a + jb} = \frac{1 - jb}{a^2 + b^2}$$

So that if $x = \frac{1}{a + jb}$

$$|x|^2 = \frac{1}{a^2 + b^2}$$

$$\angle x = \tan^{-1} \left[-\frac{a}{b} \right]$$

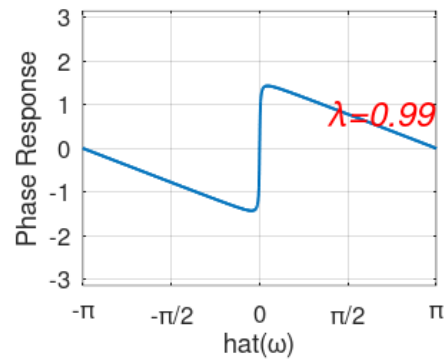
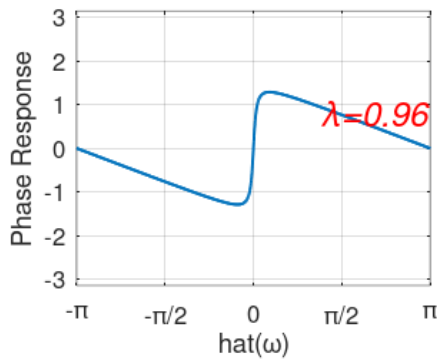
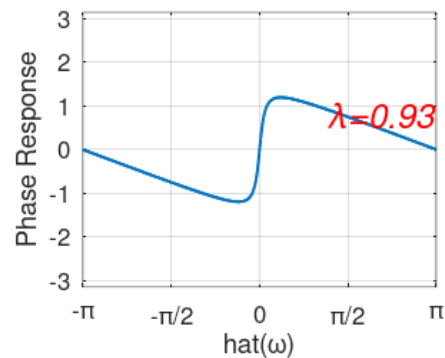
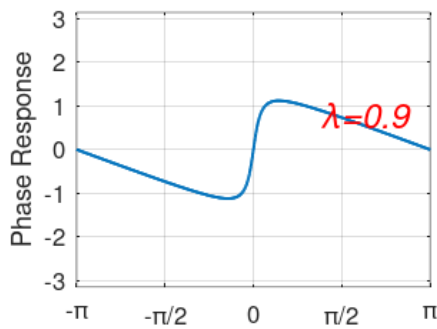
$$H(e^{j\omega}) = \frac{1 - \lambda}{(1 - \lambda \cos \omega) - j \lambda \sin \omega}$$

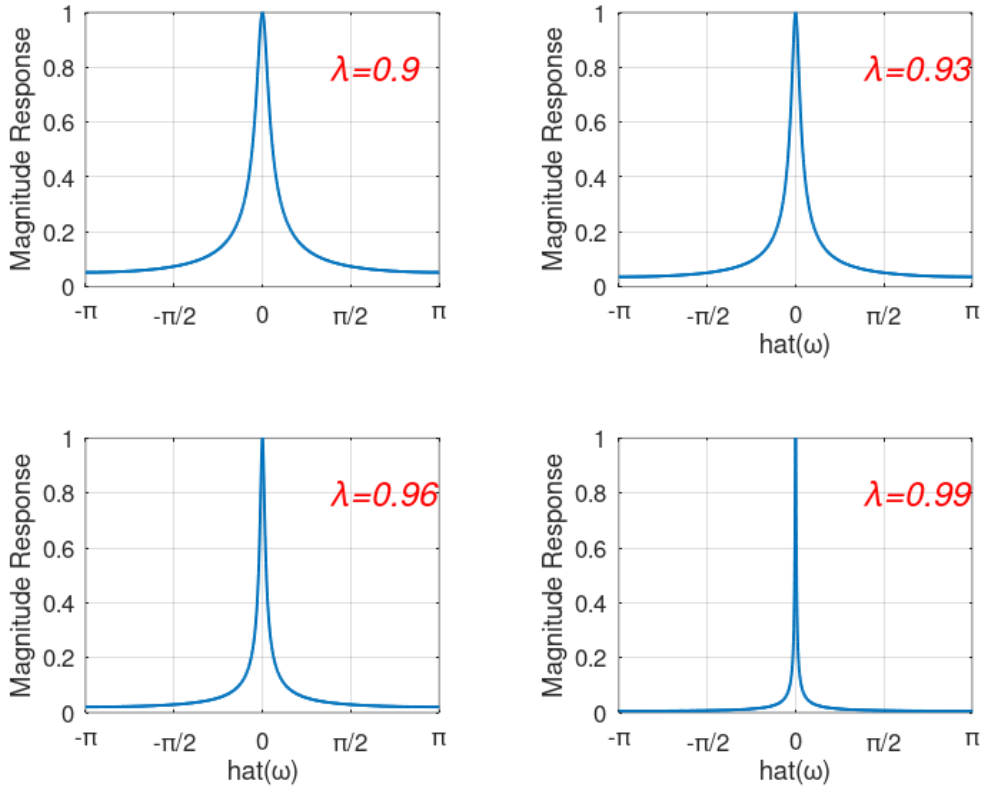
so that:

$$|H(e^{j\omega})|^2 = \frac{(1 - \lambda)^2}{1 - 2\lambda \cos \omega + \lambda^2}$$

$$\angle H(e^{j\omega}) = \tan^{-1} \left[\frac{\lambda \sin \omega}{1 - \lambda \cos \omega} \right]$$

The phase is nonlinear in this case





5.5.11. TODO Example of Frequency Response: Karplus Strong Algorithm

$$y[n] = \alpha y[n - M] + x[n]$$

The Karplus-Strong algorithm is initialized with a finite support signal x of support M . And then we use a feedback loop with a delay of M taps. To produce multiple copies of the original finite support signal, scaled by an exponentially decaying factor α .

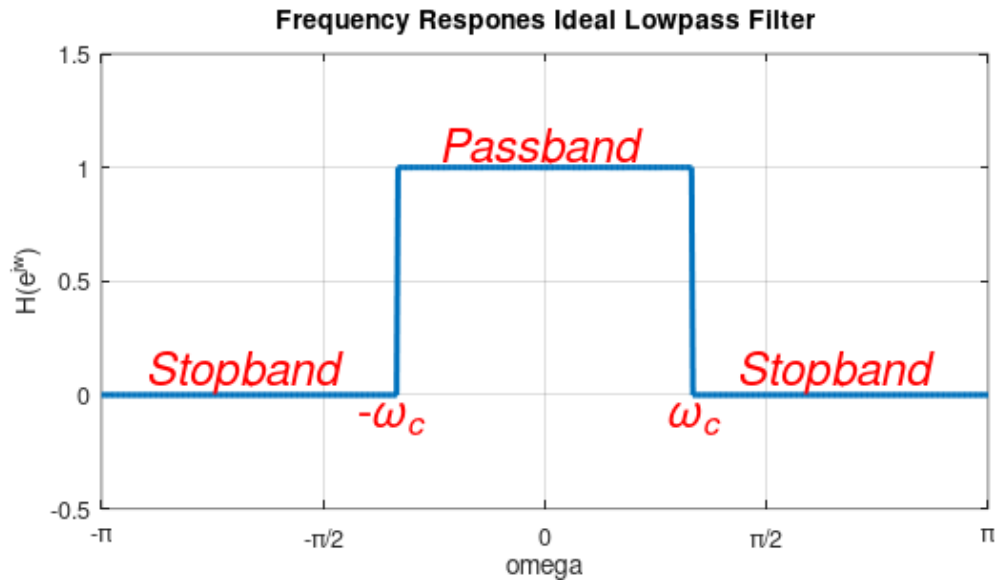
5.5.11.1. With Sawtooth Wave

$$\tilde{X}(j\omega)W(j\omega) = e^{-j\omega} \left(\frac{M+1}{M-1} \right) \frac{1 - e^{-j(M-1)\omega}}{(1 - e^{j\omega})^2} - \frac{1 - e^{-j(M+1)\omega}}{(1 - e^{j\omega})^2}$$

$$X(j\omega)W(j\omega) = \frac{1}{1 - \alpha e^{-j\omega M}}$$

5.6. Ideal Filters

5.6.1. The ideal lowpass filter frequency response



5.6.2. Ideal lowpass filter impulse response

- Lets low frequencies go through
- Attenuates i.e. kills high frequencies

Cut off Frequency ω_c - the frequency response transitions from 1 to zero

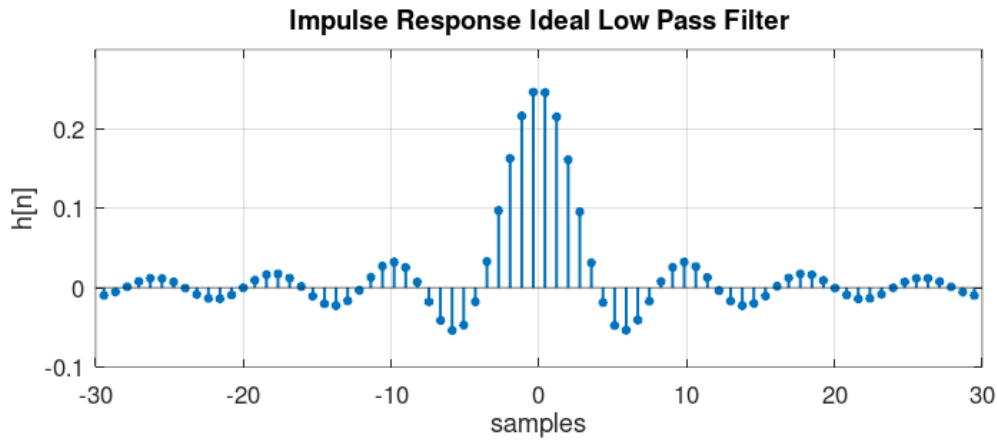
Passband $\omega_b = 2\omega_c$

$$H(e^{j\omega}) = \begin{cases} 1 & \text{for } |\omega| \leq \omega_c \\ 0 & \text{otherwise} \end{cases}$$

- perfectly flat passband
- infinite attenuation in stopband
- zero-phase (no delay)

Calculation of the impulse response from the frequency response of an ideal low pass filter. Impulse Responses

$$\begin{aligned} h[n] &= \text{IDFT}\{H(e^{j\omega})\} \\ &= \frac{1}{2\pi} \int_{-\pi}^{\pi} H(e^{j\omega}) e^{j\omega n} d\omega \\ &= \frac{1}{2\pi} \int_{-\omega_c}^{\omega_c} e^{j\omega n} d\omega \\ &= \frac{1}{\pi n} \frac{e^{j\omega_c n} - e^{-j\omega_c n}}{2j} \\ &= \frac{\sin(\omega_c n)}{\pi n} \end{aligned}$$



- from [Mathworks](#)
- The impulse response has infinite support to the right and to the left
- Independent of how the convolution is computed, it will always take an infinite number of operations.
- The impulse response decays slowly in time $\left(\frac{1}{n}\right)$, we need a lot of samples for a good approximation.

5.6.2.1. Impulse Response: From normalized Algorithm to Octave Implementation

$$\begin{aligned}
 \frac{\sin(\omega_c n)}{\pi n} &= \frac{\omega_c}{\pi} \cdot \text{sinc}\left(n \frac{\omega_c}{\pi}\right); \\
 &= \frac{c}{\pi} \cdot \text{sinc}\left(n \frac{c}{\pi}\right); \\
 &= \frac{1}{c} \cdot \text{sinc}\left(n \frac{1}{c}\right); \\
 &= \frac{1}{c} \cdot \text{sinc}\left(\frac{n}{c}\right);
 \end{aligned}$$

5.6.2.2. The sinc-rect pair:

$$\text{rect}(x) = \begin{cases} 1 & |x| \leq \frac{1}{2} \\ 0 & |x| > \frac{1}{2} \end{cases}$$

$$\text{sinc}(x) = \begin{cases} \frac{\sin(\pi x)}{\pi x} & x \neq 0 \\ 1 & x = 0 \end{cases}$$

- rect is the indicator function from $-\frac{1}{2}$ to $\frac{1}{2}$

5.6.2.3. Canonical form of the ideal low pass filter

The sinc-rect pair can be written in canonical form as follow: $\$ \sim \$$

$$H(e^{j\omega}) = \text{rect}\left(\frac{\omega}{2\omega_c}\right)$$

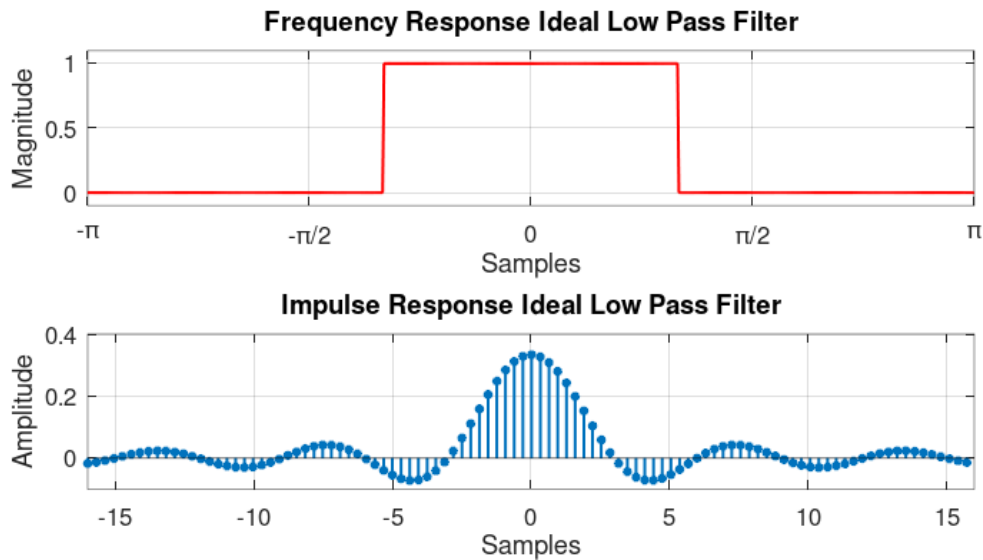
\xleftrightarrow{DTFT}

$$\frac{\omega_c}{\pi} \text{sinc}\left(\frac{\omega_c}{\pi} n\right) = h[n]$$

- The Impulse response is normalized by $\frac{\omega_c}{\pi}$

5.6.3. Example

Calculation of the impulse- and frequency response for an ideal low pass filter with $\omega_c \frac{\pi}{3}$



5.6.4. TODO Ideal filters derived from the ideal low pass filter

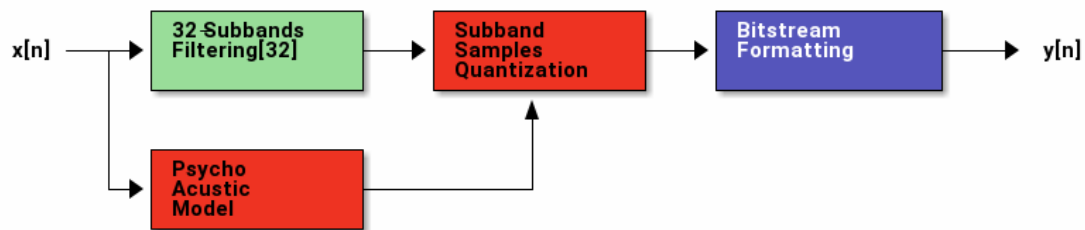
5.6.5. TODO Demodulation revisited

5.7. MP3 Encoder

- **Goal:** Reduce number of bits to represent original signal $x[n]$
- MP3: Motion Picture Expert Group



- **Lossy Compression:** $x[n] \neq y[n]$
- Put noise where not perceptible by human ear
- **Example:** Raw Storage Consumption DVD
 - Sample Rate: 48kHz
 - Bits per Sample: 16
 - Bit Rate: $\frac{48000 \text{ samples}}{\text{second}} \frac{16 \text{ bits}}{\text{samples}} = 768 \text{ kbits/s}$
 - Duration: 60s
 - Mono Raw Data Storage Usage: $60 \text{ s} \times 76.8 \text{ kbits/s} = 46 \text{ Mbit} = 5.8 \text{ MByte}$
 - Stereo Raw Data Storage Usage: $2 \times 5.8 \text{ MBytes} = 12 \text{ MBytes}$
 - MP3 Compressed Storage Usage: 1.5 MBytes



- Clever Quantization Scheme: Number of bits allocated to each subband is dependent on the perceptual importance of each sub-band with respect to overall quality of the audio wave-form
- Masking Effect of the human auditory system.

5.7.1. Psycho Acoustic Model, How it Works

- The psycho acoustic model is not part of the mp3 standard
- calculate the minimum number of bits that we need to quantize each of the 32 subband filter outputs, so that the perceptual distortion is as little as possible

- step 1** Use FFT to estimate the energy of the signal in each subband
- step 2** Distinguish between tonal (sinusoid like) and non-tonal (nois-like) component
- step 3** Determine individual masking effect of tonal and non-tonal component in each critical band
- step 4** Determine the total masking effect by summing the individual contribution
- step 5** Map this total effect to the 32 subbands
- step 6** Determine bit allocation by allocating priority bits to subbands with lowest signal-to-mask ratio

5.7.2. Subband Filter

$$h_i[n] = h[n] \cos\left(\frac{\pi i}{64}(2i+1)(n-16)\right)$$

5.8. Programing Assignment 1

```

import matplotlib
import numpy as np
matplotlib.use('Agg')
import matplotlib.pyplot as plt

def scaled_fft_db(x):
    """ ASSIGNMENT 1:
        Module 4 Part 1:
        Apply a hanning window to len(x[n]) = 512
    """

    N = len(x)          # number of samples
    n = np.arange(N)    # time vector
    # a) Compute a 512-point Hann window and use it to weigh the input data.
    sine_sqr = np.sin((np.pi*n)/(N-1))**2    # sin(x)^2 = 1/2*(1 - cos(2x))
    c = np.sqrt(511/np.sum(sine_sqr))
  
```

```

w = c/2 * (1 - np.cos((2 * np.pi * n)/(N - 1)))
# b) Compute the DFT of the weighed input, take the magnitude in dBs and
#     normalize so that the maximum value is 96dB.
y = w * x
Y = np.fft.fft(y) / N
# c) Return the first 257 values of the normalized spectrum
Y = Y[0: np.int(N/2+1)]
# Take the magnitude of X
Y_mag = np.abs(Y)
nonzero_magY = np.where(Y_mag != 0)[0]

# Convert the magnitudes to dB
Y_db = -100 * np.ones_like(Y_mag) # Set the default dB to -100
Y_db[nonzero_magY] = 20*np.log10(Y_mag[nonzero_magY]) # Compute the dB for nonzero magnitude ind

# Rescale to max of 96 dB
max_db = np.amax(Y_db)
Y_db = 96 - max_db + Y_db

return Y_db

def test():
    N = 512
    n = np.arange(N)
    x = np.cos(2*np.pi*n/10)

    # Y = scaled_fft_db(x)
    Y = scaled_fft_db(x)

    fig=plt.figure(figsize=(6,3))
    plt.semilogy(abs(Y))
    plt.grid(True)

    fig.tight_layout()
    plt.savefig('image/python-matplot-fig-04.png')
    return 'image/python-matplot-fig-04.png' # return filename to org-mode

return test()

```

Part VI.

Week 6 Module 4 Part 2:

6. Introduction to Filtering

- First strategy of filter design: Imitation
 - uuImpulse truncation
 - Window Method
 - Frequency Sampling

Trying to replicate the structure of either the impulse response or the frequency response of ideal filters.

6.1. Filter Design Part 1 (FIR Filter)

- An ideal filter is not realizable in practice because the impulse response is a two-sided infinite support sequence.

6.1.1. Reference

- [The Scientist and Engineers Guide to DSP: Recursive Filter](#)

6.1.2. Impulse truncation



Impulse Truncation

1. Pick ω_c
2. Compute ideal impulse response $h[n]$ (analytically)
3. truncate $h[n]$ to a finite-support $\hat{h}[n]$
4. $\hat{h}[n]$ defines an FIR filter

FIR approximation of length $M = 2N+1$

$$\hat{h}[n] = \begin{cases} \frac{\omega_c}{\pi} \text{sinc}\left(\frac{\omega_c}{\pi}n\right) & |n| \leq N \\ 0 & \text{otherwise} \end{cases}$$

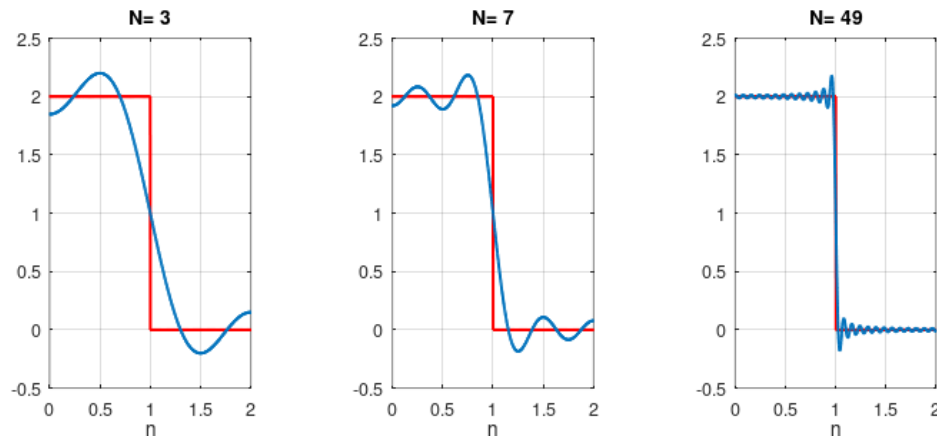
- **Why approximation by truncation could be a good idea** A justification of this method is the computation of the mean square error:

$$\begin{aligned} MSE &= \frac{1}{2\pi} \int_{-\pi}^{\pi} |H(e^{j\omega}) - \hat{H}(e^{j\omega})|^2 d\omega \\ &= ||H(e^{j\omega}) - \hat{H}(e^{j\omega})||^2 \\ &= ||h[n] - \hat{h}[n]||^2 \\ &= \sum_{n=-\infty}^{\infty} |h[n] - \hat{h}[n]|^2 \end{aligned}$$

The means square error MSE is minimized by symmetric impulse truncation around zero

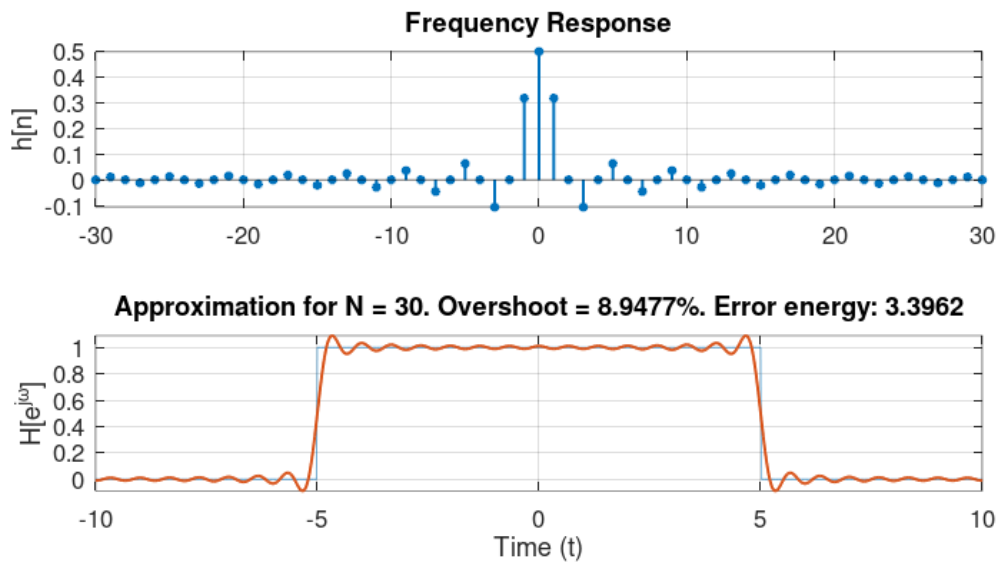
- **Why approximation by truncation is not such a good idea** The maximum error around the cutoff frequency is around 9% of the height of the jump regardless of N . This is known as the [Gibbs Phenomenon](#).

6.1.2.1. The Gibbs Phenomenon



References:

- [Matlab Answers](#)



6.1.3. Window method

The impulse truncation can be interpreted as the product of the ideal filter response and a rectangular window of N points.

From the modulation theorem, the DTFT of the product of two signals is equivalent to the convolution of their DTFTs. Hence, the choice of window influences the quality of the approximation results.

**Window Method**

The window method is just a generalization of the impulse truncation method where we use a different window shape.

For example, by using a triangular window, we reduce the Gibbs error at the price of a longer transition.

6.1.3.1. The modulation theorem revisited.

We can consider the approximated filter as

$$\hat{h}[n] = h[n] w[n]$$

with the indicator function $w[n]$

$$w[n] = \begin{cases} 1 & |n| \leq N \\ 0 & \text{otherwise} \end{cases}$$

The question is how can we express the Fourier Transform $\hat{H}(e^{j\omega}) = ?$ of the filter as the product of two sequences? For that, we have to study the modulation theorem.

- Convolution Theorem states that the Fourier Transform of the convolution of two sequences is the product in the frequency domain of the Fourier Transforms.

$$DTFT\{(x * y)[n]\} = X(e^{j\omega}) Y(e^{j\omega})$$

- Modulation Theorem The modulation theorem states that the Fourier Transform of the product of two sequences is the convolution in the frequency domain of the Fourier Transform

$$DTFT\{(x[n] y[n])\} = (X * Y)(e^{j\omega})$$

- Convolution in the Frequency Domain

in \mathbb{C}^∞ the space of infinite support signals, the convolution can be defined in terms of the inner product of the two sequences.

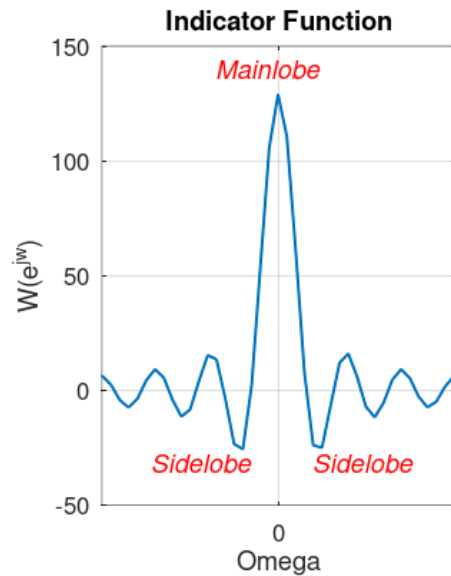
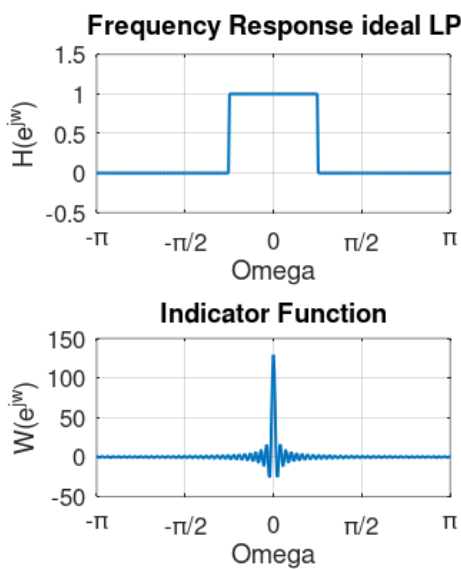
$$\begin{aligned} (x * y)[n] &= \langle x^*[k], y[n - k] \rangle \\ &= \sum_{k=-\infty}^{\infty} x[k] y[n - k] \end{aligned}$$

We can adapt the same strategie in $\mathbb{L}([- \pi, \pi])$, which is the space where the DTFT live's. So we find the convolution of two Fourier Transforms as the inner product of the first Fourier Transform conjugated and the second Fourier Transform frequency reversed and delayed by ω

$$\begin{aligned} (X * Y)(e^{j\omega}) &= \langle X^*(e^{j\sigma}), Y(e^{j\omega - \sigma}) \rangle \\ &= \frac{1}{2\pi} \int_{-\pi}^{\pi} X^*(e^{j\sigma}) Y(e^{j\omega - \sigma}) d\sigma \end{aligned}$$

If we apply the definition of the inner product for $L2([- \pi, \pi])$ we get that the convolution between two Fourier Transforms.

6.1.3.2. Mainlobe and Sidelobes



We want:

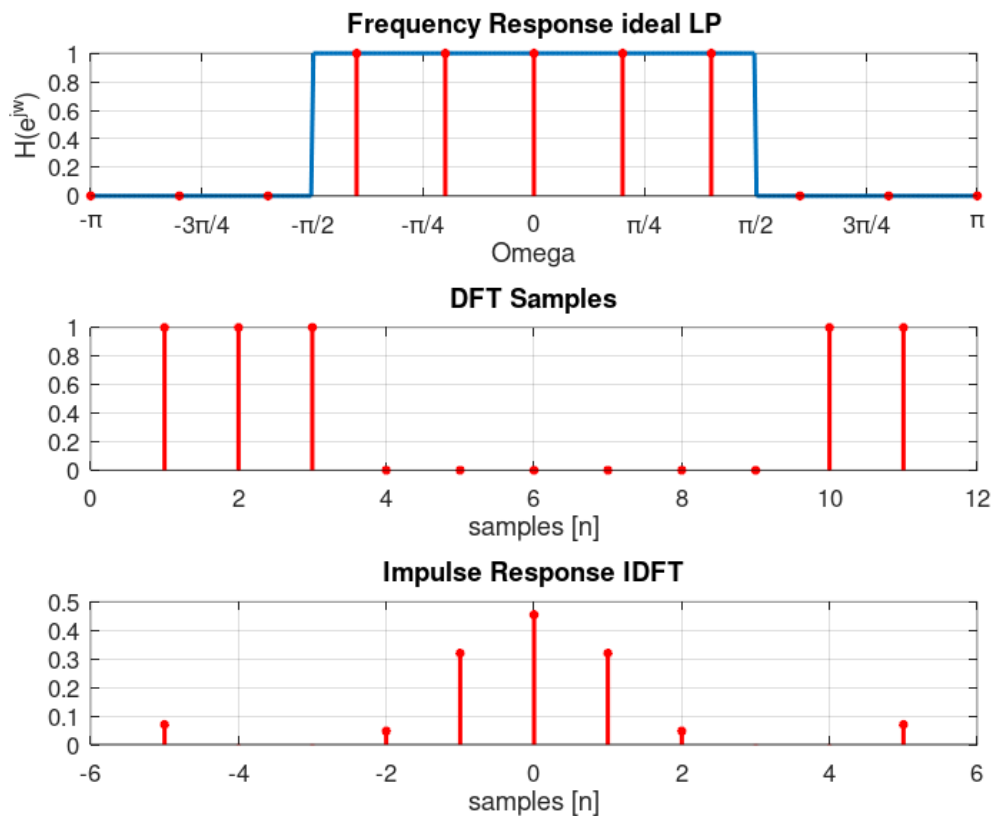
- narrow mainlobe \Rightarrow to have sharp transition
- small sidelobe \Rightarrow gibbs error is small
- short window \Rightarrow FIR is efficient

6.1.4. Frequency sampling



Frequency Sampling

1. Draw desired frequency response $H(e^{j\omega})$
2. take M values at $\omega_k = \frac{2\pi}{M} \cdot k$
3. compute IDFT of values
4. use result as M-tap impulse response $\hat{h}[n]$



- **Why Frequency Sampling is not such a good idea:**
 - frequency response is DTFT of finite-support, whose DFT we know
 - frequency response is interpolation of frequency samples
 - interpolator is transform N-tap rectangular window (no escape from the indicator function)
 - again no control over main- and sidelobe



Summery Imitation



These methods to approximate ideal filters are certainly very useful when we want to derive a quick and dirty prototype, and we don't have time to use more sophisticated filter design methods

6.2. Signal of the Day: Camera Resolution and space exploration

6.2.1. Rosettta Mission: Spacecraft

- Reaching Comet 67P. 10 years to get momentum to get its orbit.
- Resolution of taken pictures:

Resolution	at Distance	Year
1km/pixel	86'000km	28. June 2014
	12'000km	14. July 2014
100m/pixel	5'500km	20. July 2014
5.3m/pixel	285km	3. August 2014
11cm/pixel	6km	14. February 2015 most detailed pictures of a planet

Is it necessary to send a probe for 10years into space to get high resolution pictures?

6.2.2. Image Formation

$$i(x, y) = s(x, y) * h(x, y), \text{ i: image that is formed,} \\ = s(x, y) * t(x, y) * p(x, y)$$

- i: image that is formed on the retina or camera
- s: light sources (source image)
- h: transfer function of the light
- t: medium through the light is traveling
- p: point spread function (PSF), lenses and focal distance

The major enemy to image quality of telescope on earth are the atmospheric disturbances.

The pinhole camera A certain pixel density is required to distinguish light sources on the image plane. We might be tempted to say the maximum achievable resolution is only depend on the **resolution** of the sensor at the back of the camera. In reality the resolution is limited by pixel density resolution is limited by diffraction.

Diffraction (Beugung) The image of an original point light source will appear as a diffraction pattern. The diffraction pattern through a small circular aperture is called **Airy disk**.

Rayleigh's criterion Minimum angle θ between light point sources that guarantees resolution

$$\theta = 1.22 \frac{\lambda}{D}$$

- λ : wave length of the light that hits the camera
- D : Diameter of the aperture

6.2.3. Seeing the Lunar Excursion Module (LEM)

- size of LEM $\approx 5\text{m}$
- distance to the Moon \approx
- Rightarrow θ subtended by the LEM is $\approx 0.003\text{arcsec}$
- Hubble's aperture: 2.4m
- visible spectrum $\lambda \approx 550\text{nm}$
- Rayleigh's criterion: $\theta \approx 0.1\text{arcsec}$
 \Rightarrow to see the LEM, Hubble should have an aperture of $80\text{m}!!!!$

6.2.4. Rayleigh's criterion, Spatial Resolution

$$\delta x = 1.22 f \frac{f}{D} = \theta \cdot f$$

If the [pixel separation](#) on the camera sensor is not less than δx our camera will be resolution limited rather than diffraction limited.

- f : foco length
- f/D : f-number

pixel density takes into account the size of the sensor.

6.2.5. What about mega pixels?

How many mega pixels one need on an commercial camera. This actually depends on the size of the sensor and on the optics:

- f-number of all trades: $f/8$
- spatial Rayleigh's criterion: $\delta x \approx 4\mu\text{m}$
- max pixel area $16 \cdot 10^{-5}$
 \Rightarrow to opperate at the diffraction limit we need $62'500\text{pixels}/\text{mm}^2$
Highend camera usually have one of the following sensors:
- APS-C sensor (329mm^2): 20 MP \Rightarrow the camera is operating at the defraction limit
- 35-mm sensor (864mm^2): 54 MP \Rightarrow the camera is operating at the defraction limit

6.3. Realizable Filters

6.3.1. The Z-Transform

6.3.1.1. References

. [Signals and Systems for Dummies: Z-Transform](#)

6.3.1.2. Z-Transform

maps a discrete-time sequence $x[n]$ onto a function of $\sum_{n=-\infty}^{\infty} x[n] z^{-n}$.

$$x[n] = \sum_{n=-\infty}^{\infty} x[n] z^{-n} \quad (6.1)$$

The z-Transform is an extension of the DTFT to the whole complex plane and is equal to the DTFT for $z = e^{j\omega}$.

$$X(z)|_{z=e^{j\omega}} = DTFT\{x[n]\} \quad (6.2)$$

Key properties of the z-Transform are:

- linearity: $\mathcal{Z}\{\alpha x[n] + \beta y[n]\} = \alpha X(z) + \beta Y(z)$
- time shift: $\mathcal{Z}\{x[n - N]\} = z^{-N} X(z)$

Applying the z-transform to CCDE's

$$\begin{aligned} \sum_{k=0}^{N-1} a_k y[n - k] &= \sum_{k=0}^{M-1} b_k x[n - k] \\ Y(z) \sum_{k=0}^{N-1} a_k z^{-k} &= X(z) \sum_{k=0}^{M-1} b_k z^{-k} \\ Y(z) &= H(z) X(z) \end{aligned}$$

- M input values
- N output values

6.3.1.3. Constant Difference Equation

A constant coefficient difference equation (CCDE) expresses the input-, output relationship of an LTI system as a linear combination of output samples equal to a linear combination of input samples

$$\sum_{k=0}^{N-1} a_k y[n - k] = \sum_{k=0}^{M-1} b_k x[n - k]$$

In the z-domain, a Constant Coefficient Difference Equation **CCDE** is represented as a ration $H(z)$ of two polynomials of z^{-1} .

$$H(z) = \frac{\sum_{k=0}^{M-1} b_k z^{-k}}{\sum_{k=0}^{N-1} a_k z^{-k}} \quad (6.3)$$

6.3.1.4. Frequency Response

The frequency response of a filter is equal to this [transfer function](#) evaluated at $z = e^{j\omega}$.

$$H(j\omega) = H(z)|_{z=e^{j\omega}} = \frac{\sum_{k=0}^{M-1} b_k z^{-k}}{\sum_{k=0}^{N-1} a_k z^{-k}} \quad (6.4)$$

6.3.2. Z-Transform of the leaky integrator

$$\begin{aligned} y[n] &= (1 - \lambda)x[n] + \lambda y[n - 1] \\ Y(z) &= (1 - \lambda)X(z) + \lambda z^{-1}Y(z) \\ Y(z) - \lambda z^{-1}Y(z) &= (1 - \lambda)X(z) \\ Y(z)(1 - \lambda z^{-1}) &= (1 - \lambda)X(z) \\ Y(z) &= H(z)X(z) \\ H(z) &= \frac{Y(z)}{X(z)} = \frac{1 - \lambda}{1 - \lambda z^{-1}} \\ H(e^{j\omega}) &= \frac{1 - \lambda}{1 - \lambda e^{-j\omega}} \end{aligned}$$

6.3.2.1. LTI Systems

An LTI system can be represented as the convolution $y[n] = x[n] * h[n]$. From the convolution property of the Z-transform, it follows that the z-transform of $y[n]$ is:

$$Y(z) = H(z) X(z) \quad (6.5)$$

6.3.3. Region of convergence

Conditions for convergences

- The zeros/poles are the roots of the numerator/denominator of the rational transfer function
- the region of convergence is only determined by the magnitude of the poles
- the z-transform of a causal LTI system extends outwards from the largest magnitude pole



BIBO-Stable

↗ An LTI system is stable if its region of convergence includes the unit circle

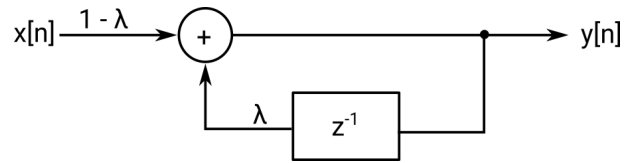
6.4. Filter Design Part 2

- many signal processing problems can be solved using simple filters
- we have seen simple lowpass filters already (Moving Average, Leaky Integrator)
- simple (low order) transfer functions allow for intuitive design and tuning

6.4.1. Intuitive IIR Designs

6.4.1.1. Leaky Integrator

6.4.1.1.1. Filter Structure



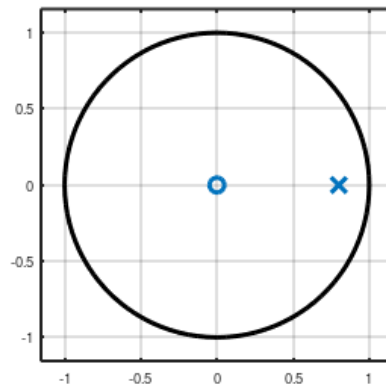
6.4.1.1.2. Transfer Function

$$H(z) = \frac{1 - \lambda}{1 - \lambda z^{-1}}$$

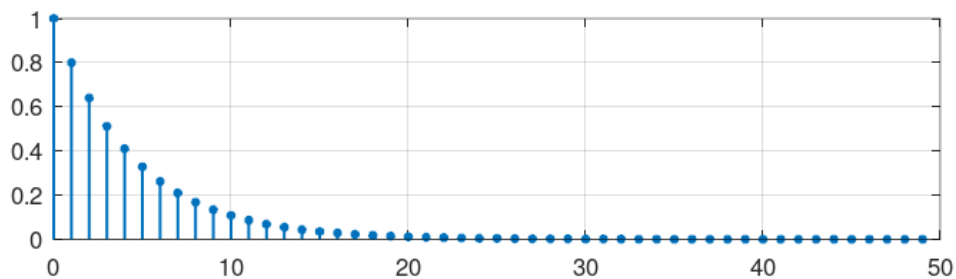
6.4.1.1.3. CCDE

$$y[n] = (1 - \lambda) x[n] + \lambda y[n - 1]$$

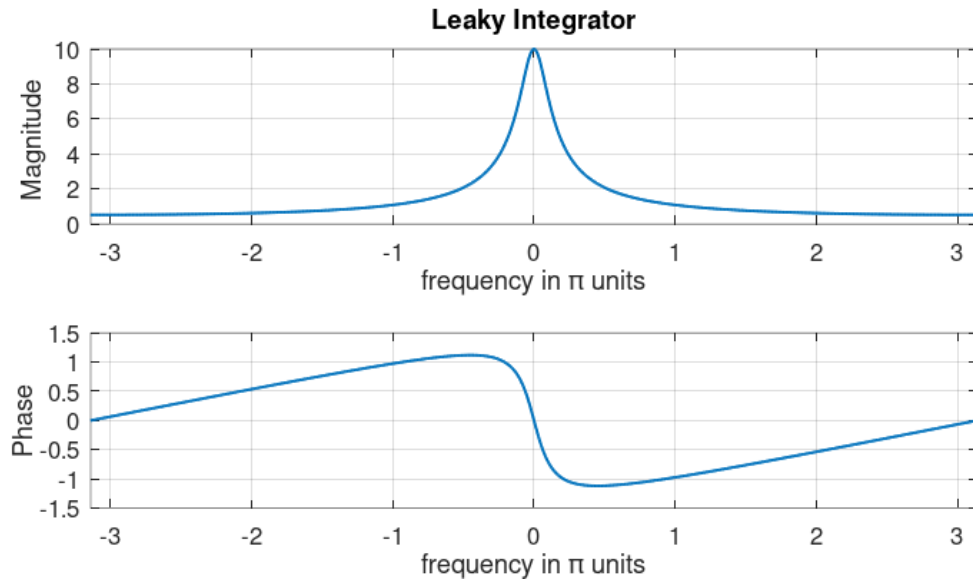
6.4.1.1.4. Pole-Zero Plot



6.4.1.1.5. Impulse response



6.4.1.1.6. Frequency Response



6.4.1.2. Resonator

- a resonator is a narrow bandpass filter
- used to detect presence of a given frequency
- useful in communication systems and telephone (DTMF)
- [Idea](#): shift passband of the Leaky Integrator

6.4.1.2.1. Transfer Function

$$H(z) = \frac{G_0}{(1 - pz^{-1})(1 - p^*z^{-1})}$$

$$p = \lambda e^{j\omega_0}$$

$$H(z) = \frac{G_0}{1 - 2\mathcal{R}p z^{-1} + |p|^2 z^{-2}}$$

$$H(z) = \frac{G_0}{1 - 2\lambda\omega_0 z^{-1} + |\lambda|^2 z^{-2}}$$

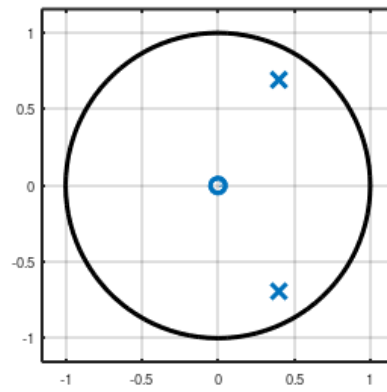
The coefficient to be used in the CCDE

$$a_1 = 2\lambda \cos \omega_0$$

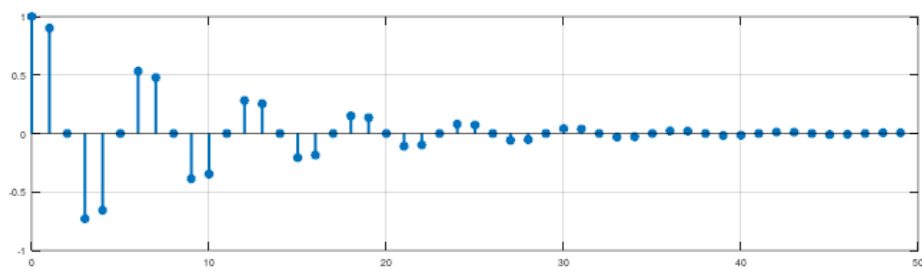
$$a_2 = -|\lambda|^2$$

6.4.1.2.2. Pole-Zero Plot

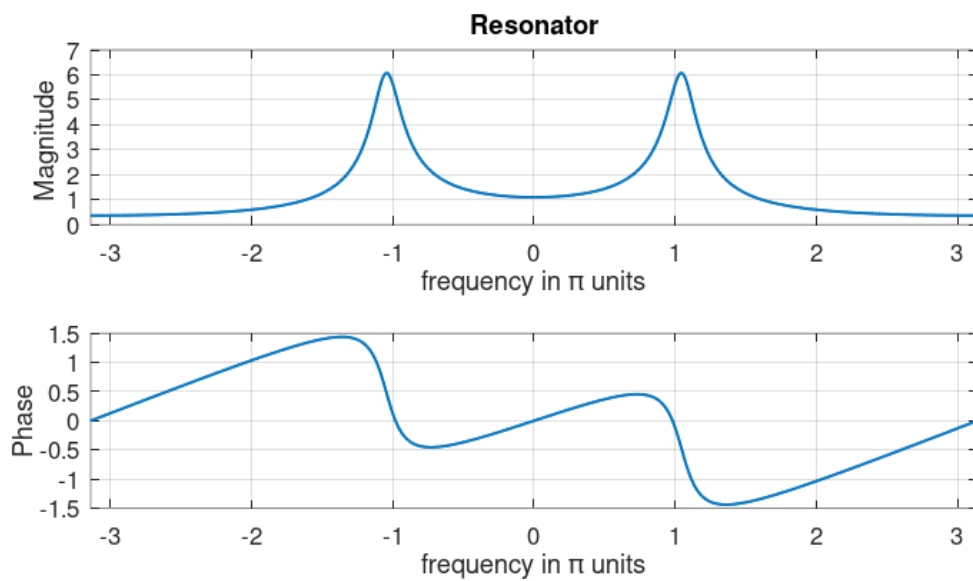
- Move the pole of the leaky integrator radially around the circle of radius λ to shift the passband at the frequency that we are interested in, i.e. ω_0 . interested in selecting. Since we want a real filter, we also have to create a complex conjugate pole at an angle that is $-\omega_0$.



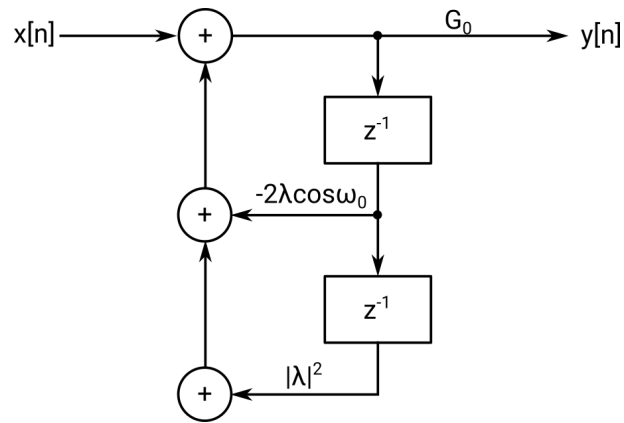
6.4.1.2.3. Impulse response



6.4.1.2.4. Frequency Response



6.4.1.2.5. Filter Structure



6.4.1.3. DC Removal

- a DC-balanced signal has zero sum: $\lim_{N \rightarrow \infty} \sum_{n=-N}^N x[n] = 0$ i.e. there is no Direct Current component
- its DTFT value at zero is zero for an $\omega = 0$
- we want to remove the DC bias from a non zero-centered signal
- we want to kill the frequency component at $\omega = 0$

6.4.1.3.1. Transfer Function

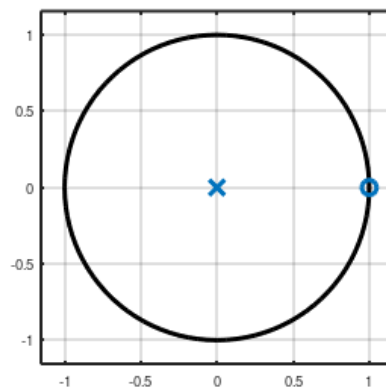
$$H(z) = 1 - Z^{-1}$$

6.4.1.3.2. CCD

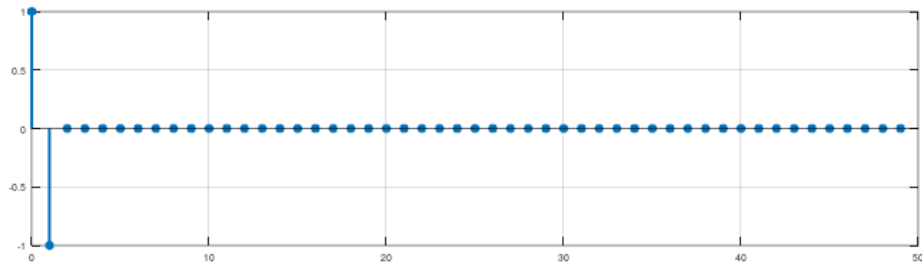
$$y[n] = x[n] - x[n-1]$$

6.4.1.3.3. Pole-Zero Plot

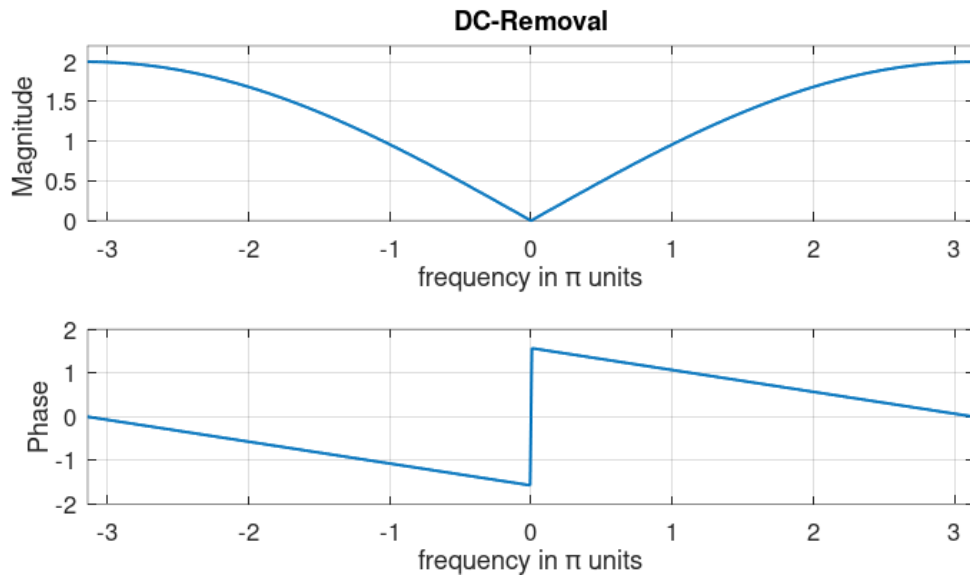
- Simply place a zero at $z = 1$



6.4.1.3.4. Impulse response



6.4.1.3.5. Frequency response



This is not an acceptable characteristic because it introduces a very big attenuation over almost the entirety of the frequency support.

6.4.1.4. DC Removal Improved - DC-Notch Filter

6.4.1.4.1. Transfer Function

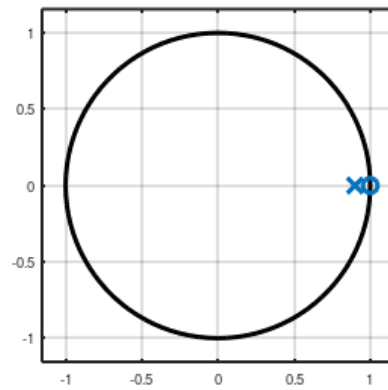
$$H(z) = \frac{1 - z^{-1}}{1 - \lambda z^{-1}}$$

6.4.1.4.2. CCDE

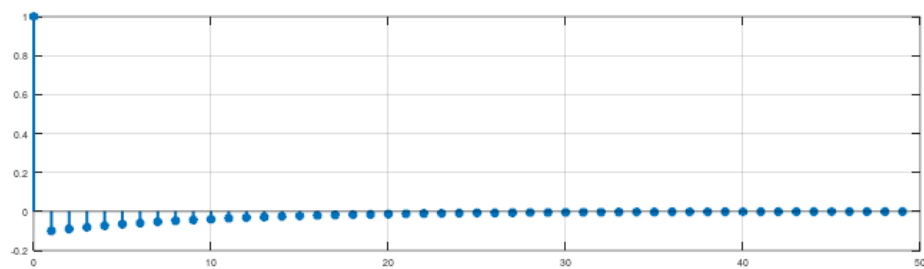
$$y[n] = \lambda y[n-1] + x[n] - x[n-1]$$

6.4.1.4.3. Pole-Zero Plot

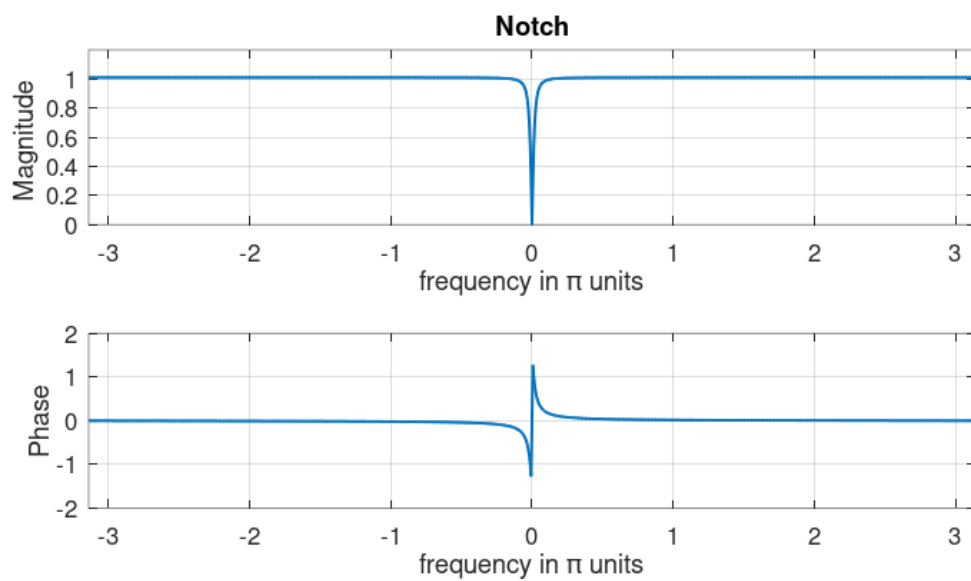
- and if we remember the circus tent method, we know that we can push up the z-transform by putting a pole in the vicinity of the 0. So we try and do that and we combine therefore, the effect of a 0 and 1 with the effect of a pole close to one, and inside the unit circle, for obvious reasons of stability.



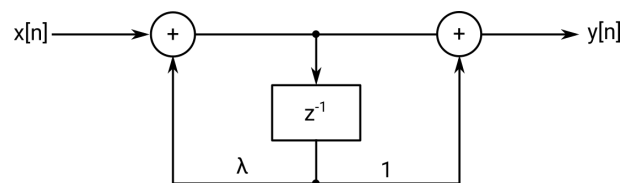
6.4.1.4.4. Impulse response



6.4.1.4.5. Frequency Response



6.4.1.4.6. Filter Structure



6.4.1.5. Hum Removal

- The hum removal filter is to the dc notch what the resonator is to the leaky integrator
- similar to DC removal but want to remove a specific nonzero frequency
- very useful for musicians amplifiers for electronic guitars pick up the hum from the electronic mains (50Hz in Europe and 60Hz in North America)
- we need to tune the hum removal according the country

6.4.1.5.1. Transfer Function

$$\begin{aligned}
 H(z) &= \frac{(1 - e^{j\omega_0} z^{-1})(1 - e^{-j\omega_0} z^{-1})}{(1 - \lambda e^{j\omega_0} z^{-1})(1 - \lambda e^{-j\omega_0} z^{-1})} \\
 p &= e^{j\omega_0} \\
 q &= \lambda e^{j\omega_0} \\
 &= \frac{(1 - pz^{-1})(1 - p^* z^{-1})}{(1 - qz^{-1})(1 - q^* z^{-1})} \\
 H(z) &= \frac{1 - 2\mathcal{R}pz^{-1} + |p|^2 z^{-2}}{1 - 2\mathcal{R}qz^{-1} + |q|^2 z^{-2}} \\
 &= \frac{1 - 2\cos\omega_0 z^{-1} + z^{-2}}{1 - 2\lambda\cos\omega_0 z^{-1} + |\lambda|^2 z^{-2}}
 \end{aligned}$$

The coefficient to be used in the CCDE

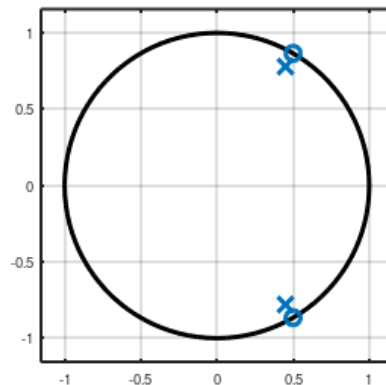
$$\begin{aligned}
 a_1 &= -2\lambda\cos\omega_0 \\
 a_2 &= |\lambda|^2 \\
 b_1 &= -2\cos\omega_0 \\
 b_2 &= 1
 \end{aligned}$$

6.4.1.5.2. CCDE

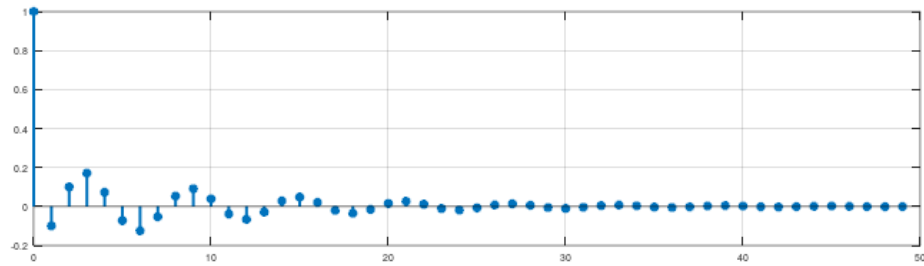
$$y[n] = 2\lambda\cos\omega_0 y[n-1] + |\lambda|^2 y[n-2] + x[n] - 2\cos\omega_0 x[n-1] + x[n-2]$$

6.4.1.5.3. Pole-Zero Plot

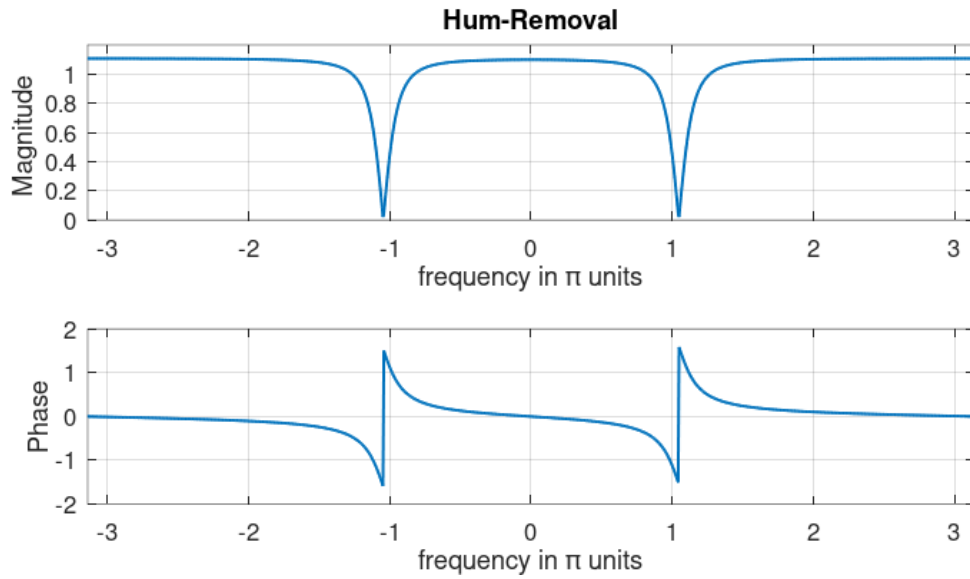
- and if we remember the circus tent method, we know that we can push up the z-transform by putting a pole in the vicinity of the 0. So we try and do that and we combine therefore, the effect of a 0 and 1 with the effect of a pole close to one, and inside the unit circle, for obvious reasons of stability.



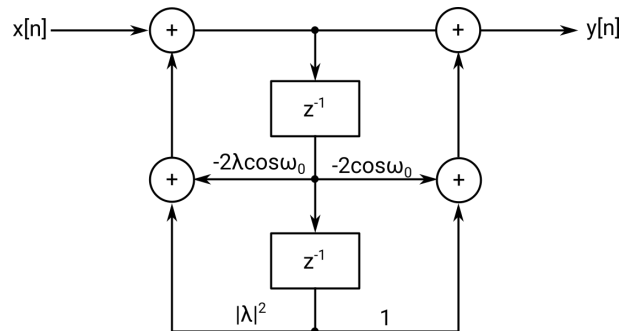
6.4.1.5.4. Impulse response



6.4.1.5.5. Frequency Response



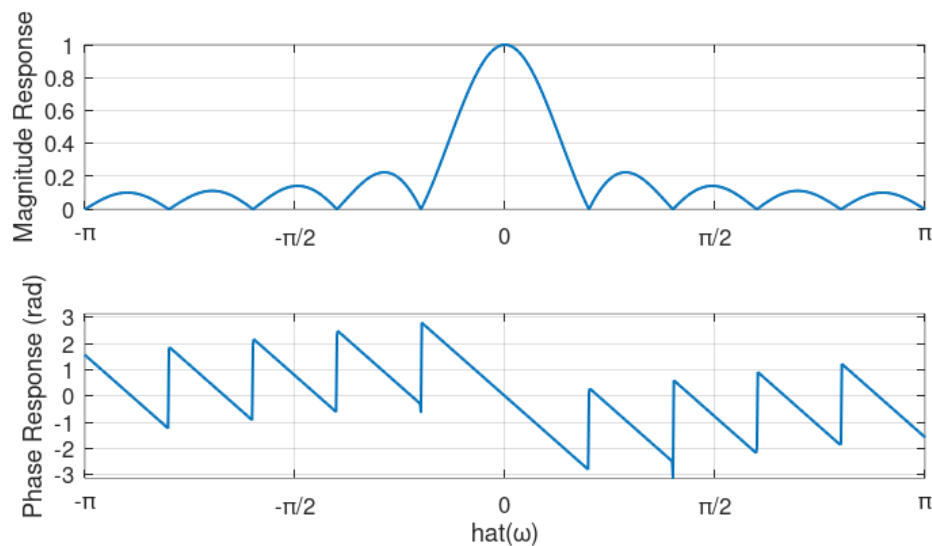
6.4.1.5.6. Filter Structure



6.4.2. Matlab

Dirichlet The Dirichlet or periodic sinc function can be used to analyze Moving Average Filters $D_M(j\omega) = \frac{\sin(\frac{\omega}{2}M)}{\sin(\frac{\omega}{2})}$

Freqz The frequency response can be plotted most easily using `freqz()` function.



6.5. Filter Design Part 3

6.5.1. Filter Specification

6.5.2. IIR Design

Filterdesign was established art long before digital processing appeared

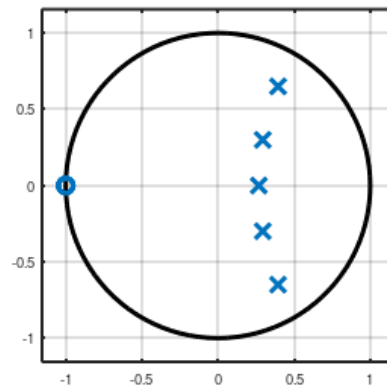
- AFD: Analog Filter Design
- lots of nice analog filters exist
- methods exist to "translate" the analog design into a rational transfer function
 - **impulse invariance transformation**, preserves the shape of the impulse response
 - finite difference approximation, converts a differential equation into a ccde
 - step invariance, preserves the shape of the step response
 - matched-z transformation, matches the pole-zero representation
 - **bilinear transformation**, preserves the system function representation
- most numerical packages (Matlab, etc.) provide ready-made routines
- design involves specifying some parameters and testing that the specs are fulfilled

6.5.2.1. Butterworth lowpass

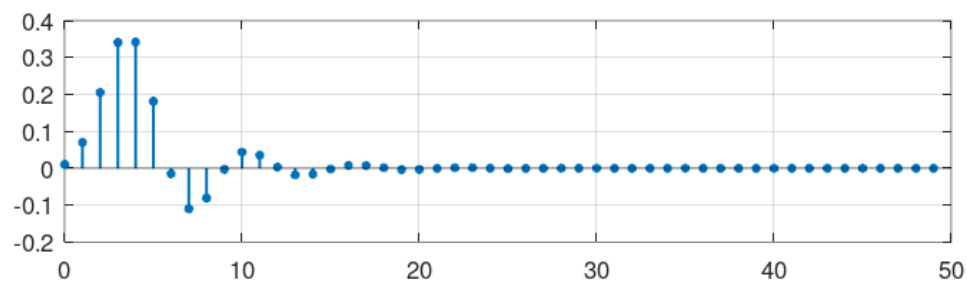
Table 6.1.: Butterworth lowpass

Magnitude response	Design Parameters	Test values
maximally flat	order N	width of transition band
monotonic over $[0, \pi]$	cutoff frequency	passband error

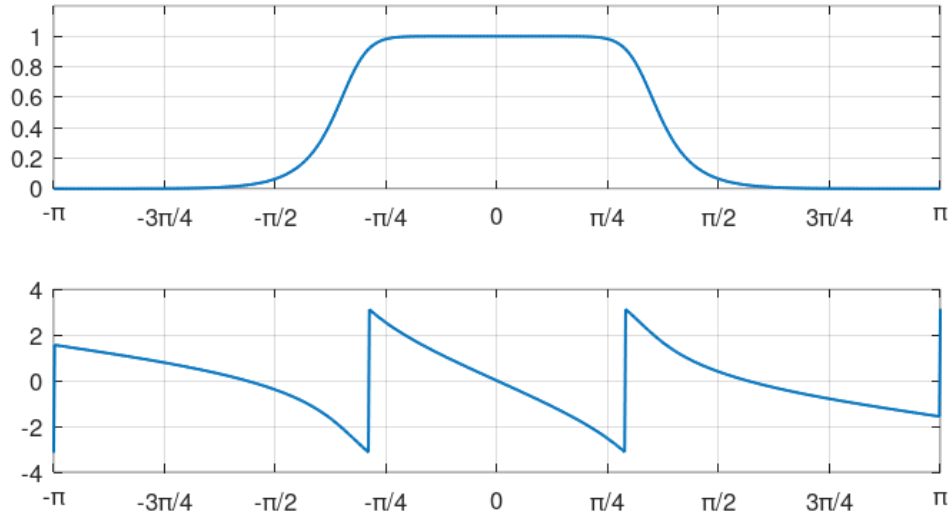
6.5.2.1.1. Pole-Zero Plot



6.5.2.1.2. Impulse Response



6.5.2.1.3. Frequency Response

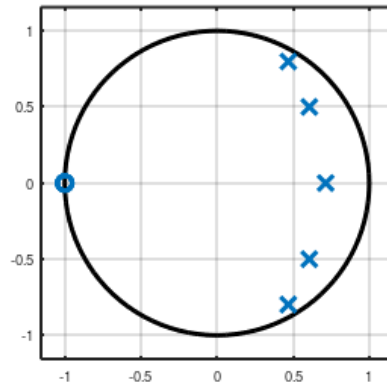


6.5.2.2. Chebyshev lowpass

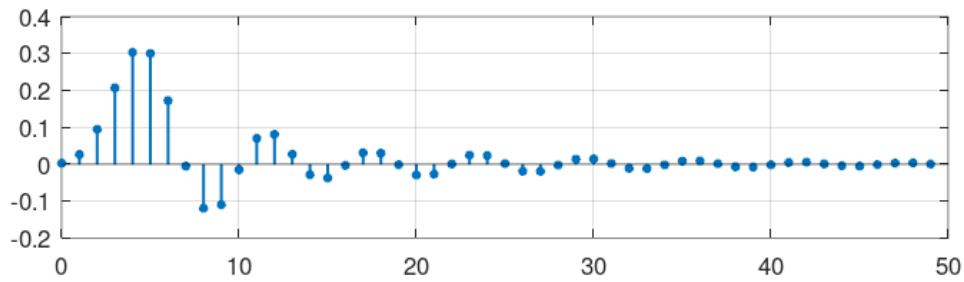
6.5.2.2.1. Pole-Zero Plot

Table 6.2.: Chebyshev lowpass

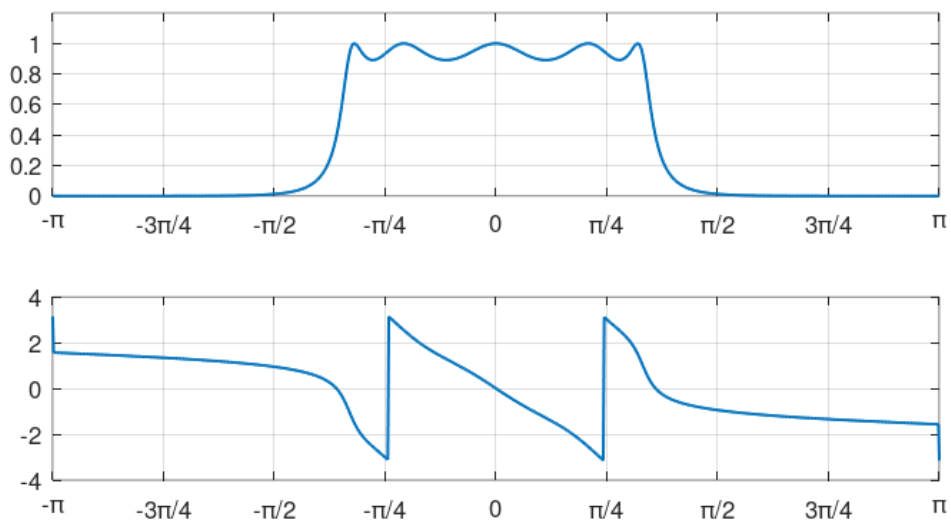
Magnitude response	Design Parameters	Test values
equiripple in passband	order N	width of transition band
monotonic in stopband	passband max error	stopband error
	cutoff frequency	



6.5.2.2.2. Impulse Response



6.5.2.2.3. Frequency Response

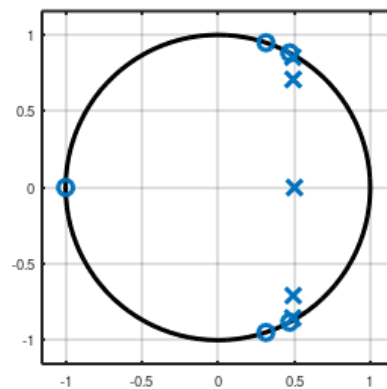


6.5.2.3. Elliptic Lowpass

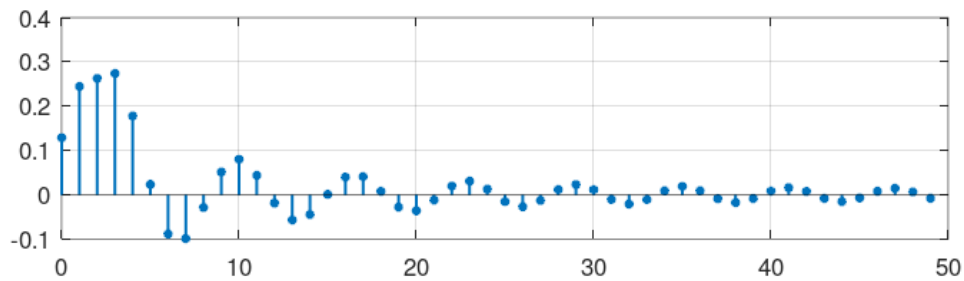
Table 6.3.: Elliptic Lowpass

Magnitude response	Design Parameters	Test values
equiripple in passband	order N	width of transition band
equiripple in stopband	cutoff frequency	
	passband max error	
	stopband min attenuation	

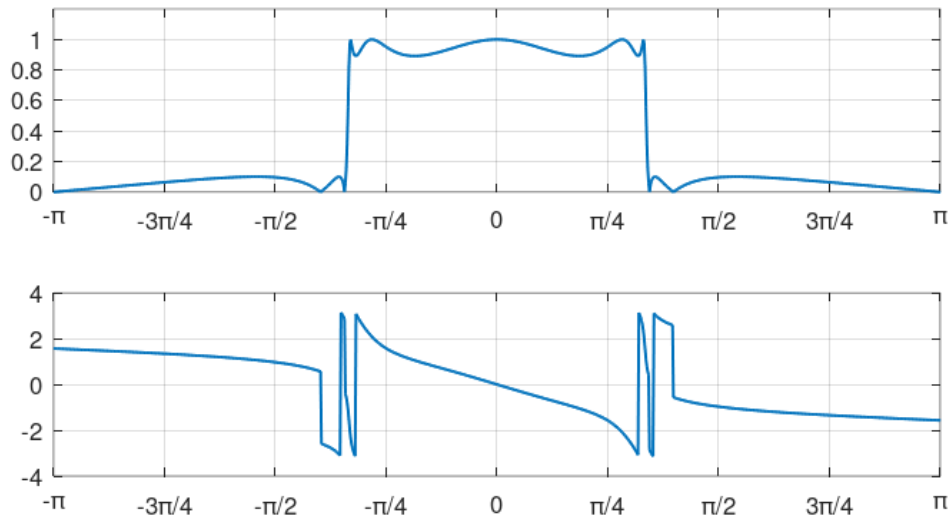
6.5.2.3.1. Pole-Zero Plot



6.5.2.3.2. Impulse Response



6.5.2.3.3. Frequency Response



6.5.3. FIR Design

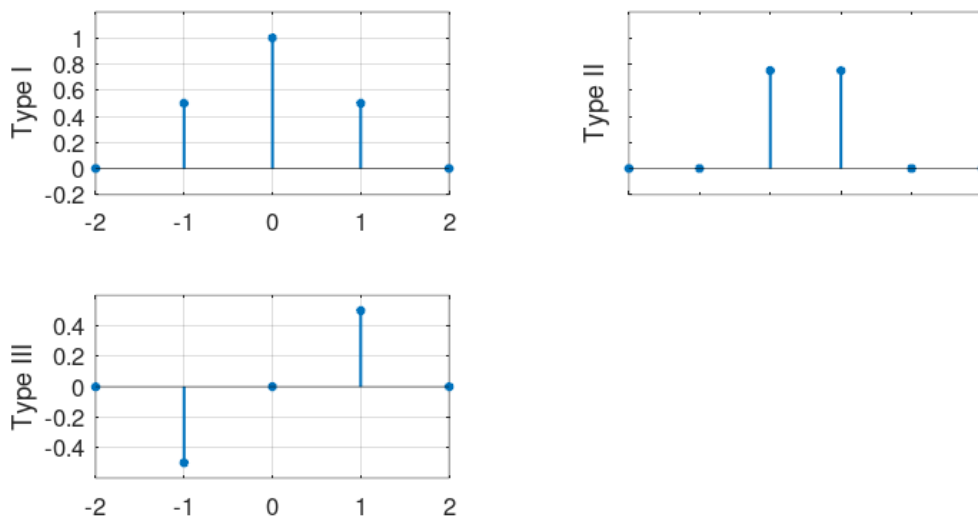
6.5.3.1. Optimal minmax design

FIR filters are digital signal processing "exclusivity". In the 70s Parks and McClellan developed an algorithm to design optimal FIR filters:

- linear phase
- equiripple error in passband and stopband

algorithm proceeds by **minimizing** the maximum error in passband and stopband

6.5.3.1.1. Linear Phase Linear phase derives from a symmetric or antisymmetric impulse responses



Type I-Filters Odd length impulse response, and are symmetric

Type II-Filters Even length impulse response, and are symmetric

Type III-Filters Odd length impulse response, and are antisymmetric

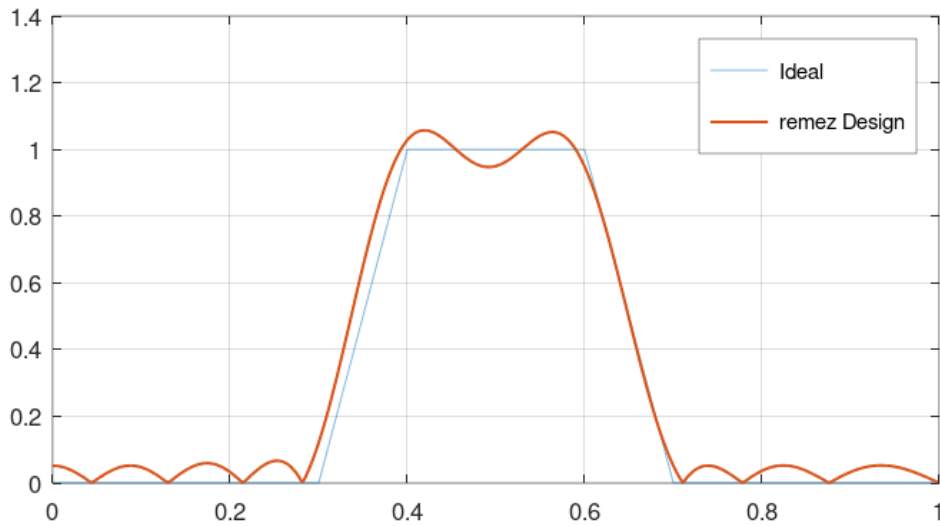
Type IV-Filters Even length impulse response, and are antisymmetric

Type-II and Type-IV Filters are symmetric and antisymmetric filters, respectively, both of which have an even number of taps. That means that the center symmetry of these filters fall in between samples. And so they both introduce a non integer linear phase factor, of one half sample.

6.5.4. The Park McMellon Design Algorithm

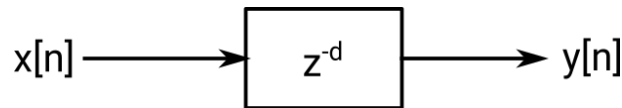
Table 6.4.: Park McMellon

Magnitude response	Design Parameters	Test values
equiripple in passband and stopband	order N	passband max error
	passband edge ω_p	stopband max error
	stopband edge ω_s	
	ratio of passband to stopband error $\frac{\delta_p}{\delta_s}$	



6.6. ONGOING Notes and Supplementary Materials

6.6.1. The Fractional Delay Filter (FDF)



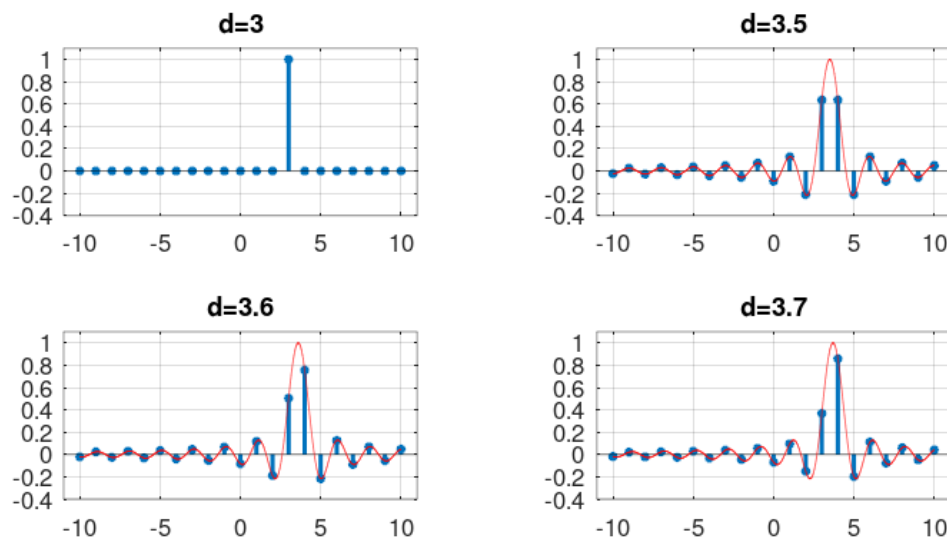
The transfer function of a simple delay z^{-d} is:

$$H(e^{j\omega}) = e^{-j\omega d}, d \in \mathbb{Z}$$

what happens if, in $H(e^{j\omega})$ we use a non-integer $d \in \mathbb{R}$?

6.6.1.1. Impulse Response

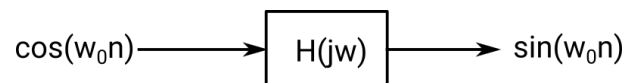
$$\begin{aligned}
 h[n] &= IDFT \{ e^{j\omega d} \} \\
 &= \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{j\omega d} e^{j\omega n} d\omega \\
 &= \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{j\omega(n-d)} d\omega \\
 &= \frac{1}{\pi(n-d)} \frac{e^{j\pi(n-d)} - e^{-j\pi(n-d)}}{2j} \\
 &= \frac{\sin \pi(n-d)}{\pi(n-d)} \\
 &= \text{sinc}(n-d)
 \end{aligned}$$



For now suffice it to say that we can actually interpolate in discrete time and find intermediate values of a discrete time sequence using just discrete times filters like the fractional delay

6.6.2. **ONGOING** The Hilbert Filter

- Demodulator



can we build such a thing?

6.6.3. **TODO** Implementing of Digital Filters

6.6.3.1. Leaky Integrator in C

```

using namespace std;

double leaky(double x) {
    static const double lambda = 0.9;
    static double y = 0;    // 1x memory cell
    // plus initialization

```

```

    // algorithm: 2x multiplication, 1x addition
    y = lambda * y + (1-lambda) *x;
    return y;
}

int main() {
    int n;
    for(n = 0; n <20; n++)
    {
        //call with delta signal
        printf("%.4f ", leaky(n==0 ? 1.0 : 0.0));
        //if(!((n+1)%10)) printf("\n");
    }
}

```

0.1000 0.0900 0.0810 0.0729 0.0656 0.0590 0.0531 0.0478 0.0430 0.0387 0.0349 0.0314 0.0282 0.0254 0.0225

- we need a "memory cell" to store previous state
- we need to initialize the storage before first use
- we need 2 multiplications and one addition per output sampel

6.6.3.2. Moving Average in C

```

using namespace std;
double ma(double x) {
    static const int M = 5;
    static double z[M]; // Mx memory cells
    static int ix = -1;

    int n;
    double avg = 0;

    if(ix == -1) { // initalize storage
        for(n=0; n<M; n++)
            z[n] = 0;
        ix = 0;
    }

    z[ix] = x;
    ix = (ix + 1) % M; // circular buffer

    for(n=0; n<M; n++) // Mx additions
        avg += z[n];

    return avg / M; // 1x division
}

int main() {
    int n;
    for (n = 0; n<20; n++)
    {
        // call with delta signal
        printf("%.4f ", ma(n==0 ? 1.0 : 0.0));
        if(!((n+1)%10)) printf("\n");
    }
}

```



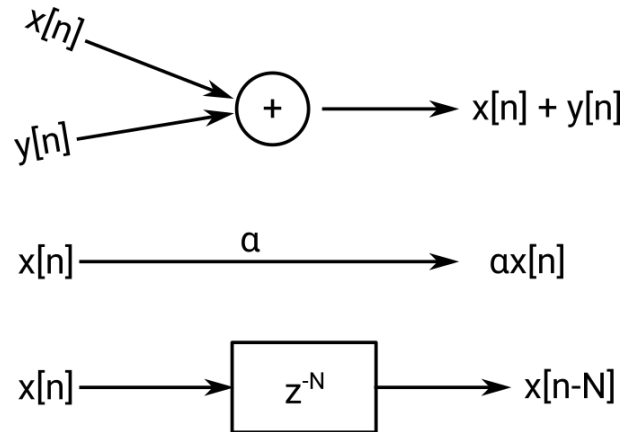
```
}  
}
```

- we need M memory cells to store previous input values
- we need to initialize the storage before first use
- we need 1 division and M additions per output sample

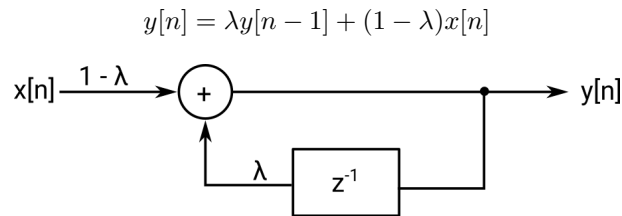
6.6.3.3. Programming Abstraction

With this three building blocks we can describe and Constant Coefficient Equation.

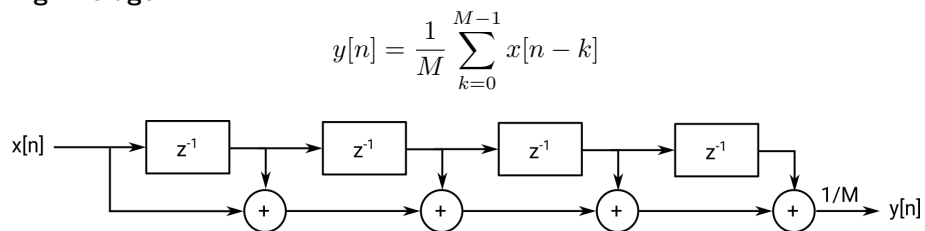
6.6.3.3.1. Building Blocks



6.6.3.3.2. Leaky Integrator



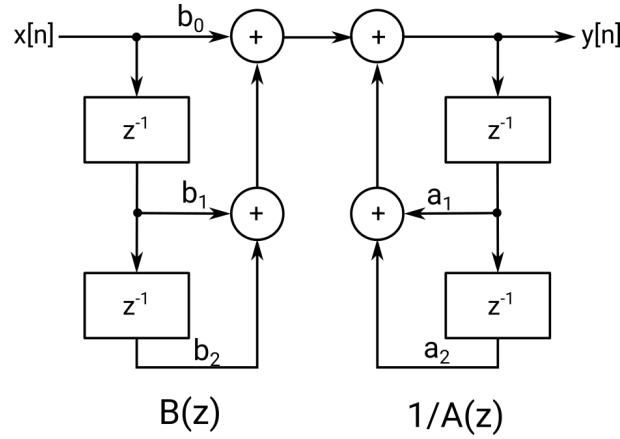
6.6.3.3.3. Moving Average



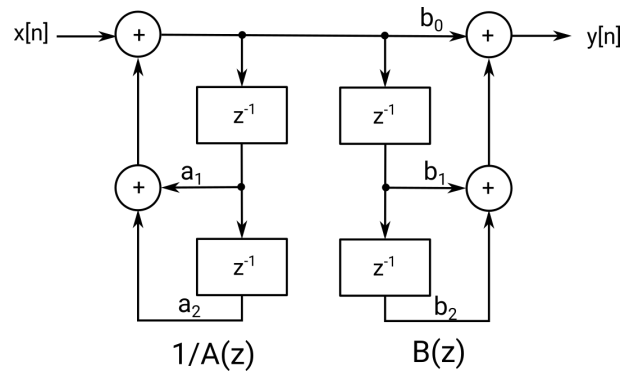
6.6.3.3.4. The second-order section

$$H(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 - a_1 z^{-1} - a_2 z^{-2}} = \frac{B(z)}{A(z)}$$

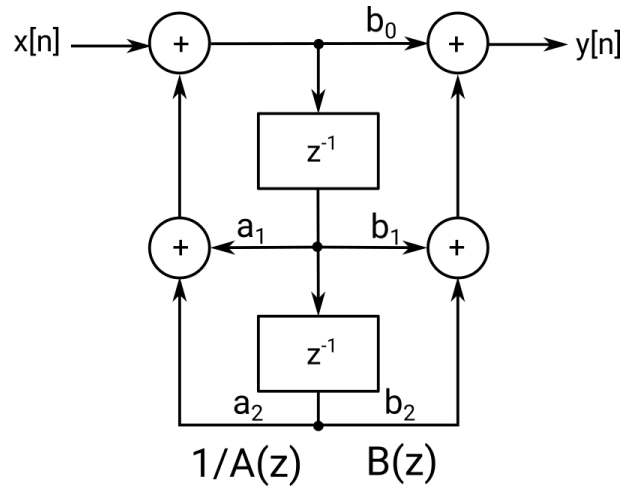
6.6.3.3.5. Second-order section, direct form I



6.6.3.3.6. Second-order section, inverted direct form I Because the convolution is commutative, numerator and denominator may be swapped.



6.6.3.3.7. Second-order section, direct form II Since the content of the delay cells are exactly the same for all time, so we can lump the delay cells together.



6.6.4. TODO Real-Time Processing

6.6.4.1. I/O and DMA Everything works in synch with a system clock of period T_s

- record a value $x_i[n]$
- process the value in a casual filter

- play the output $x_o[n]$



↪ Everything needs to happen in at most T_s seconds!

Buffering:

- interrupt for each sample would be too much overhead
- soundcard consumes samples in buffers
- soundcard notifies when buffer used up
- CPU can fill a buffer in less time than soundcard can empty it

Double Buffering

- Delay $d = T_s \times \frac{L}{2}$ L: Length of the Buffer
- If CPU doesn't fill the buffer fast enough: **underflow**

Multiple I/O Processing

- Delay: $d = T_s \times L$
- usually start out process first

6.6.4.2. Implementation Framework

Low Level

- study soundcard data sheet
- write code to program soundcard via writes to IO Ports
- write an interrupt handler
- write the code to handle the data

High Level

- choose a good API
- write a callback function to handle the data

6.6.4.3. Callback Prototype

```
int Callback( const void *input,      // pointer to the input buffer
              void *output,          // pointer to the output buffer
              unsigned long samples, // length of samples
            );
{
    float* pIn = (float*)input;      // Convert the generic buffers
    float* pOut = (float*)output;     // to the right data type
    for (int n=0; n < samples; n++)  // Calls process for each sample in input the buffer
        *pOut++ = Process(*pIn++);  // and store the result into the output buffer.
}
```

6.6.4.4. Processing Gateway

```

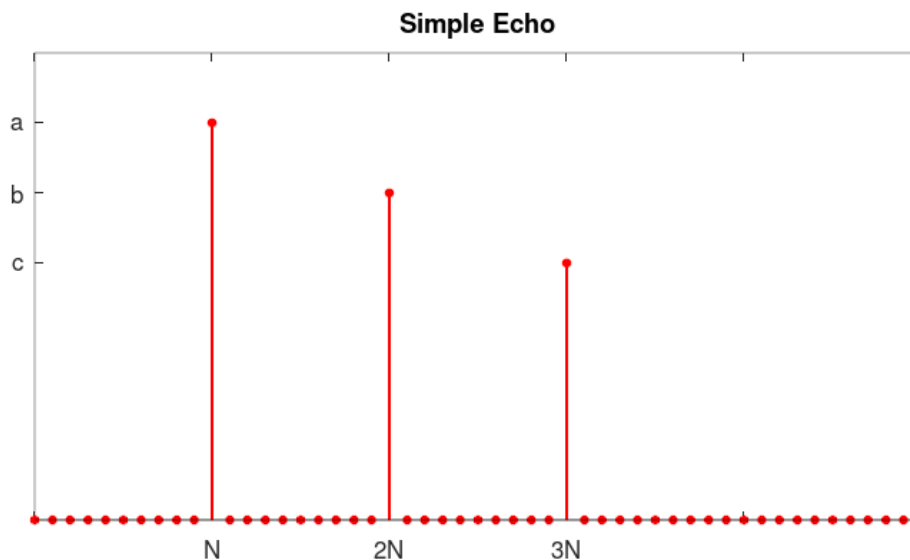
// 10 sec @ 24kHz
enum {BUF_LEN = 0x10000}; // Buffer length, power of 2
enum {BUF_MASK = BUF_LEN - 1}; // Circular buffer mask
float m_pY[BUF_LEN]; // 2 Buffers
float m_pX[BUF_LEN];
int m_Ix; // 2 indices into the buffers
int m_Iy;
float Process(float Sample)
{
    m_PX[m_Ix] = Sample; // store the sample into input buffer
    float y = Effect(); // call Effect()
    m_pY[m_Iy] = y; // store the output into output buffer
    m_Ix = (m_Ix + 1) & BUF_MASK; // Update indices with the circular strategy
    m_IY = (m_Iy + 1) & BUF_MASK;
    return y; // return current output sample
}

```

6.6.4.5. Effect

Implementing the echo effect as a reflection of the original signal, scaled with a factor at subsequent points in time:

$$y[n] = \frac{ax[n] + bx[n - N] + cx[n - 2N]}{a + b + c}$$



```

float Echo() {
    static float a = 0.85; // the three scaling factors
    static float b = 0.6f;
    static float c = 0.45f;
    static float norm = 1.0f/(a+b+c); // the normalisation factor
    static int N = (int)(0.3 * m_SR); // delay between reflection

    return norm * ( a * m_pX[m_Ix]
                  + b * m_pX[(m_Ix + BUF_LEN - N) & BUF_MASK]
                  + c * m_pX[(m_Ix + BUF_LEN - 2*N) & BUF_MASK] ); }

```

6.6.5. TODO Dereverberation and echo cancellation

Part VII.

Week 7 Module 5:

7. Sampling and Quantization

Interpolation describes the process of building a continuous-time signal $\mathbf{x}(\mathbf{t})$ from a sequence of samples $\mathbf{x}[\mathbf{n}]$. In other words, interpolation allows moving from the discrete-time world to the continuous-time world. Interpolation raises two interesting questions:

The first one is how to interpolate between samples?

- In the case, of two samples, this is simple enough and there is there is a straight line that goes between these two samples.
- In the case of three samples, similarly, you have a parabola that goes through these 3 samples.
- If you have many samples, you can try to do the same and go through all samples but you see this is a trickier issue compared to what we have done with two or three samples.

The second question is:

- is there a minimum set of values you need to measure the function at so that you can perfectly reconstruct it.

Later on in the module, we are going to study sampling, i.e. the process of moving from a continuous-time signal to a sequence of samples. In other words, sampling allows moving from the continuous-time world to the discrete-time world. Suppose we take equally-spaced samples of a function $\mathbf{x}(\mathbf{t})$. The question is when is there a one-to-one relationship between the continuous-time function and its samples, i.e. when do the samples form a unique representation of the continuous-time function? To answer this question, we are going to use all the tools in the toolbox that we have looked at so far:

- Hilbert spaces
- projections
- filtering
- sinc functions
- and so on.

Everything comes together in this module to develop a profound and very useful result, the **sampling theorem**.

Before moving to the heart of the topic, let us briefly review its history. The Shannon sampling theorem has a very interesting history which goes back well before Shannon. Numerical analysts were concerned about interpolating tables of functions and the first one to prove a version of the sampling theorem was Whittaker in England in 1915. Harry Nyquist at Bell Labs came up with the Nyquist criterion, namely that a function that has a maximum frequency $F_{0F_{0F_0}}$ could be sampled at $2F_{02F_{02F_0}}$. In the Soviet Union, Kotelnikov proved a sampling theorem. The son of the first Whittaker further proved results on the sampling theorem. Then Herbert Raabe in Berlin wrote his PhD thesis about a sampling theorem that, wrong time wrong city, he got zero credit for. Denis Gabor worked on a version of the sampling theorem in the mid 1940s. Then Claude Shannon, the inventor of information theory, wrote a beautiful paper that is in the further reading for this class where the Shannon sampling theorem appears in the form that we use today. Last but not least, in 1949 Someya in Japan also proved the sampling theorem. You can see that it's a very varied history, it's a fundamental result where many people independently came up with this result.

7.1. The Continuous-Time World

7.1.1. Introduction

The continuous-time world is the world we live in, the physical reality of the world, in contrast with the discrete-time world, the world inside a computer. We are first going to look at models of the world and compare digital with analog views of the world. Then we are going to study continuous-time signal processing in greater details. Furthermore, we will introduce the last form of Fourier transform we have not yet encountered in this class, the continuous-time Fourier transform.

7.1.2. The continuous-time paradigm

Two views of the world

Table 7.1.: Two views of the world 1

Digital World	Analog World
arithmetic	calculus
combinatorics	distributions
computer science	system theory
DSP	electronics

Table 7.2.: Two views of the world 2

Digital World	Analog World
countable integer index M	real-valued time t [sec]
sequences $x[n] \in \ell_2(\mathbb{Z})$	function $x(t) \in L_2(\mathbb{R})$
frequency $\omega \in [-\pi, \pi]$	frequency $\Omega \in \mathbb{R}(\text{rad/sec})$
DTFT: $\ell_2(\mathbb{Z}) \rightarrow L_2[-\pi, \pi]$	FT: $L_2(\mathbb{R}) \rightarrow L_2(\mathbb{R})$

$\ell_2(\mathbb{Z})$	Square-Summable infinite sequences
$L_2([a, b])$	Square-integrable functions over an interval
Sampling	$x(t) \rightarrow x[n]$
Interpolation	$x[n] \rightarrow x(t)$

7.1.3. Continuous-time signal processing

time	real variable t
signal $x(t)$	complex function of areal variable
finite energy	$x(t) \in L_2(\mathbb{R})$
inner product in $L_2(\mathbb{R})$	$\langle x(t), y(t) \rangle = \int_{-\infty}^{\infty} x^*(t) y(t) dt$
energy	$\ x(t)\ ^2 = \langle x(t), x(t) \rangle$

7.1.3.1. Analog LTI filters

$$\begin{aligned}
 y(t) &= (x * h)(t) \\
 &= \langle h * (t - \tau), x(\tau) \rangle \\
 &= \int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau
 \end{aligned}$$

7.1.3.2. Fourier analysis

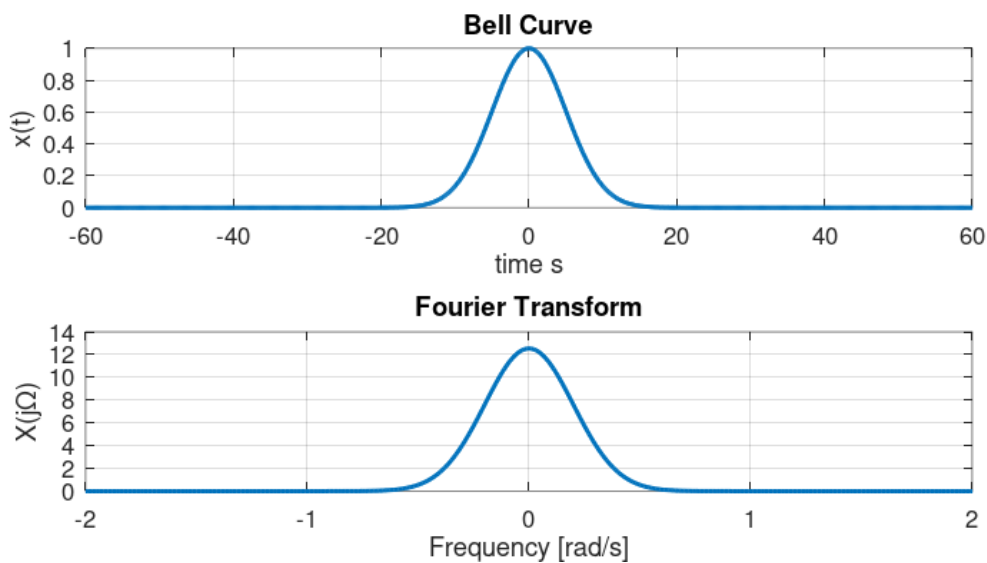
- in discrete time max angular frequency is $\pm\pi$
- in continuous time no max frequency: $\Omega \in \mathbb{R}$
- concept is the same:

$$X(j\Omega) = \int_{-\infty}^{\infty} e^{-j\Omega t} dt$$

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(j\Omega) e^{j\Omega t} d\Omega$$

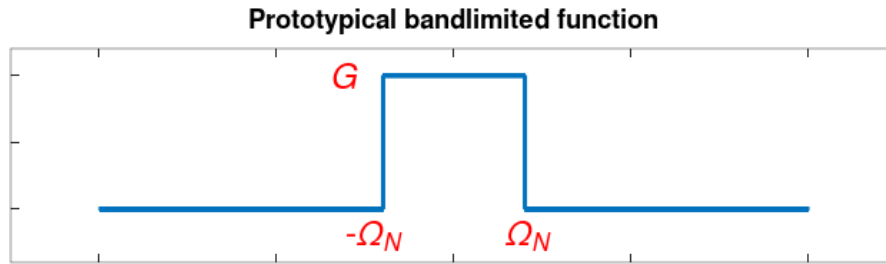
7.1.3.3. Real-world frequency

- Ω expressed in rad/s
- $F = \frac{\Omega}{2\pi}$, expressed in Hertz (1/s)
- period $T = \frac{1}{F} = \frac{2\pi}{\Omega}$

7.1.3.4. Example**7.1.3.5. Convolution theorem**

$$Y(j\Omega) = X(j\Omega) H(j\Omega)$$

7.1.3.6. Prototypical Bandlimited Functions



$$\Phi(j\Omega) = G \operatorname{rect}\left(\frac{\Omega}{2\Omega_N}\right)$$

The time domain function can be determined by means of its **Inverse Fourier Transform**

$$\begin{aligned}\phi(t) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} \Phi(j\Omega) e^{j\Omega t} d\Omega \\ &= G \frac{\Omega_N}{\pi} \operatorname{sinc}\left(\frac{\Omega_N}{\pi} t\right)\end{aligned}$$

The time domain function is up to a scaling, one of these sinc functions. We will normalize this sinc function, so that the area is equal to 2π in the Frequency Domain. Then the inverse continuous time Fourier Transform will have a maximum of 1 at the origin.

normalization	$G = \frac{\pi}{\Omega_N}$
total bandwidth	$\Omega_B = 2\Omega_N$
define	$T_s = \frac{2\pi}{\Omega_B} = \frac{\pi}{\Omega_N}$

This leads to the normalized prototypical bandlimited function:

Frequency Domain

$$\Phi(j\Omega) = \frac{\pi}{\Omega_N} \operatorname{rect}\left(\frac{\Omega}{2\Omega_N}\right)$$

Time Domain

$$\phi(t) = \operatorname{sinc}\left(\frac{t}{T_s}\right)$$

7.1.4. TODO Plot Normalized prototypicale bandlimited function

7.2. Interpolation

Main Task	$x[n] \Rightarrow x(t)$
Gaps	fill the gaps between samples

7.2.1. Interpolation requirements

- decide on T_s
- make sure $x(nT_s) = x[n]$
- make sure $x(t)$ is smooth

7.2.2. Why smoothness

- jumps (1st order discontinuities) would require the signal to move "faster than light"
- 2nd order discontinuities would require infinite acceleration
- the interpolation should be infinitely differentiable
- "natural" solution: polynomial interpolation

7.2.3. Polynomial interpolation

- N points \Rightarrow polynomial of degree $(N-1)$
- $p(t) = a_0 + a_1 t + a_2 t^2 + \dots + a_{N-1} t^{(N-1)}$
- "naive" approach

$$\left\{ \begin{array}{lcl} p(0) & = & x[0] \\ p(T_s) & = & x[1] \\ p(2T_s) & = & x[2] \\ \dots & & \\ p((N-1)T_s) & = & x[N-1] \end{array} \right.$$

Without loss of generality:

- consider a symmetric interval $I_N = [-N \dots N]$
- set $T_s = 1$

$$\left\{ \begin{array}{lcl} p(-N) & = & x[-N] \\ p(-N+1) & = & x[-N+1] \\ \dots & & \\ p(0) & = & x[0] \\ p(N) & = & x[N] \end{array} \right.$$

7.2.4. Lagrange interpolation

The natural solution to this interpolation problem is given by Lagrange interpolation

- P_N : space of degree- $2N$ polynomials over I_N
- a basis for P_N is the family of $2N + 1$ Lagrange polynomials

$$L_n^{(N)}(t) = \prod_{k=-N, k \neq n}^N \frac{t - k}{n - k} \text{ for } n = -N, \dots, N$$

The formula:

$$p(t) = \sum_{n=-N}^N x[n] L_n^{(N)}(t)$$

The Lagrange interpolation is the sought-after polynomial interpolation:

- polynomial of degree $2N$ through $2N+1$ points is unique

- the Lagrangian interpolator satisfies

$$p(N) = x[N] \text{ for } -N \leq M \leq N$$

since

$$L_n^{(N)}(N) = \begin{cases} 1 & \text{if } M = N \\ 0 & \text{if } M \neq N \end{cases} \quad -N \leq M, N \leq N$$

key property maximally smooth (infinitely many continuous derivatives)

drawback interpolation "bricks" depend on N

7.2.5. Sinc interpolation formula

A remarkable result:

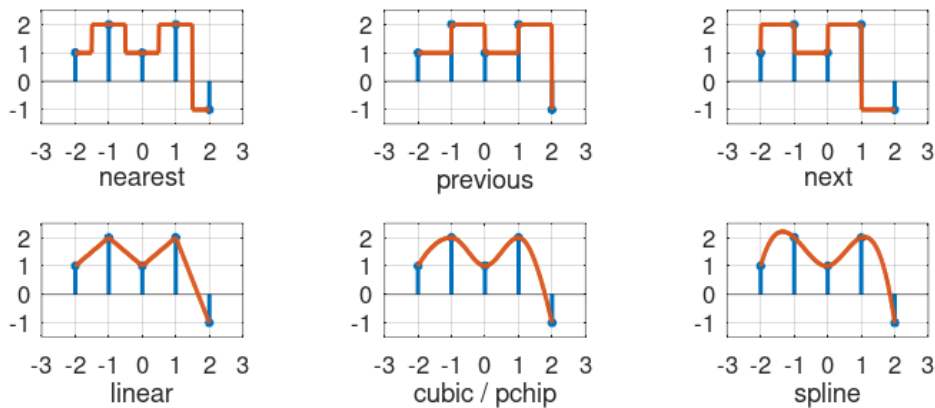
$$\lim_{N \rightarrow \infty} L_n^{(N)}(t) = \text{sinc}(t - n)$$

In the limit, local and global interpolation are the same!

$$x(t) = \sum_{n=-N}^N x[n] \text{sinc}\left(\frac{t - nT_s}{T_s}\right)$$

7.2.6. Octave Interpolation Overview

Octave manual Chapter 29.1 One-dimensional Interpolation



$$x(t) = \sum_{n=-N}^N x[n] i_c(t - n)$$

7.3. Sampling of bandlimited functions

7.3.1. The spectrum of interpolated signals

7.3.1.0.1. Sinc interpolation the ingredients:

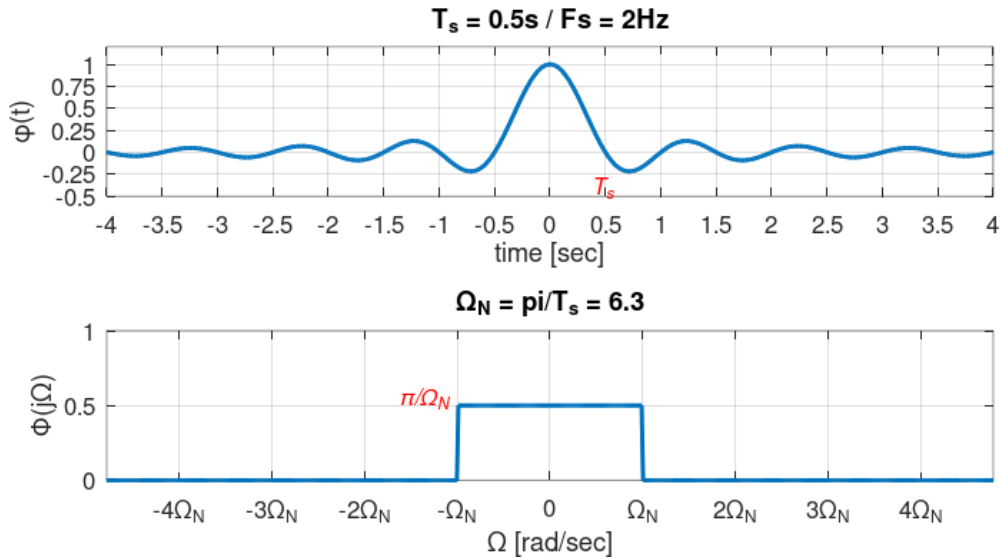
- discrete-time signal $x[n]$, $n \in \mathbb{Z}$ (with DTFT $X(e^{j\omega})$)
- interpolation interval T_s
- the sinc function (properly scaled to have zero crossing at multiple of T_s the result
- a smooth, continuous-time signal $x(t)$, $t \in \mathbb{R}$

What does the spectrum of $x(t)$ look like?

7.3.1.0.2. Key Facts about the sinc

$$\phi(t) = \text{sinc}\left(\frac{t}{T_s}\right) \longleftrightarrow \Phi(j\Omega) = \frac{\pi}{\Omega_N} \text{rect}\left(\frac{\Omega}{2\Omega_N}\right)$$

$$T_s = \frac{\pi}{\Omega_N} \quad \Omega_N = \frac{\pi}{T_s}$$



7.3.1.0.3. Sinc interpolation

$$x(t) = \sum_{n=-\infty}^{\infty} x[n] \text{sinc}\left(\frac{t - nT_s}{T_s}\right)$$

7.3.1.0.4. Spectral representation (I)

$$\begin{aligned} X(j\Omega) &= \int_{-\infty}^{\infty} x(t) e^{-j\Omega t} dt \\ &= \int_{-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x[n] \text{sinc}\left(\frac{t - nT_s}{T_s}\right) e^{-j\Omega t} dt \\ &= \sum_{n=-\infty}^{\infty} x[n] \int_{-\infty}^{\infty} \text{sinc}\left(\frac{t - nT_s}{T_s}\right) e^{-j\Omega t} dt \\ &= \sum_{n=-\infty}^{\infty} x[n] \left(\frac{\pi}{\Omega_N}\right) \text{rect}\left(\frac{\Omega}{2\Omega_N}\right) e^{-jnT_s\Omega} \end{aligned}$$

7.3.1.0.5. Spectral representation (II) Let's analyse the formula

$$\begin{aligned} X(j\Omega) &= \sum_{n=-\infty}^{\infty} x[n] \left(\frac{\pi}{\Omega_N}\right) \text{rect}\left(\frac{\Omega}{2\Omega_N}\right) e^{-jnT_s\Omega} \\ &= \left(\frac{\pi}{\Omega_N}\right) \text{rect}\left(\frac{\Omega}{2\Omega_N}\right) \sum_{n=-\infty}^{\infty} x[n] e^{-j(\pi/\Omega_N)\Omega n} \\ &= \begin{cases} \left(\frac{\pi}{\Omega_N}\right) X(e^{j\pi(\Omega/\Omega_N)}) & |\Omega| \leq \Omega_N \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

The DTFT is periodic and the periodic is

$$\sum_{n=-\infty}^{\infty} x[n]e^{-j(\pi/\Omega_N)\Omega n} = \sum_{n=-\infty}^{\infty} x[n]e^{-j\omega n}, \text{ with } \omega = 2 \cdot \Omega_N$$



Spectrum of Sinc-Sampling



The spectrum of $x(t)$ is equal to the scaled version of the DTFT of the sequence between $-\Omega_N$ and Ω_N .

7.3.2. The space of bandlimited functions

Claims:

- the space of Ω_N – *bandlimited* functions is a Hilbert space
- the functions $\phi^{(n)}(t) = \text{sinc}((t - n)/T_s)$, with $n \in \mathbb{Z}$ form a basis for the space
- if $x(t)$ is π –BL the sequence $x[n] = x(nT_s)$, with $n \in \mathbb{Z}$, is a sufficient representation, i.e. we can reconstruct $x(t)$ from $x[n]$

The space π – BL

- is a vector space because π – BL $\subset L_2(\mathbb{R})$
- inner product is standard inner product in $L_2(\mathbb{R})$
- completeness... that's more delicate



Basis for π – BL



The sinc function $\text{sinc}\left(\frac{t - nT_s}{T_s}\right)$ is an orthonormal basis for the π – BL space.

Inner product:

$$\langle x(t), y(t) \rangle = \int_{-\infty}^{\infty} x(t)y(t)dt$$

Convolution:

$$(x * y)(t) = \langle x * (\tau), y(t - \tau) \rangle$$

A basis for the π – BL space

$$\phi^{(M)}(t) = \text{sinc}(t - n), \text{ for } M \in \mathbb{Z}$$

$$FT \text{sinc}(t) = \text{rect}\left(\frac{\Omega}{2\pi}\right)$$

$$(\text{sinc} * \text{sinc})(m - n) = \begin{cases} 1 & \text{for } m = n \\ 0 & \text{otherwise} \end{cases}$$

7.3.3. The sampling Theorem

7.3.3.0.1. Sampling as a basis expansion To see sampling as an orthonormal expansion, we take our sample of orthonormal vectors $\phi^{(n)}$, taking a product with x and we look what comes out.

Analysis Formula

$$x[n] = \langle \text{sinc}\left(\frac{t - nT_s}{T_s}\right), x(t) \rangle = T_s x(nT_s)$$

Synthesis Formula

$$x(t) = \frac{1}{T_s} \sum_{n=-\infty}^{\infty} x[n] \text{sinc}\left(\frac{t - nT_s}{T_s}\right)$$

- the space of Ω_N – *bandlimited* functions is a Hilbert space
- set $T_s = \pi/\Omega_N$
- the functions $\phi^{(n)}(t) = \text{sinc}((t - nT_s)/T_s)$ form a basis for the space
- for any $x(t) \in \Omega_N - BL$ the coefficients in the sinc basis are the (scaled) samples $T_s x(nT_s)$



Corollary

for any $x(t) \in \Omega_N - BL$, a sufficient representation is the sequence $x[n] = x(nT_s)$



The sampling theorem in Hertz

Any signal $x(t)$ bandlimited to F_N Hz can be sampled with no loss of information using a sampling frequency $F_s \geq 2F_N$ (i.e. sampling period $T_s \leq 1/2 F_N$)

7.4. Sampling of nonbandlimited functions

7.4.1. Raw Sampling

Raw sampling is when we don't care about first taking the inner product with the sinc function. So we just take $x(t)$ and every T_s seconds, we take a sample.

The continuous-time complex exponential

$$x(t) = e^{j\Omega_0 t}$$

- always periodic, period $T = \frac{2\pi}{\Omega_0}$
- all angular speeds are allowed
- $FT \{e^{j\Omega_0 t}\} = 2\pi\delta(\Omega - \Omega_0)$
- bandlimited to Ω_0

Table 7.3.: Aliasing

sampling period	digital frequency	$\{\hat{x}\}$
$T_s < \pi/\Omega_0$	$0 < \omega_o < \pi$	$e^{j\Omega_0}$
$\pi/\Omega_0 < T_s < 2\pi/\Omega_0$	$\pi < \omega_o < 2\pi$	$e^{j\Omega_1}: \Omega_1 = \Omega_0 - 2\pi/T_s$
$T_s > 2\pi/\Omega_0$	$\omega_o > 2\pi$	$e^{j\Omega_2}: \Omega_2 = \Omega_0 \bmod(2\pi/T_s)$

7.4.2. Sinusoidal Aliasing

$$x(t) = \cos(2\pi F_o t)$$

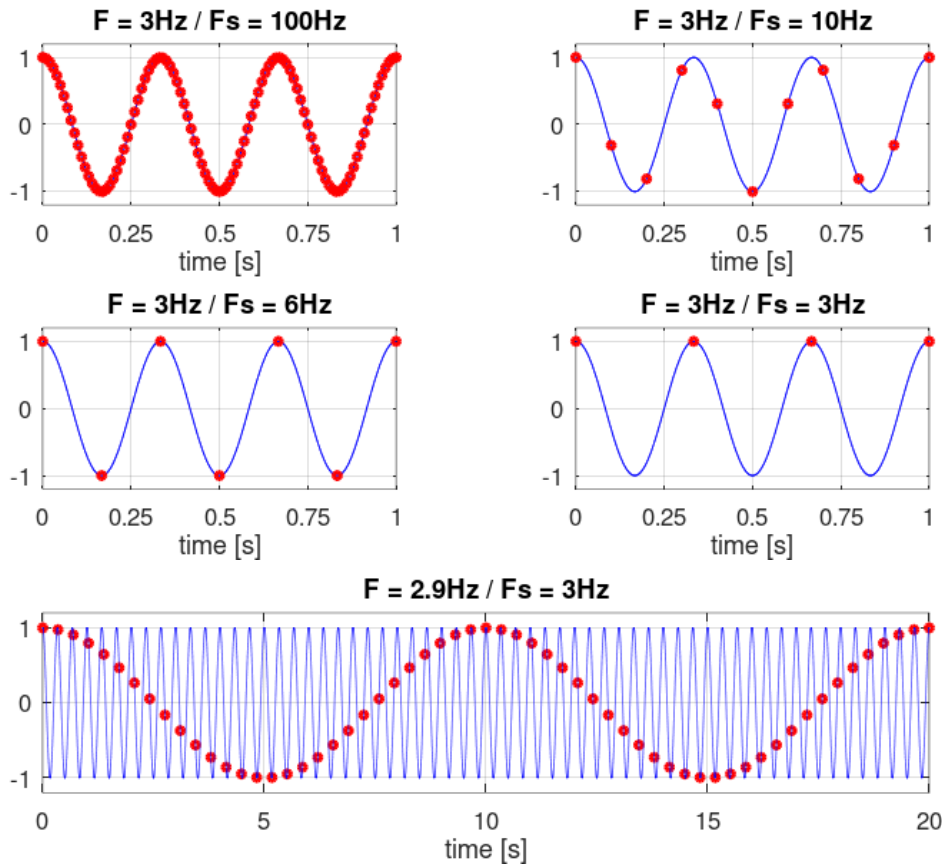
$$x[n] = x(nT_s) = \cos(\omega_o n)$$

with

$$F_s = \frac{1}{T_s}$$

$$\omega_o = 2\pi\left(\frac{F_o}{F_s}\right)$$

7.4.2.1. Aliasing: Sampling a Sinusoid



7.4.3. Aliasing for arbitrary spectra

A continuous time signal x_c sampled every T_s seconds gives a sequence $x[n]$. Which is equal to the continuous time signals at multiples of the sampling intervals T_s .

- $x_c(t) \Rightarrow x[n] = x_c(nT_s)$

In Fourier Transform domain we have a spectra of the continuous time signal $X_c(j\Omega)$. And at the output we have a discrete time Fourier Transform of the sequence $X(j\omega)$. What is that going to be in general? And how is it going to be related to the input spectrum?

- $X(j\Omega) \Rightarrow X(j\omega) = ?$

The key idea:

- pick T_s and set $\Omega_N = \pi/T_s$
- pick $\Omega_0 < \Omega_N$

$$\begin{aligned}
 e^{j\Omega_0 t} &\rightarrow e^{j\Omega_0 T_s n} \\
 e^{j(\Omega_0 + 2\Omega_N)t} &\rightarrow e^{j(\Omega_0 + 2\Omega_N)T_s n}, \text{ add } 2\Omega_N \\
 e^{j(\Omega_0 + 2\Omega_N)t} &\rightarrow e^{j(\Omega_0 T_s n + 2\Omega_N T_s n)}, \text{ expand this product} \\
 e^{j(\Omega_0 + 2\Omega_N)t} &\rightarrow e^{j(\Omega_0 T_s n + \frac{2\pi}{T_s} T_s n)} \\
 e^{j(\Omega_0 + 2\Omega_N)t} &\rightarrow e^{j(\Omega_0 T_s n + 2\pi n)}, e^{j2\pi n} \text{ is equal to one} \\
 e^{j(\Omega_0 + 2\Omega_N)t} &\rightarrow e^{j\Omega_0 T_s n}, \text{ the same discrete time sequence as before}
 \end{aligned}$$

So we do not see the higher frequency complex exponential, it simply looks like the lower frequency exponential Ω_0 .



Aliasing



So in general, if we have two frequencies sampled, the higher frequency is aliased back onto the lower frequency and we simply see the sum of these two.

7.4.3.0.1. Spectrum of raw-sampled signals

- start with the inverse Fourier Transform

$$x[n] = x_c(nT_s) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X_c(j\Omega) e^{j\Omega M T_s} d\Omega$$

- frequencies $2\Omega_N$ apart will be aliased, so split the integration interval

$$x[n] = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \int_{(2k-1)\Omega_N}^{(2k+1)\Omega_N} X_c(j\Omega) e^{j\Omega M T_s} d\Omega$$

- with a change of variable and using $e^{j(\Omega + 2k\Omega_N)T_s M} = e^{j\Omega T_s M}$

$$x[n] = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \int_{-\Omega T_s M}^{\Omega T_s M} X_c(j(\Omega - 2k\Omega_N)) e^{j\Omega M T_s} d\Omega$$

- interchange summation and integral

$$x[n] = \frac{1}{2\pi} \int_{-\Omega T_s M}^{\Omega T_s M} \left[\sum_{k=-\infty}^{\infty} X_c(j(\Omega - 2k\Omega_N)) \right] e^{j\Omega M T_s} d\Omega$$

- periodization of the spectrum; define

$$\tilde{X}_c(j\Omega) = \sum_{k=-\infty}^{\infty} X_c(j(\Omega - 2k\Omega_N))$$

- so that

$$x[n] = \frac{1}{2\pi} \int_{-\Omega T_s M}^{\Omega T_s M} \tilde{X}_c(j\Omega) e^{j\Omega M T_s} d\Omega$$

- set $\omega = \Omega T_s$

$$\begin{aligned} x[n] &= \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{1}{T_s} \tilde{X}_c(j\frac{\omega}{T_s}) e^{j\omega M} d\omega \\ &= IDTFT \left\{ \frac{1}{T_s} \tilde{X}_c(j\frac{\omega}{T_s}) \right\} \\ X(e^{j\omega}) &= \frac{1}{T_s} \sum_{k=-\infty}^{\infty} \tilde{X}_c \left(j\frac{\omega}{T_s} - j\frac{2\pi k}{T_s} \right) \end{aligned}$$

$$X(e^{j\omega}) = \frac{1}{T_s} \sum_{k=-\infty}^{\infty} \tilde{X}_c \left(j\frac{\omega}{T_s} - j\frac{2\pi k}{T_s} \right)$$

7.4.3.0.2. TODO Example: signal bandlimited to Ω_0 and $\Omega_N > \Omega_0$

7.4.3.0.3. TODO Example: signal bandlimited to Ω_0 and $\Omega_N = \Omega_0$

7.4.3.0.4. TODO Example: signal bandlimited to Ω_0 and $\Omega_N < \Omega_0$

7.4.3.0.5. TODO Example: non-bandlimited signal

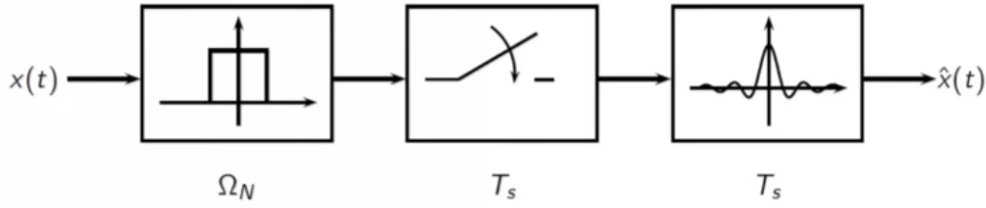
7.4.4. Sampling strategies

given a sampling period T_s

- if the signal is bandlimited to π/T_s or less, raw sampling is fine i.e. equivalent to sinc sampling up to scaling factor T_s .
- if the signal is not bandlimited, two choices:
 - bandlimit via lowpass filter in the *continuous-time domain* before sampling i.e. sinc sampling
 - or raw sample the signal and incur aliasing
- aliasing sounds horrible, so usually we choose to bandlimit in continuous time

7.4.4.0.1. Sinc Sampling and Interpolation

$$\begin{aligned} \hat{X}[n] &= \langle \text{sinc} \left(\frac{t - nT_s}{T_s} \right), x(t) \rangle = (\text{sinc} T_s * x)(nT_s) \\ \hat{X}[n] &= \sum_n x[n] \text{sinc} \left(\frac{t - nT_s}{T_s} \right) \end{aligned}$$



7.5. Quantization

7.5.1. Stochastic signal processing

7.5.1.1. Terminology (from W.Smith)

Mean, Average

$$\mu = \frac{1}{N} \sum_{i=0}^{N-1} x_i = (x_0 + x_1 + x_2 + \dots + x_{N-1})/N$$

In electronics, the mean is commonly called the **DC** (direct current) value. Likewise, **AC** (alternating current) refers to how the signal fluctuates around the mean value. For simple repetitive waveform, its excursion can be described by its peak-to-peak value. If the signal has a random nature, a more generalized method must be used.

Standard Deviation

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2} = \sqrt{(x_0 - \mu)^2 + (x_1 - \mu)^2 + \dots + (x_{N-1} - \mu)^2 / (N-1)}$$

$|x_i - \mu|$ describes how far the i^{th} sample **deviates** (differs) from the mean. The **average deviation** of a signal is found by summing the deviations of all the individual samples, and then dividing by the number of samples N. We take the absolute value of each deviation before summation; otherwise the positive and the negative terms would average to zero.

The **standard deviation** is similar to the average deviation, except the averaging is done with power instead of amplitude.

The standard deviation is a measure of how far the signal fluctuates from the mean.

Variance

$$\sigma^2 = \frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2$$

The variance represents the power of signal fluctuation from the mean.

RMS Root Mean Square The standard deviation measures only the AC portion of a signal, while rms value measures both the AC and DC components. If a signal has no DC component, its rms value is identical to its standard deviation.

SNR Signal to Noise Ratio

$$snr = \frac{\text{mean}}{\text{standard deviation}} = \frac{\mu}{\sigma} = \frac{\frac{1}{N} \sum_{i=0}^{N-1} x_i}{\sqrt{\frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2}}$$

CV Coefficient Variation

$$CV = \frac{\text{standard deviation}}{\text{mean}} \times 100 = \frac{\sqrt{\frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \mu)^2}}{\frac{1}{N} \sum_{i=0}^{N-1} x_i} \times 100$$

Probability Density Function PDF The probability density function is a measure of the likelihood of a particular value occurring in some function.

- PDF values are never negative $f(x) \geq 0$
- The sum of all the PDF values is one: $\int_{-\infty}^{\infty} f(x)dx = 1$
- Mean: $\mu_x = \int_{-\infty}^{\infty} x \cdot f(x)dx$
- Variance: $\mu_x^2 = \int_{-\infty}^{\infty} (x - \mu)^2 \cdot f(x)dx = \int_{-\infty}^{\infty} x^2 \cdot p(x)dx - \mu_x^2$

7.5.1.2. TODO Deterministic vs. stochastic

7.5.1.3. A simple discrete-time random signal generator

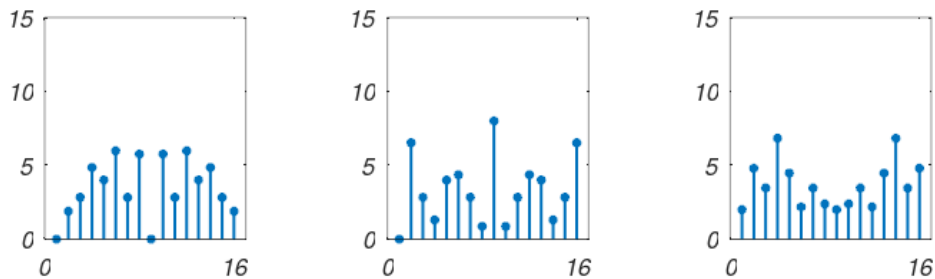
For each new sample, toss a fair coin:

$$x[n] = \begin{cases} +1 & \text{if the outcome of the n-th toss is head} \\ -1 & \text{if the outcome of the n-th toss is tail} \end{cases}$$

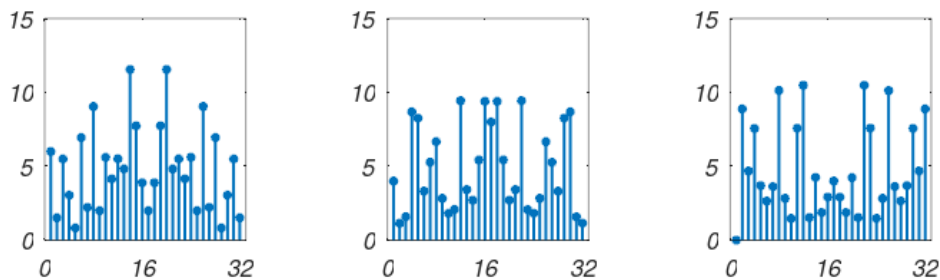
- each sample is independent from all others
- each sample value has 50% probability
- every time we turn on the generator we obtain a different *realization* of the signal
- we know the "mechanics" behind each instance
- but how can we analyze a random signal?

7.5.1.4. Spectral Properties

- let's try with the DFT of a finite set of random samples



- every time it's a different
- try with more data



- no clear pattern

7.5.1.5. Averaging

- when faced with random data an intuitive response is to take "averages"
- in probability theory the average is across realizations and it's called [Expectation](#)
- Expectation for the coin-toss signal

$$E[x[n]] = -1 \times P[\text{n-th toss is tail}] + 1 \times P[\text{n-th toss is head}] = 0$$

- so the average value for each sample is zero....
- as a consequence, averaging the DFT will not work
- $E[x[n]] = 0$
- however the signal "moves", so its energy over power must be nonzero

7.5.1.6. TODO Averaging the DFT**7.5.1.7. Energy and power**

- the coin-toss signal has infinite energy

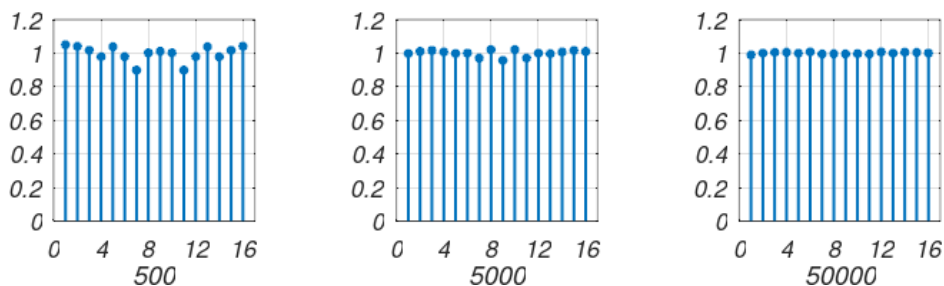
$$E_x = \sum_{k=-\infty}^{\infty} |x[n]|^2 = \lim_{N \rightarrow \infty} = \infty$$

- however it has finite power over any interval:

$$P_x = \lim_{N \rightarrow \infty} \frac{1}{2N+1} \sum_{n=-N}^N |x[n]|^2 = 1$$

7.5.1.8. Averaging the DFT's square magnitude, normalized

- pick an interval length N
- pick an number of iterations M
- run the signal generator M times and obtain M N-point realizations
- compute the DFT of each realizations
- average their square magnitude divided by N



7.5.1.9. Power spectral density

Power Spectral Density

$$P[k] = E \left[|X_N[k]|^2 / N \right]$$

- it looks very much as if $P[k] = 1$
- if $|X_N[k]|^2$ tends to the *energy* distribution in frequency...
- ... $|X_N[k]|^2 / N$ tends to the *power* distribution (aka **density**) in frequency

**PSD**

The frequency-domain representation for stochastic processes is the power spectral density:

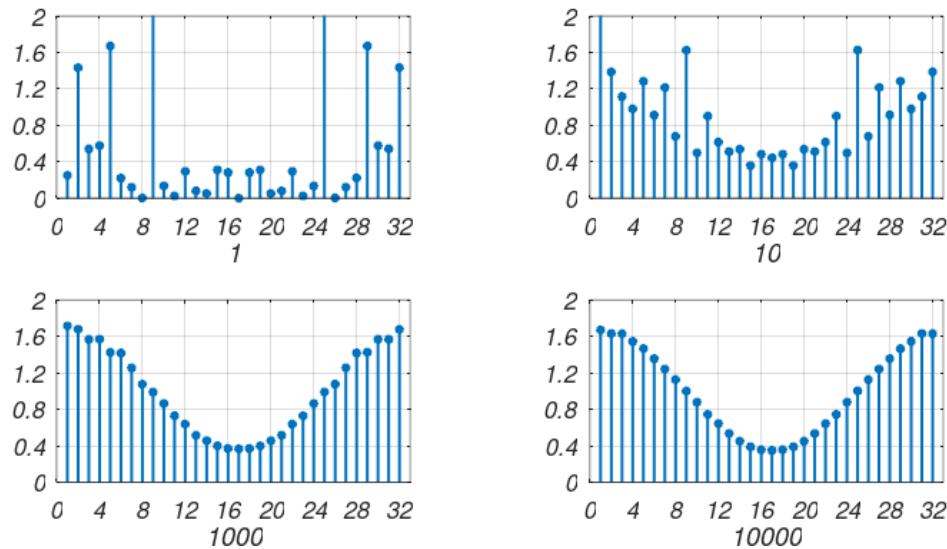
$$P[k] = \left| \frac{1}{N} X_N[k] \right|^2$$

7.5.1.10. Power spectral density: Intuition

- $P[k] = 1$ means that the power is equally distributed over all frequencies
- i.e. we cannot predict the signal moves "slowly" or "super-fast"
- this is because each sample is independent of each other: we could have a realization of all ones or a realization in which the sign changes every other sample or anything in between.

7.5.1.11. Filtering a random process

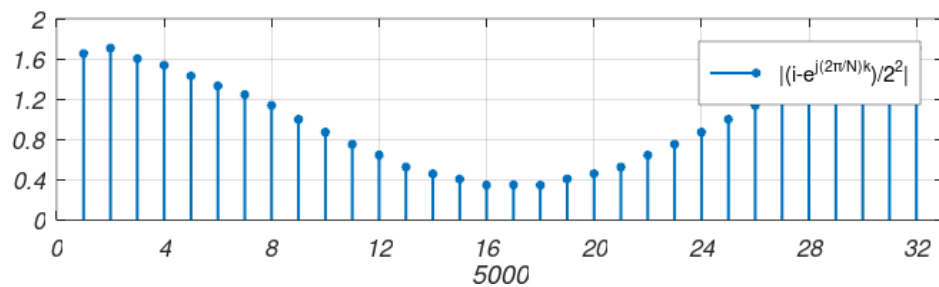
- let's filter the random process with a 2-point Moving Average filter
- $y[n] = (x[n] + x[n-1])/2$
- what is the power spectral density
- pick an interval length N
- pick an number of iterations M
- run the signal generator M times and obtain M N -point realizations
- filter all M -realization
- compute the DFT of each filtered realizations
- average their square magnitude divided by N



The frequency response of the moving average filter

$$H(e^{j\omega}) = \frac{1 - e^{j\omega}}{2}$$

whereas the plotted shape is nothing but the square magnitude of the moving average filter evaluated at the DFT point $\frac{2\pi}{N}k$



7.5.1.12. Stochastic signal processing

- a stochastic process is characterized in frequency by its power spectral density (PSD)
- it can be shown (see text book) that the PSD is the DTFT of the autocorrelation of the process:

$$P_x(e^{j\omega}) = DTFT\{r_x[n]\}$$

where each sample of the [autocorrelation](#) is obtained by taking the Expectation of the product of the stochastic signal times a delayed copie of itself:

$$r_x[n] = E[x[k]x[n+k]]$$

- for a filtered stochastic process $y[n] = H\{x[n]\}$ the general result is that the power spectral density (PSD) is equal to the PSD of the input times the frequency response in magnitude square.

$$P_y(e^{j\omega}) = |H(e^{j\omega})|^2 P_x(e^{j\omega})$$



General Result for a Stochaistic Process



The power spectral density of the output of a LTI system is equal to the power spectral density of the input times squared magnitude of the Fourier transform of the filter frequency response.

- Key Results**
- filters designed for deterministic signals work (in magnitude) in the stochastic case
 - we lose the concept of phase since we don't know the shape of a realization in advance. All we know is the PSD in frequency

7.5.1.13. Noise

- Noise is everywhere**
- thermal noise
 - sum of extraneous interferences
 - quantization and numerical errors
 - ...

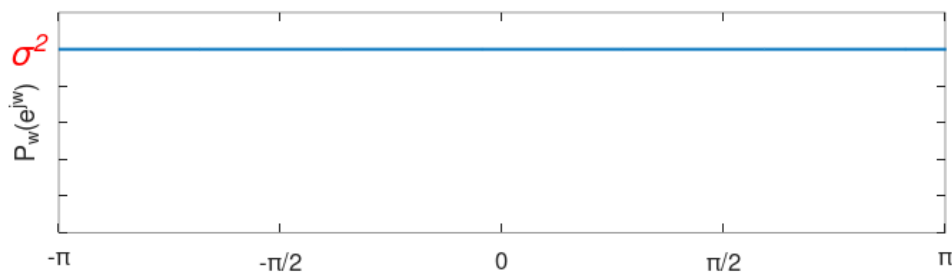
we can model noise as a stochastic signal

the most important noise is white noise

7.5.1.14. White noise

- white indicates uncorrelated samples
- $r_w[n] = \sigma^2 \delta[n]$: The autocorrelation is zero except at zero where it will take the value of the variance
- $P_w(e^{j\omega}) = \sigma^2$: The power spectral density is the constant σ^2 where σ is the variance of the stochastic signal.

Graphically the power spectral density of a white signal couldn't be any simpler.



- the PSD is independent of the probability distribution of the **single** samples (depends only on the variance)
- distribution is important to estimate bounds for the signal
- very often a Gaussian distribution models the experimental data the best
- **AWN**: additive white Gaussian noise



Power Spectral Density



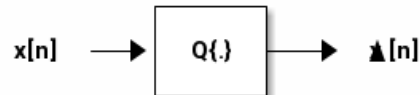
- The PSD of a random signal is the average squared magnitude of its Fourier transform. The average is taken across multiple realizations of the process.
- The PSD is the Fourier transform of the autocorrelation function
- The PSD of the output of a LTI system is the product of the PSD of the input and squared

, magnitude of the Fourier transform of the filter frequency response.

7.5.2. Quantization

7.5.2.1. Quantization schemes

- digital devices can only deal with integers (b bits per sample)
- we need to map the range of a signal onto a finite set of values
- irreversible loss of information → [Quantization Noise](#)



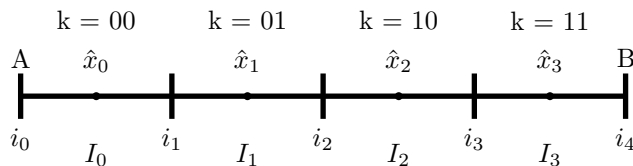
Several factors at play:

- storage budget (bits per sample)
- storage scheme (fixed point, floating point)
- properties of the input (input $\in \mathbb{C} \rightarrow$ output $\in \mathbb{N}$)

7.5.2.2. Scalar quantization

The simplest quantizer:

- each sample is encoded individually (hence scalar)
- each sample is quantized independently (memoryless quantization)
- each sample is encoded using R bits



- what are the optimal interval boundaries I_k ?
- what are the optimal quantization values \hat{x}_k ?

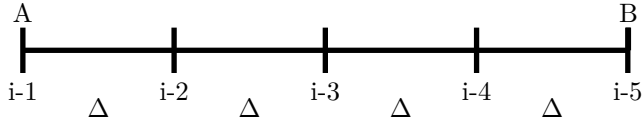
7.5.2.3. Quantization Error

$$e[n] = Q\{x[n]\} - x[n] = \hat{x}[n] - x[n]$$

- model $x[n]$ as a stochastic process
- model error as a white noise sequence
 - error samples are uncorrelated
 - all error samples have the same distribution
- we need statistics of the input to study the error

7.5.2.3.1. Uniform quantization

- simple but very general case
- range is split into 2^R equal intervals of width $\Delta = (B - A)2^{-R}$
- $f_x(\tau)$: PDF of the input
- **With a Bit-Rate R of 2 bits** is a region split into 4 equally spaced intervals



Mean Square Error is the variance of the error signal

$$\begin{aligned}
 \sigma_e^2 &= E[|Q\{x[n]\} - x[n]|^2] \\
 &= \int_A^B f_x(\tau)(Q\{\tau\} - \tau)^2 d\tau \\
 &= \sum_{k=0}^{2^R-1} \int_{I_k} f_x(\tau)(\hat{x}_k - \tau)^2 d\tau
 \end{aligned}$$

- $Q\{\tau\} - \tau$: Error function

error depends on the probability density of the input. The calculation is done in the following subsections here we already substitute the results.

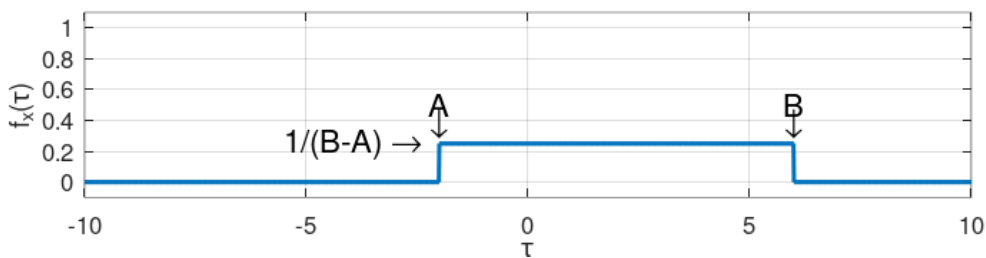
$$\begin{aligned}
 \sigma_e^2 &= \sum_{k=0}^{2^R-1} \int_{A+k\Delta}^{A+(k+1)\Delta} \frac{(A + k\Delta + \Delta/2 - \tau)^2}{B - A} d\tau \\
 &= 2^R \int_0^\Delta \frac{(\Delta/2 - \tau)^2}{B - A} d\tau \\
 &= \frac{\Delta^2}{12} \text{ with } \Delta = \frac{B - A}{2^R}
 \end{aligned}$$

Quantization Error

$$\sigma_e^2 = \frac{\Delta^2}{12} \text{ with } \Delta = \frac{B - A}{2^R}$$

7.5.2.3.2. Uniform quantization of uniform input

Continuous uniform probability density function



February 8, 2022

Signal to Noise Ratio

$$SNR = 2^{2R}$$

Signal to Noise Ratio in db

$$SNR_{db} = 10 \cdot \log_{10} 2^{2R} \approx 6R \text{ db}$$

7.5.3. The 6db/bit rule of thumb

- a compact disk has 16 bits/sample:

$$\max SNR_{db} \approx 6R \text{ db} = 6 \cdot 16 \text{ db} = 96 \text{ db}$$

- a DVD has 24 bits/sample:

$$\max SNR_{db} \approx 6R \text{ db} = 6 \cdot 24 \text{ db} = 144 \text{ db}$$

7.6. Notes and External Resources**7.6.1. TODO Clipping, saturation and interpolation****7.6.2. Practical interpolation and sampling****7.6.2.1. Time Domain to Discrete**

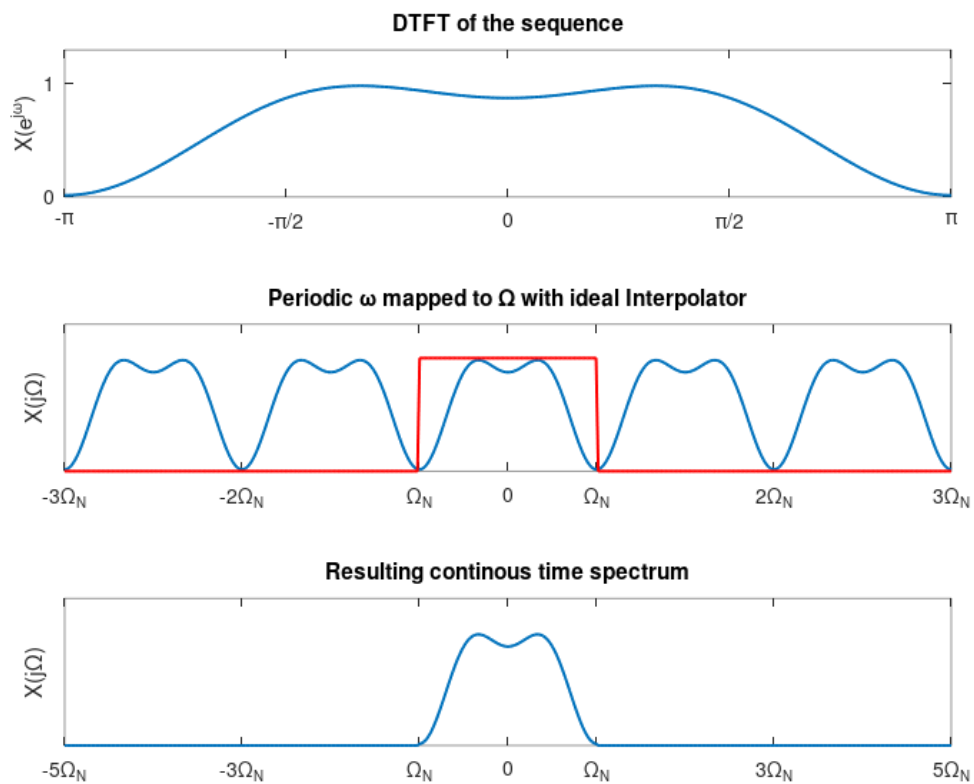
ideally	$x(t) \Rightarrow x[n]$	in practice
$x(t) = \sum_{n=-\infty}^{\infty} x[n] \text{sinc}(t - nT_s)$		$x(t) = \sum_{n=-\infty}^{\infty} x[n] i\left(\frac{t - nT_s}{T_s}\right)$
$X(j\Omega) = \frac{\pi}{\Omega_N} X(e^{j\pi\Omega/\Omega_N}) \text{rect}\left(\frac{\Omega}{2\Omega_N}\right)$		$X(j\Omega) = \frac{\pi}{\Omega_N} I\left(j\pi\frac{\Omega}{\Omega_N}\right) X(e^{j\pi\frac{\Omega}{\Omega_N}})$

7.6.2.2. Discrete to Time Domain

ideally	$x[n] \Rightarrow x(t)$	in practice
$x(t) = \sum_{n=-\infty}^{\infty} x[n] \text{sinc}\left(\frac{t - nT_s}{T_s}\right)$		$x(t) = \sum_{n=-\infty}^{\infty} x[n] i\left(\frac{t - nT_s}{T_s}\right)$
$X(j\Omega) = \frac{\pi}{\Omega_N} X(e^{j\pi\Omega/\Omega_N}) \text{rect}\left(\frac{\Omega}{2\Omega_N}\right)$		$X(j\Omega) = \frac{\pi}{\Omega_N} I\left(j\pi\frac{\Omega}{\Omega_N}\right) X(e^{j\pi\frac{\Omega}{\Omega_N}})$

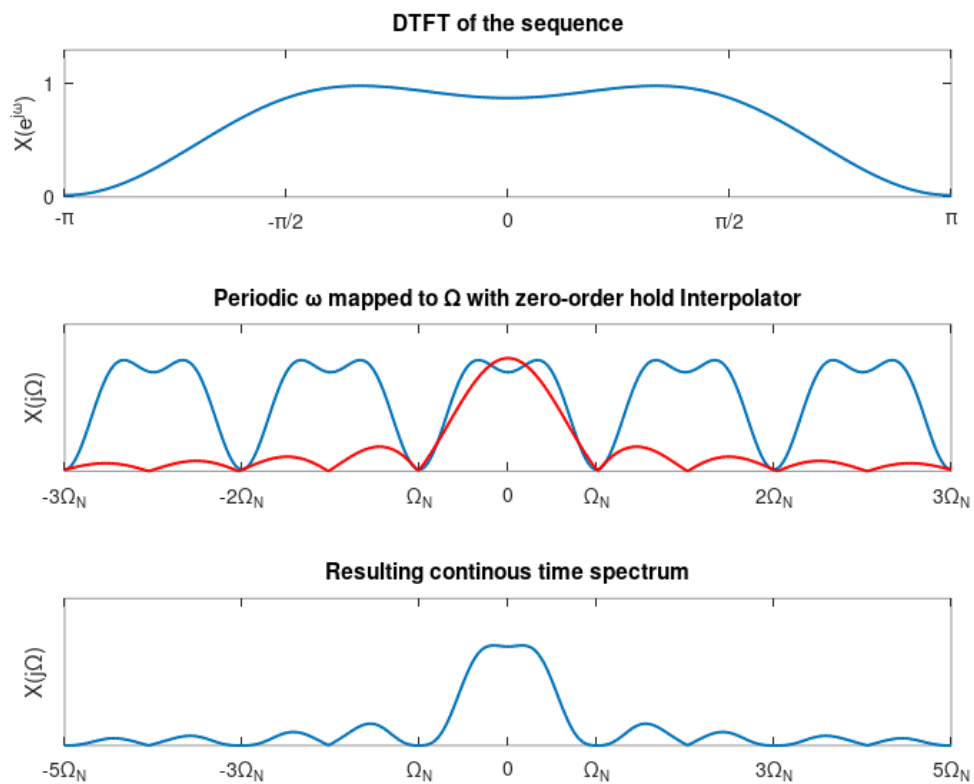
7.6.2.2.1. Ideal Interpolator

- Frequency Domain: Rect
- Time Domain: sinc



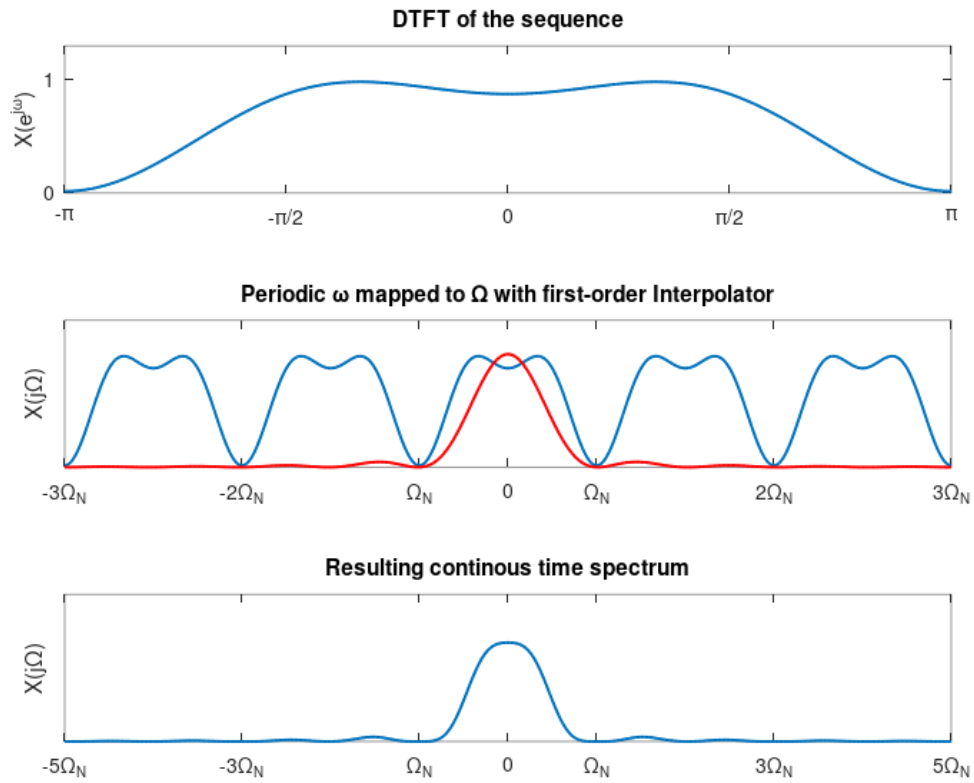
7.6.2.2.2. Zero-Order Hold Interpolator

- Frequency Domain: sinc
- Time Domain: rect



7.6.2.2.3. First-Order Interpolator

- Frequency Domain: sinc^2
- Time Domain: Triangle



7.6.3. TODO Bandpass sampling

7.6.4. Multirate Signal Processing

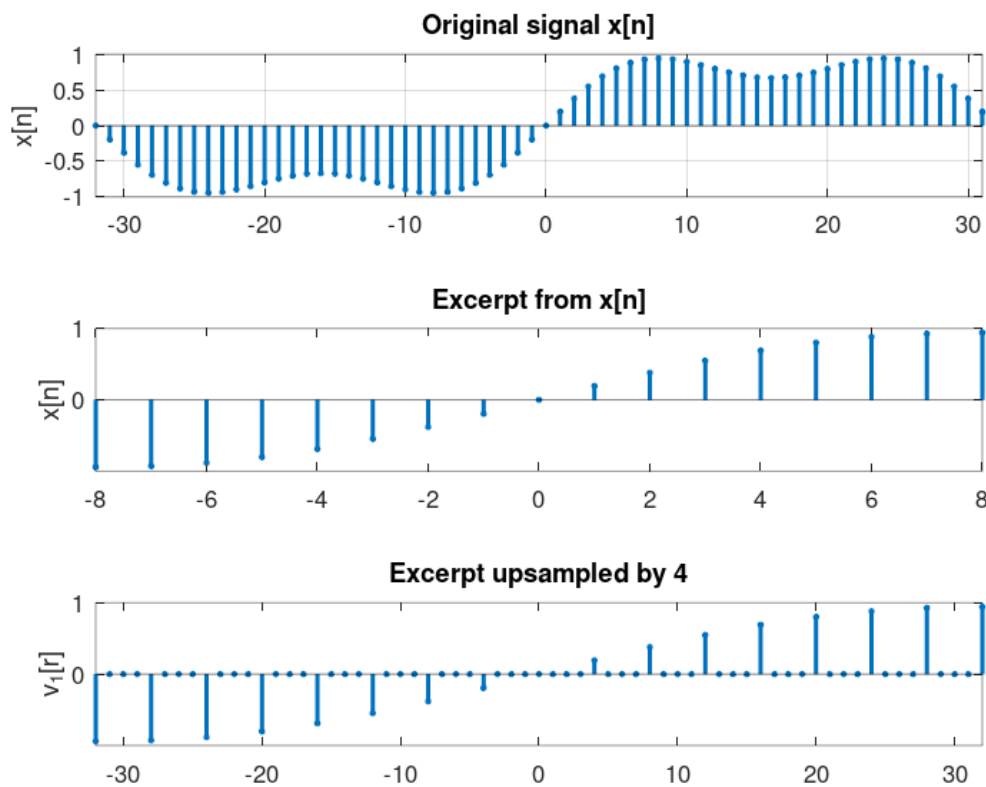
Book: [Multirate Filtering for Digital Signal Processing Matlab Applications](#)

7.6.4.1. Upsampling

$$x_{NU}[n] = \begin{cases} x[k] & \text{for } n = kN, k \in \mathbb{Z} \\ 0 & \text{otherwise} \end{cases}$$

$$x[n] \longrightarrow \textcircled{N \uparrow} \longrightarrow x_{NU}[n]$$

We create an upsampled sequence from any discrete time sequence simply by building a sequence where we output one sample of the original sequence followed by capital N minus 1 samples.

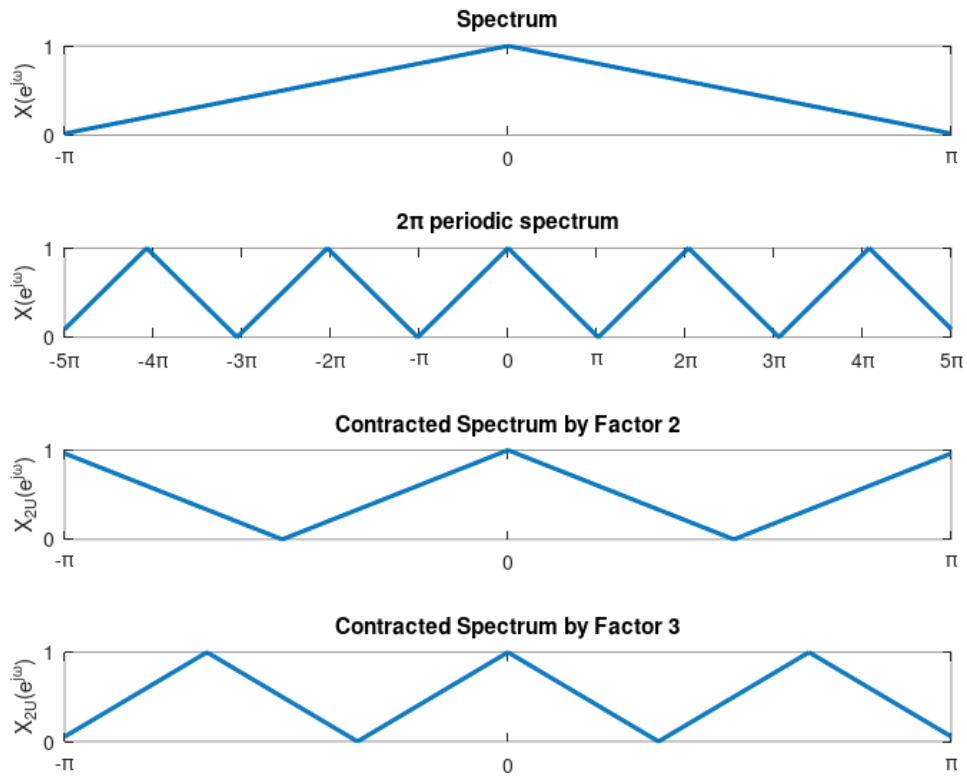


Spectral Representation

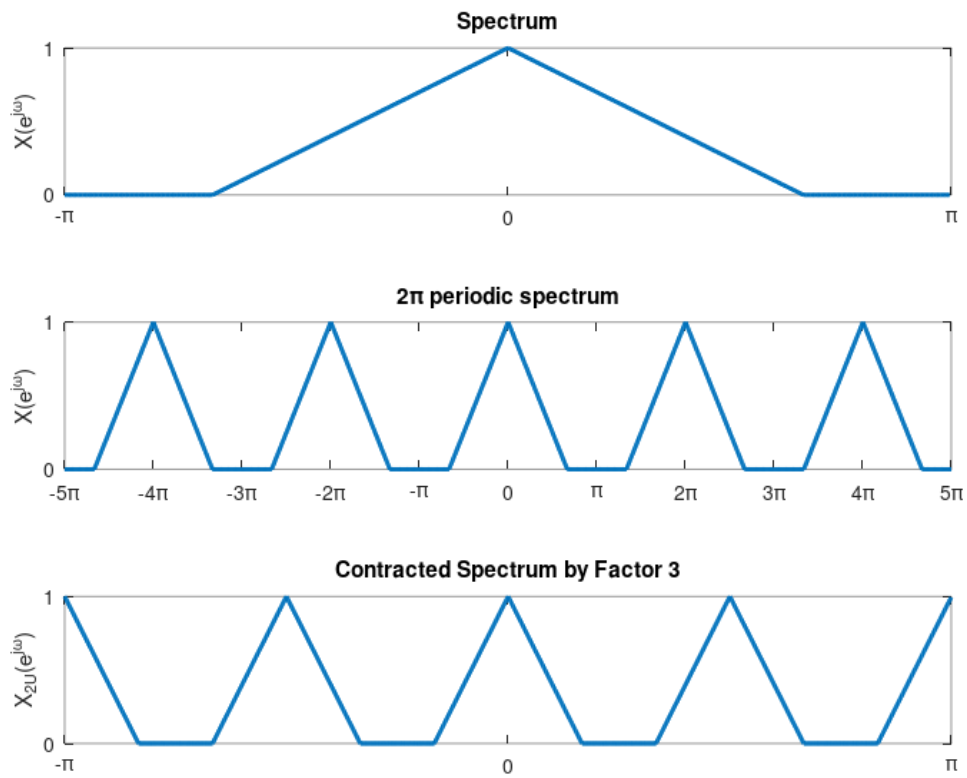
$$X_{NU}(e^{j\omega}) = X(e^{j\omega N})$$

7.6.4.1.1. Spectral Representation

The spectrum of the upsampled sequence is equal to the spectrum of the original sequence contracted by a factor N .



7.6.4.1.2. Non fullband spectrum



7.6.4.1.3. What we don't like

- in the time domain: zeros between nonzero samples are not "natural"
- in the frequency domain: extra replicas of the spectrum; can we get rid of them?

We need to interpolate the signals in the Frequency domain:

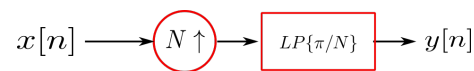
- zero-order hold interpolator
- first-order interpolator

7.6.4.1.4. The ideal digital interpolator

$$H(e^{j\omega}) = \text{rect}\left(\frac{\omega N}{2\pi}\right)$$

$$h[n] = \frac{1}{N} \text{sinc}\left(\frac{n}{N}\right)$$

This can not be achieved but as good as possible add an Low Pass with cut off frequency $\frac{\pi}{N}$,

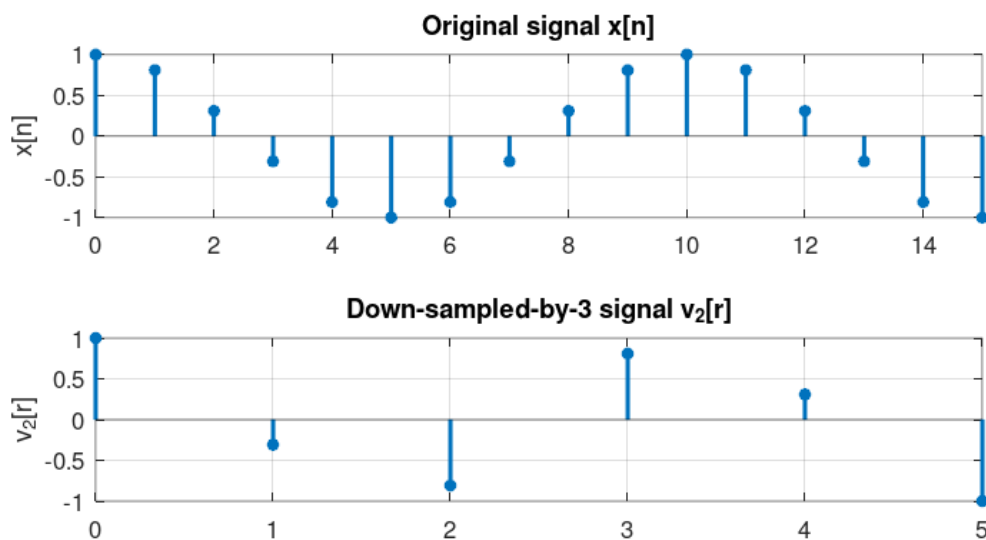


with a discrete time ideal low pass filter with cut off frequency π/N

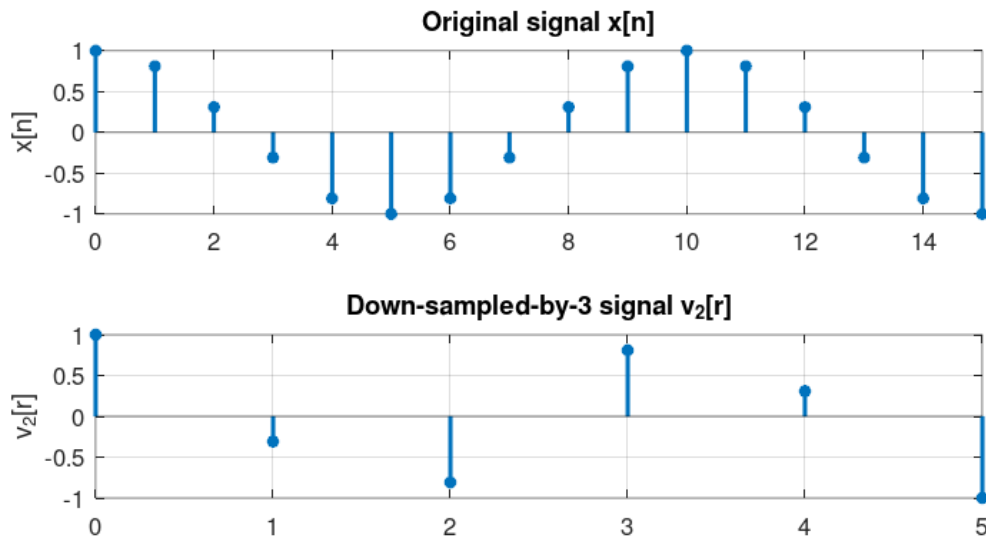
7.6.4.2. Downsampling

$$x_{ND}[n] = x[nN]$$

Every $N - 1$ input sample is discarded resp. only every N -th sample is used.



[[



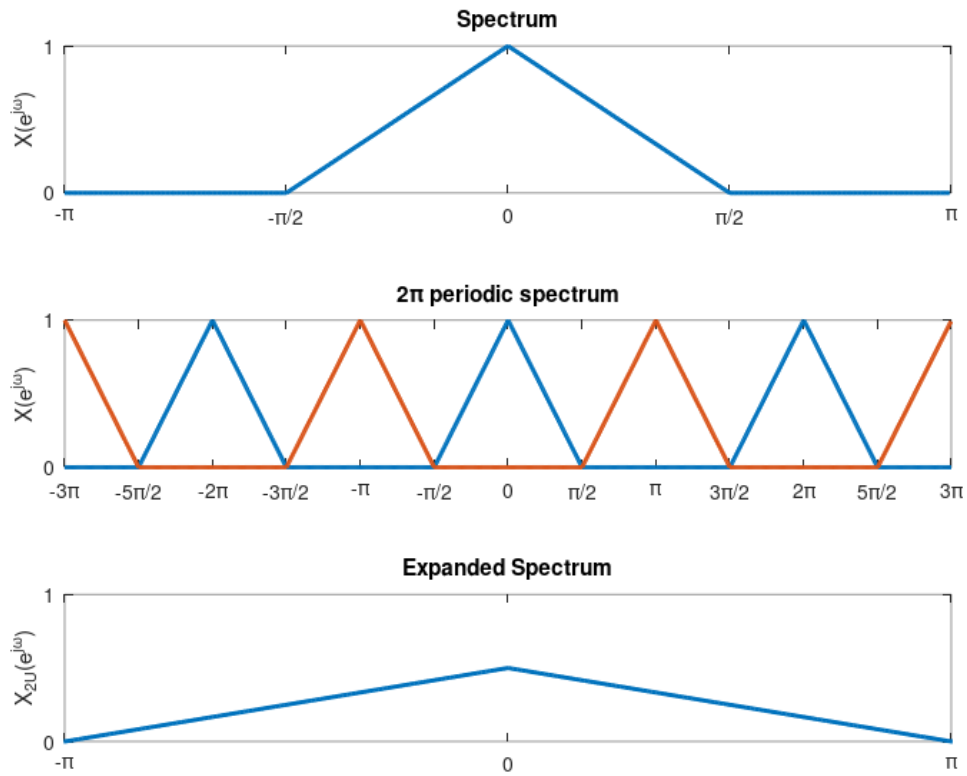
]

Spectral Representation

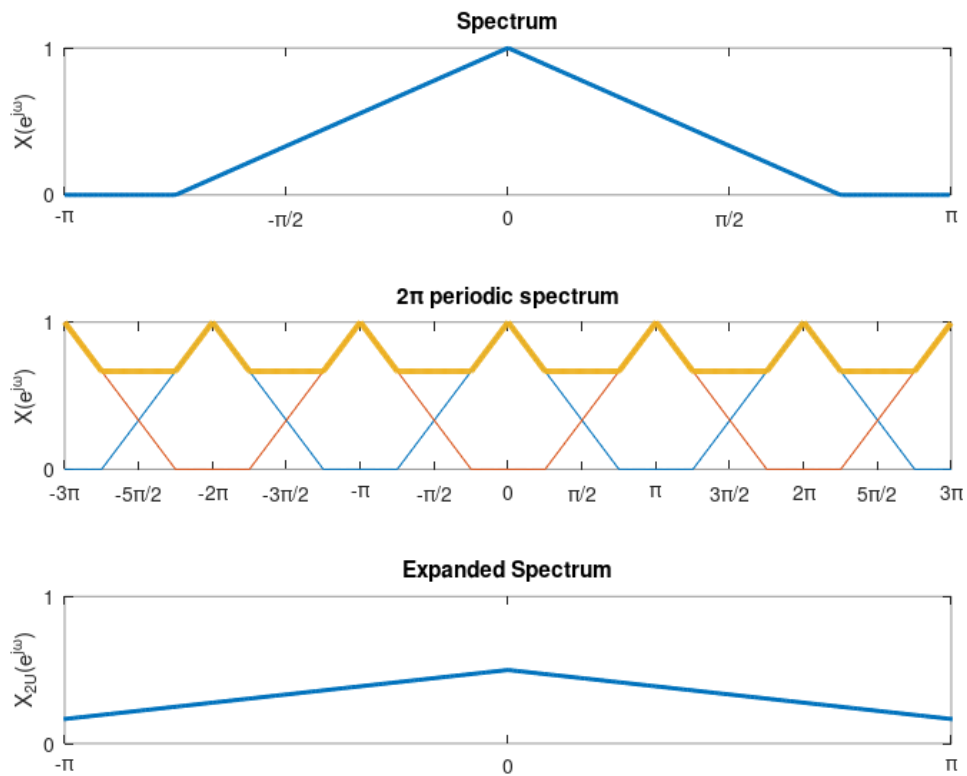
$$X_{ND}(e^{j\omega}) = \frac{1}{N} \sum_{m=0}^{N-1} X(e^{j\frac{\omega - 2\pi m}{N}})$$

7.6.4.2.1. Spectral Representation

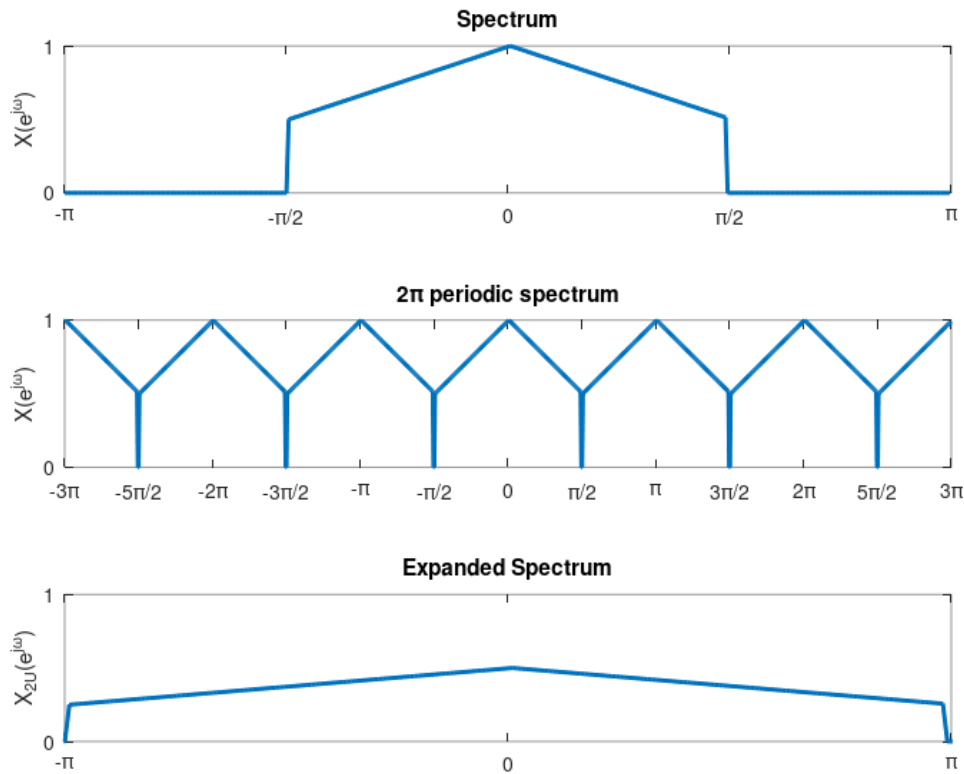
There's $1/N$ normalization factor in front, that multiplies the sum of capital N copies of the original spectrum, where each copy has been shifted by a multiple of $2\pi/N$, and where the frequency axis has been stretched out by a factor of capital N . So the interval $-\pi/N, \pi/N$ becomes the interval $-\pi, \pi$.



7.6.4.2.2. Downsampling by 2 with aliasing



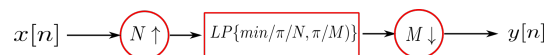
7.6.4.2.3. Downsampling by 2 with antialiasing filter



To avoid aliasing we have to filter the input sequence with a low-pass filter with cutoff frequency π/N , where N is the downsampling factor that will follow.

7.6.4.3. Sampling Rate Change

Downsampling and upsampling change the implicit sampling rate by integer factor. But we can combine them so that the resulting sampling rate change will be an arbitrary fractional number. The combination always goes in the sense that we first upsample the signal, which is the operation that does not change the information content of the original sequence, and then we perform downsampling.



Example:

- CD: $F_s = 44100 \text{ Hz}$
- DVD: $F_s = 48000 \text{ Hz}$
- $\frac{N}{M} = \frac{160}{147}$
- in practice, we use time-varying local interpolation

7.6.5. TODO FIR-based sampling rate conversion

- Sampling rate change through time-varying local interpolation

7.6.5.1. Subsample interpolation

7.6.5.2. 2nd-order Lagrange interpolation polynomials

7.6.5.3. Lagrange interpolation (N=1)

7.6.5.4. CD to DVD revisited

7.6.6. TODO Analog-to-digital and digital-to-analog converters

7.6.7. TODO Oversampling

- Oversampled A/D -> reduce quantization error
- Oversampled D/A -> use cheaper hardware for interpolation

Part VIII.

Week 8 Module 6:

8. Digital Communication Systems

8.1. Introduction to digital communications

8.1.1. The success factors for digital communications

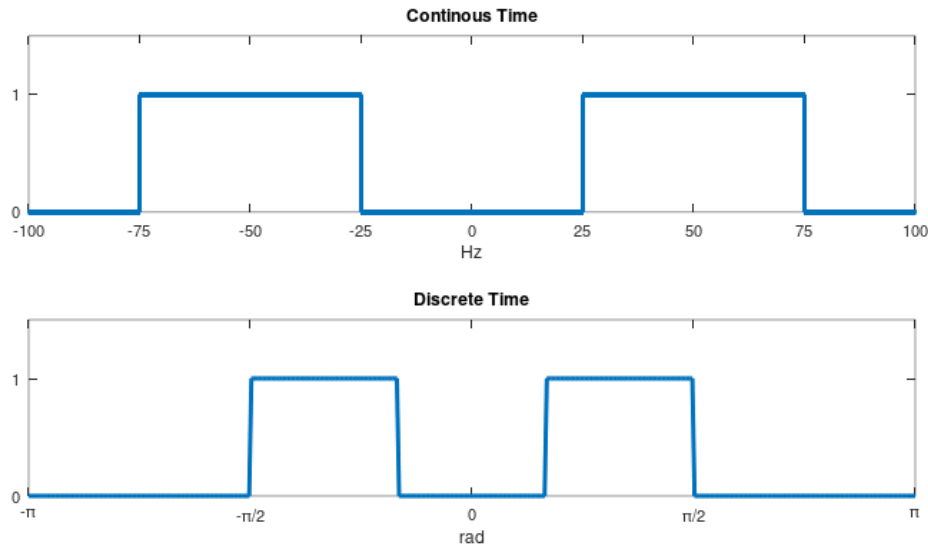
1. Power of the DSP paradigm
 - integers are easy to **regenerate**
 - good phase control
 - adaptive algorithms
2. Algorithmic nature of DSP is a perfect match with information theory:
 - Image Coding: JPEG's entropy coding
 - Encoding of of accustic or video informatiion: CD's and DVD's error correction
 - Communication Systems: trellis-coded modulation and Vierbi coding
3. Hardware advancement
 - minituarization
 - general-purpose platforms
 - power efficiency

8.1.2. The analog channel constraints

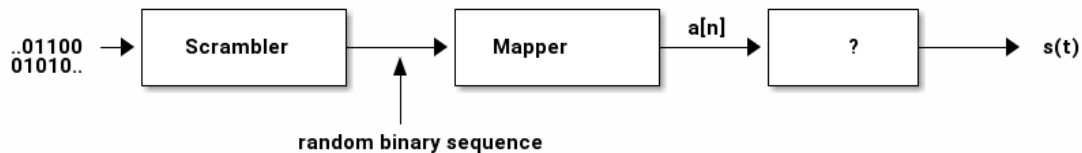
- unescapable "limits" of physical channels:
 - **Bandwith:** the signal that canbe send over a channel has a limited frequency band
 - **Power:** the signal has limited power over this band, e.g. due to power limit of the equipment
- Both constraints will affect the final **capacity** of the channel.
- The maximum amount of information that can be reliably delivered over a channel - bits per second -
- Bandwidth vs. capacity:
 - small sampling period $T_s \Rightarrow$ high capacity
 - but the bandwidth signal grows as $\frac{1}{T_s} \Rightarrow \Omega_N = \frac{\pi}{T_s}$

8.1.3. The design Problem

- We are going to adapt the all-digital paradigm
- Converting the specs to digital design



- with:
 - Sampling Frequency $F_s \geq 2f_{max}$
 - Continuous Time $F_s/2$: Nyquist frequency
 - Maximum Frequency: $\frac{F_s}{2} \Rightarrow \pi$
 - Bandwidth: $\omega_{min,max} 2\pi \frac{f_{min,max}}{F_s}$
- Transmitter design
 - convert a bitstream into a sequence of symbols $a[n]$ via a mapper
 - model $a[n]$ as **white random sequence** \Rightarrow add a **scrambler**
 - now we need to convert $a[n]$ into a continuous-time signal within the constraints



If we assume that the data is randomized and therefore the symbol sequence is a white sequence, we know that the power spectral density is simply equal to the variance. And so the power of the signal will be constant over the entire frequency band. But we actually need to fit it into the small band here as specified by the bandwidth constraint. So how do we do this? Well, in order to do that, we need to introduce a new technique called **upsampling**, and we will see this in the next module.

We are talking about digital communication systems and in this lesson we will talk about how to fulfill the **bandwidth constraint**. The way we are going to do this is by introducing an operation called **upsampling** and we will see how upsampling allows us to fit the spectrum generated by the transmitter onto the band allowed for by the channel.

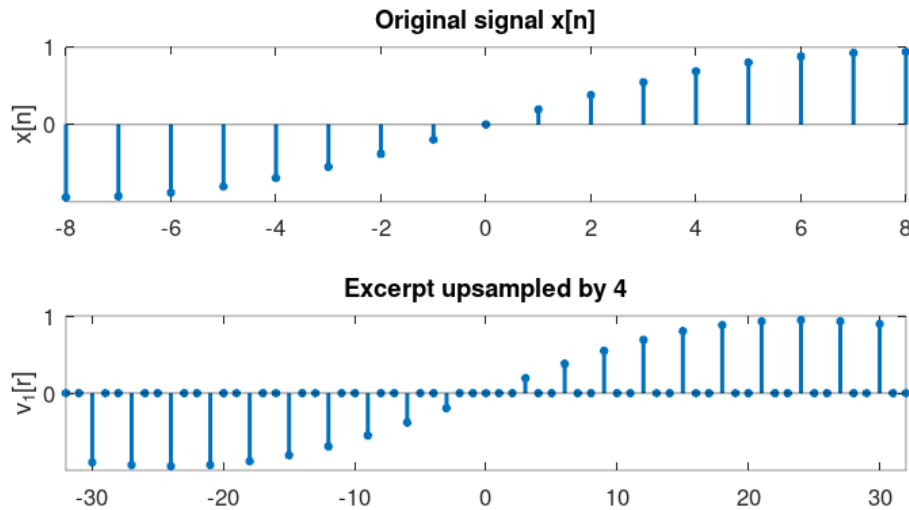
8.2. Controlling the bandwidth

- Shaping the bandwidth Remember that our assumption is that the signal generated by the transmitter is a wide sequence and therefore its power spectral density will be full band. What we need to do is to shrink the support of its power spectral density so.

- the answer is [multirate](#) techniques

8.2.1. Upsampling

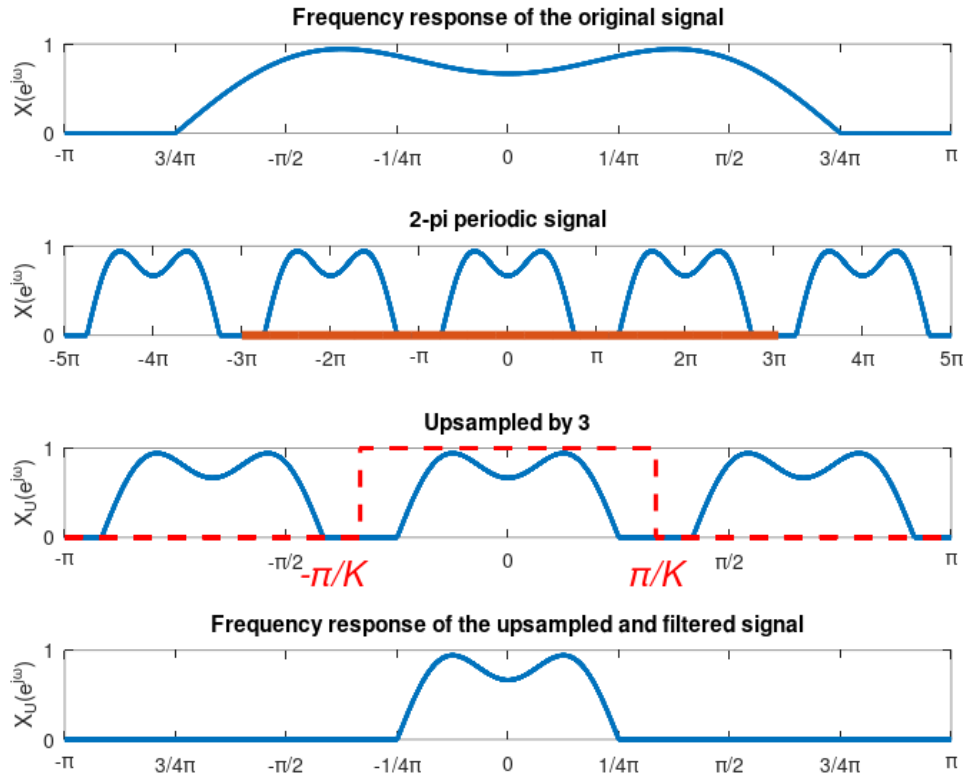
- Our Problem
- bandwidth constraint requires us to control the spectral support of a signal
 - we need to be able to shrink the support of a full-band signal
- Upsampling can be obtained by interpolating a discrete time sequence to get a continuous time signal. And resample the signal with a sampling period which is k-times smaller than the original interpolation sample.
- Or we do it entirely digitally.
 1. we need to "increase" the number of samples by k
 2. obviously $x_U[m] = x[n]$ when m is a multiple of K
 3. for lack of better strategy, put zeros elsewhere
- Upsampling in the time domain



- Upsampling in the digital domain

$$\begin{aligned}
 X_U(e^{j\omega}) &= \sum_{m=-\infty}^{\infty} x_U[m]e^{-j\omega m} \text{ with } x_U = 0 \text{ if } m \neq nK \\
 &= \sum_{m=-\infty}^{\infty} x[n]e^{-j\omega nK} \\
 &= X(e^{j\omega K})
 \end{aligned}$$

This is simply a scaling of the frequency axis by a factor of K. Graphical interpretation: since we are multiplying the frequency axis by a factor of K, there will be a shrinkage of the frequency axis.



- $\frac{\pi}{K}$: *FilterCut – OffFrequency*
- The bandwidth of the signal was shrunk by factor $K=3$: from $\frac{3}{3}\pi$ to $\frac{1}{4}\pi$
- back in the time domain
 1. insert $K-2$ zeros after every sample
 2. ideal lowpass filtering with $\omega_c \Rightarrow \frac{\pi}{K}$

$$\begin{aligned}
 x[n] &= x_U(n) * \text{sinc}(n/K) \\
 &= x_U[i] \text{sinc}\left(\frac{n-i}{K}\right) \\
 &= x[m] \text{sinc}\left(\frac{n}{K} - m\right)
 \end{aligned}$$

8.3. Fitting the transmitter spectrum

The bandwidth constraint says that only frequencies between F_{min} and F_{max} are allowed. To translate it to the digital domain, follow the preceding steps:

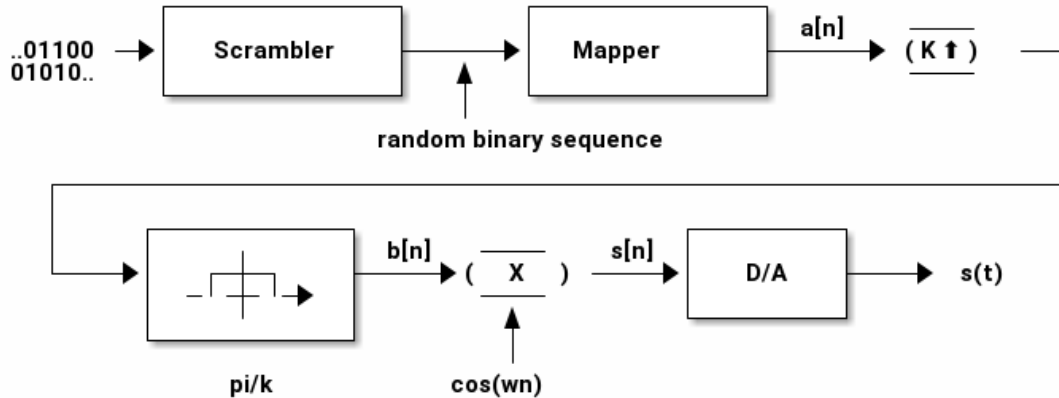
- let $W = F_{max} - F_{min}$
- pick F_s so that:
 - $F_s > 2F_{max}$
 - $F_s = KW, k \in \mathbb{N}$

- $\omega_{max} - \omega_{min} = 2\pi \frac{W}{F_s} = \frac{2\pi}{K}$
- we can simply upsample by K



Bandwith constrainth

- And so we can simply upsample the sample sequence by K, so that its bandwidth will move from 2π to $2\pi/K$, and therefore, its width will fit on the band allowed for by the channel.



Scrambler Randomizes the data

Mapper Segments the bitstream into consecutive groups of M bits. And this bits select one of 2^M possible signaling values. The set of all possible signaling values is called the [alphabet](#).

a[n] The actual discrete-time signal. The sequence of symbols to be transmitted.

K The upsampler narrows the spectral occupancy of the symbol sequence. The following low pass filter is known as the [shaper](#), since it determines the time domain shape of the transmitted symbols.

b[n] The [baseband](#) signal. Produced

s[n] The [passband](#) signal. $s[n] = \text{Re}\{c[n]\} = \text{Re}\{b[n]e^{j\omega_c n}\}$ The signal which is fed to the D/A converter is simply the real part of the complex bandpass signal. With $\omega_c = \frac{\omega_{max} - \omega_{min}}{2}$

Data Rates

- upsampling does not change the data rate
- we produce (and transmit) W symbols per seconds
- W is sometimes called the [Baud Rate](#) of the system and is equal to the available bandwidth.

Raised Cosine

Part IX.

Week 8 Module 7:

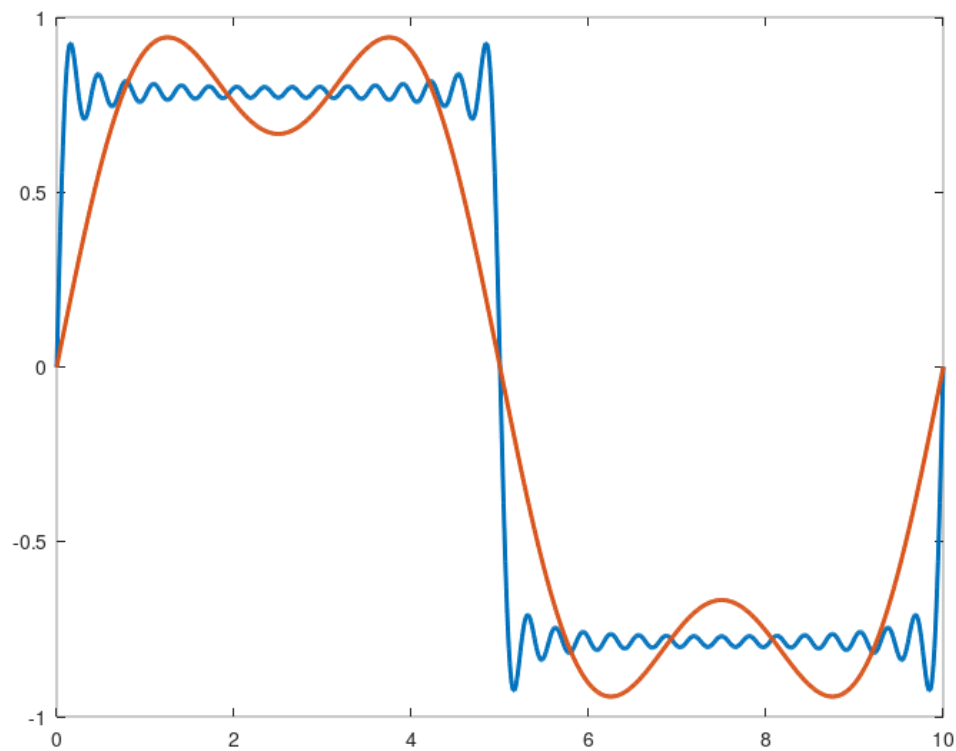
9. Image Processing

Part X.

Appendix

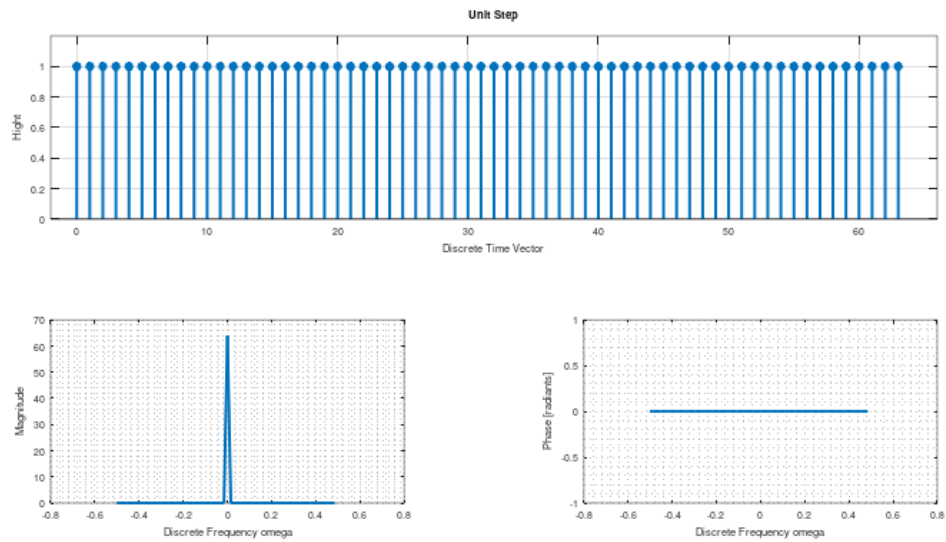
10. Plots

10.1. Sqaurewave Fourier Series

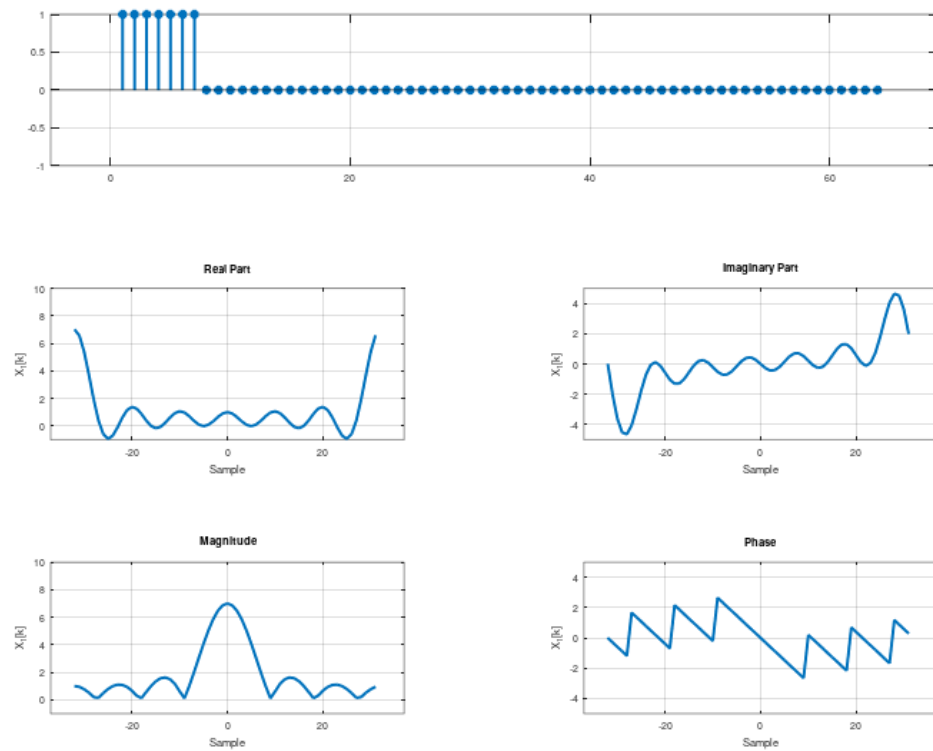


10.2. DFT Unit Step

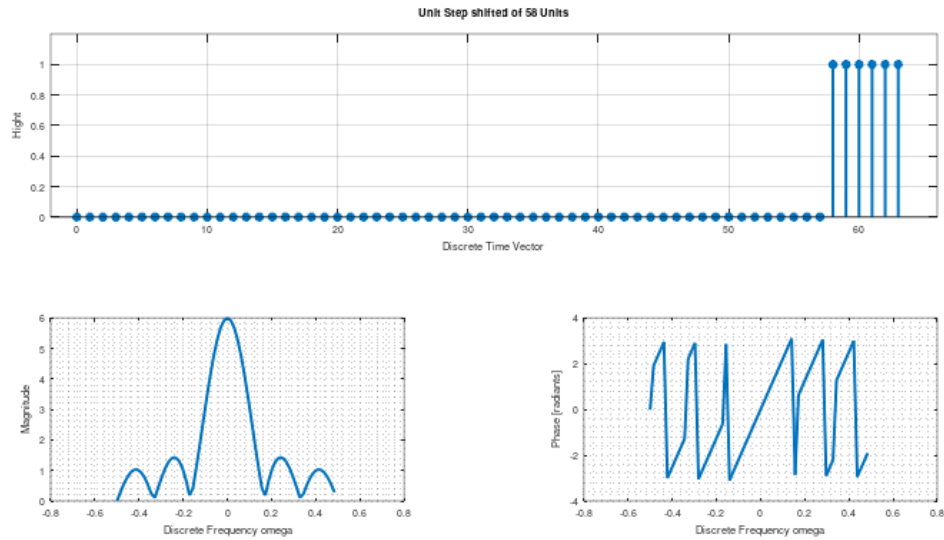
- [FFT Tutorial University Rhode Island](#)



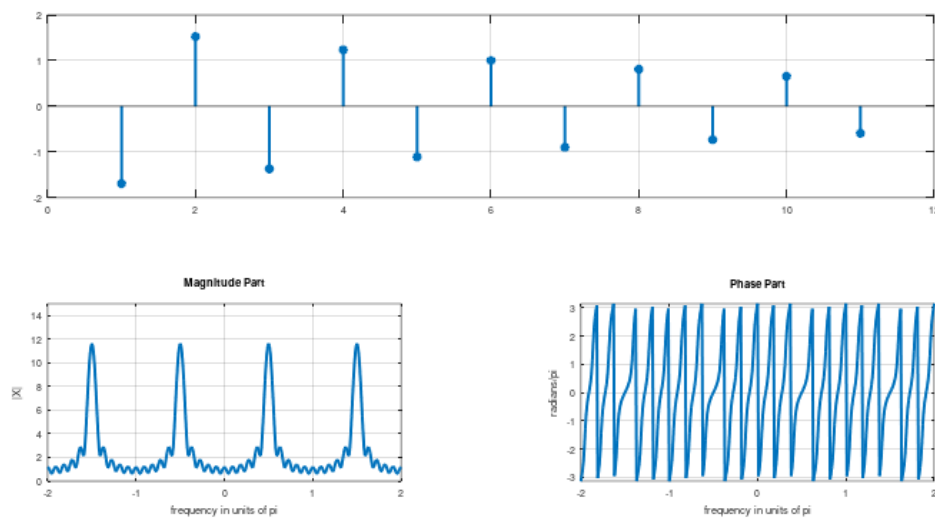
10.3. DFT Pulse Function



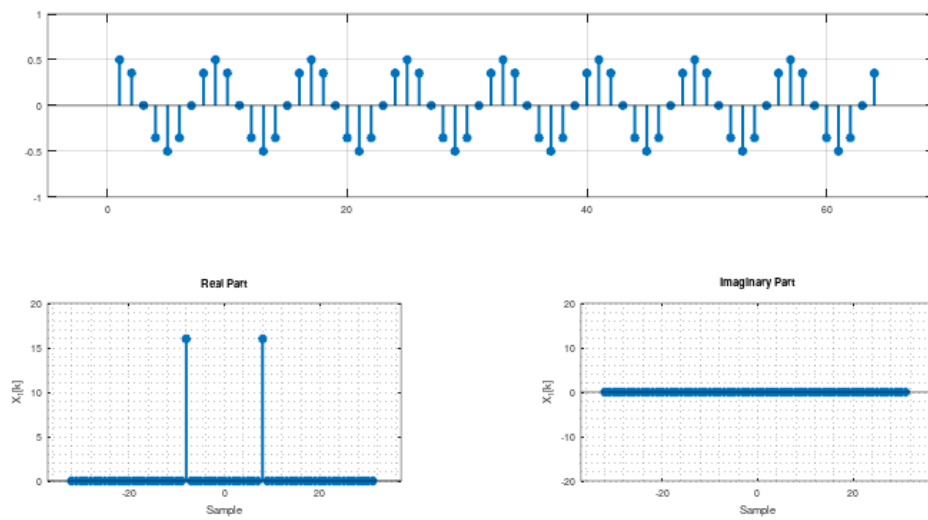
10.4. DFT Shifted Pulse Function



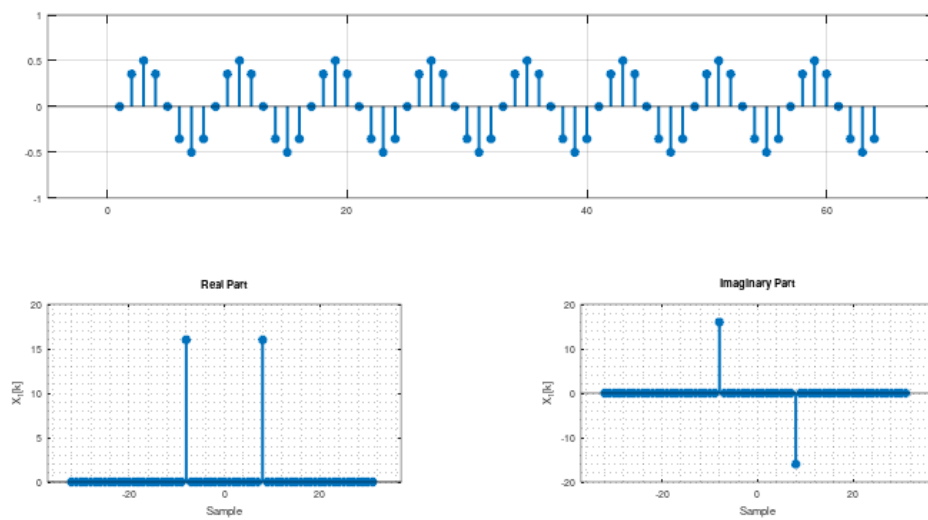
10.5. DFT Complex Exponential



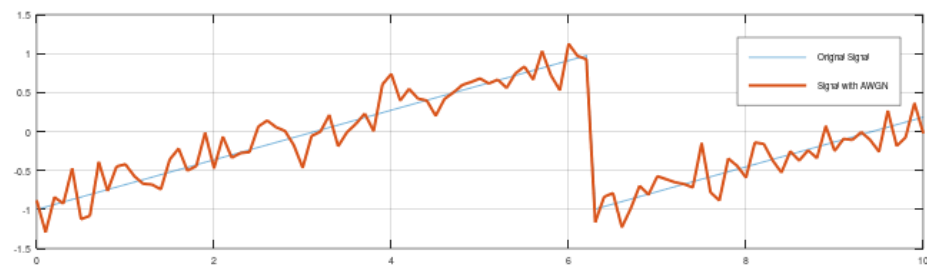
10.6. DFT Cosine



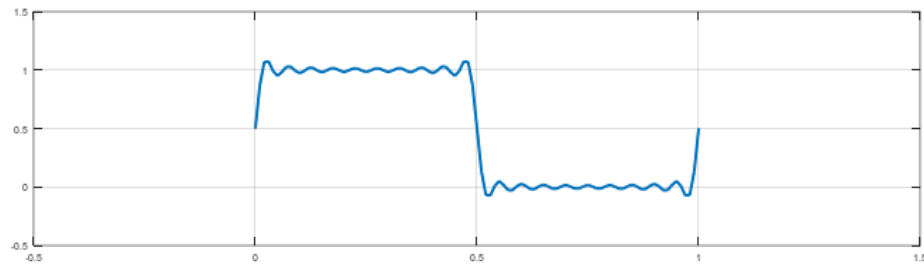
10.7. DFT Sinusoid Sine



10.8. Noise



10.9. Normalized Pulse

 ω_s 

10.10. Butterworth Filter

[DSP Related.COM](http://DSP.Related.COM)

11. Plotting the DFT

11.1. With Python

11.1.1. Plotting the DFT

In this notebook we will look at the practical issues associated to plotting the DFT and in particular the DFT of real-world signals. We will examine how to map the DFT coefficients to real-world frequencies and we will investigate the frequency resolution of the DFT and the effects of zero padding.

As a quick reminder, the definition of the DFT for a length- N signal is:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j \frac{2\pi}{N} nk}, \quad k = 0, 1, \dots, N-1$$



FFT Module

↪ In Python, we will use the `fft` module in Numpy to compute the DFT

```
# First the usual bookkeeping
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import IPython
from scipy.io.wavfile import write
```

```
# Sets the size of the output plots
plt.rcParams["figure.figsize"] = (14,4)
```

Typically, we will take a vector of data points, compute the DFT and plot the magnitude of the result. For instance, consider the DFT of a linear ramp:

```
x = np.arange(0, 10.2, 0.2) - 5
#draw figure
plt.stem(x);
```

```
X = np.fft.fft(x);
plt.stem(abs(X));
```

11.1.2. Positive and negative frequencies

The coefficient number k indicates the contribution (in amplitude and phase) of a sinusoidal component of frequency

$$\omega_k = \frac{2\pi}{N}k$$

Because of the rotational symmetry of complex exponentials, a positive frequency ω between π and 2π is equivalent to a negative frequency of $\omega - 2\pi$; this means that half of the DFT coefficients correspond to

negative frequencies and when we concentrate on the physical properties of the DFT it would probably make more sense to plot the coefficients centered around zero with positive frequencies on the right and negative frequencies on the left.

The reason why this is not usually done are many, including

- convenience
- since we are manipulating finite-length signals, the convention dictates that we start at index zero
- when dealing with real-valued data, the DFT is symmetric in magnitude, so the first half of the coefficients is enough
- if we're looking for maxima in the magnitude, it's just easier to start at zero.

There is also another subtle point that we must take into account when shifting a DFT vector: **we need to differentiate between odd and even length signals**. With $k = 0$ as the center point, odd-length vectors will produce symmetric data sets with $(N-1)/2$ points left and right of the origin, whereas even-length vectors will be asymmetric, with one more point on the positive axis; indeed, the highest positive frequency for even-length signals will be equal to $\omega_{N/2} = \pi$. Since the frequencies of π and $-\pi$ are identical, we can copy the top frequency data point to the negative axis and obtain a symmetric vector also for even-length signals. Here is a function that does that:

```
def dft_shift(X):
    N = len(X)
    if (N % 2 == 0):
        # even-length: return N+1 values
        return np.concatenate((X[(N/2):], X[:-(N/2)+1]))
    else:
        # odd-length: return N values
        return np.concatenate((X[(N+1)/2:], X[:-(N-1)/2]))
```

```
plt.stem(abs(dft_shift(X)));
```

While the function does shift the vector, the indices are still from zero to $N-1$. Let's modify it so that we return also the proper values for the indices:

```
def dft_shift(X):
    N = len(X)
    if (N % 2 == 0):
        # even-length: return N+1 values
        return (np.arange(-int(N/2), int(N/2) + 1),
                np.concatenate((X[int(N/2):], X[:-(N/2)+1])))
    else:
        # odd-length: return N values
        return (np.arange(-int((N-1)/2), int((N-1)/2) + 1),
                np.concatenate((X[(N+1)/2:], X[:-(N-1)/2])))
```

```
n, y = dft_shift(X)
plt.stem(n, abs(y));
```

11.1.3. Mapping the DFT index to real-world frequencies

The next step is to use the DFT to analyze real-world signals. As we have seen in previous examples, what we need to do is set the time interval between samples or, in other words, set the "clock" of the system. For audio, this is equivalent to the sampling rate of the file.

```
# import IPython not used in orgmode
from scipy.io import wavfile
Fs, x = wavfile.read("./sound/piano.wav")
# IPython.display.Audio(x, rate=Fs) not used in orgmode
```

Play piano sound

In order to look at the spectrum of the sound file with a DFT we need to map the digital frequency "bins" of the DFT to real-world frequencies.

The k -th basis function over \mathbb{C}^N completes k - periods over N samples. If the time between samples is $1/F_s$, then the real-world frequency of the k -th basis function is periods over time, namely $k(F_s/N)$.

Let's remap the DFT coefficients using the sampling rate:

```
def dft_map(X, Fs, shift=True):
    resolution = float(Fs) / len(X)
    if shift:
        n, Y = dft_shift(X)
    else:
        Y = X
        n = np.arange(0, len(Y))
    f = n * resolution
    return f, Y
```

```
# let's cut the signal otherwise it's too big
x = x[:32768]
X = np.fft.fft(x);
f, y = dft_map(X, Fs)
plt.plot(f, abs(y));
```

The plot shows what a spectrum analyzer would display. We can see the periodic pattern in the sound, like for all musical tones. If we want to find out the original pitch we need to zoom in in the plot and find the first peak. This is one of the instances in which shifting the DFT does not help, since we'll be looking in the low-frequency range. So let's re-plot without the shift, but still mapping the frequencies:

```
X = np.fft.fft(x);
f, y = dft_map(X, Fs, shift=False)
plt.plot(f[:2000], abs(y[:2000]));
```

We can see that the first peak is in the vicinity of 200Hz; to find the exact frequency (to within the resolution afforded by this DFT) let's find the location

```
dft_resolution = float(Fs) / len(x)
print("DFT resolution is", dft_resolution, "Hz")

# let's search up to 300Hz
max_range = int(300 / dft_resolution)
ix = np.argmax(abs(y[:max_range]))
pitch = f[ix]
print("the note has a pitch of", pitch, "Hz")
```

```
('DFT resolution is', 0.48828125, 'Hz')
```



Concert Pitch

↗ So the note is a A, half the frequency of concert pitch.

11.1.4. Zero-padding

Since the resolution of a DFT depends on the length of the data vector, one may erroneously assume that, by artificially extending a given data set, the resulting resolution would improve. Note that here we're not talking about collecting more data; rather, we have a data set and we append zeros (or any other constant value) to the end of it. This extension is called zero-padding.

The derivation of why zero-padding does not increase the resolution is detailed in the book. Here we will just present a simple example.

```
N = 256
Delta = 2*np.pi / N
n = np.arange(0, N)

# main frequency (not a multiple of the fundamental freq for the space)
omega = 2*np.pi / 10

x = np.cos(omega * n) + np.cos((omega + 3*Delta) * n)
plt.plot(abs(np.fft.fft(x))[:100]);
```

we can tell the two frequencies apart and, if you zoom in on the plot, you will see that they are indeed three indices apart. Now let's build a signal with two frequencies that are less than $\Delta\Delta$ apart:

```
x = np.cos(omega * n) + np.cos((omega + 0.5*Delta) * n)
plt.plot(abs(np.fft.fft(x))[:100]);
```

The two frequencies cannot be resolved by the DFT. If you try to increase the data vector by zero padding, the plot will still display just one peak:

```
xzp = np.concatenate((x, np.zeros(2000)))
plt.plot(abs(np.fft.fft(xzp))[:500]);
```

11.2. With Matlab/Octave

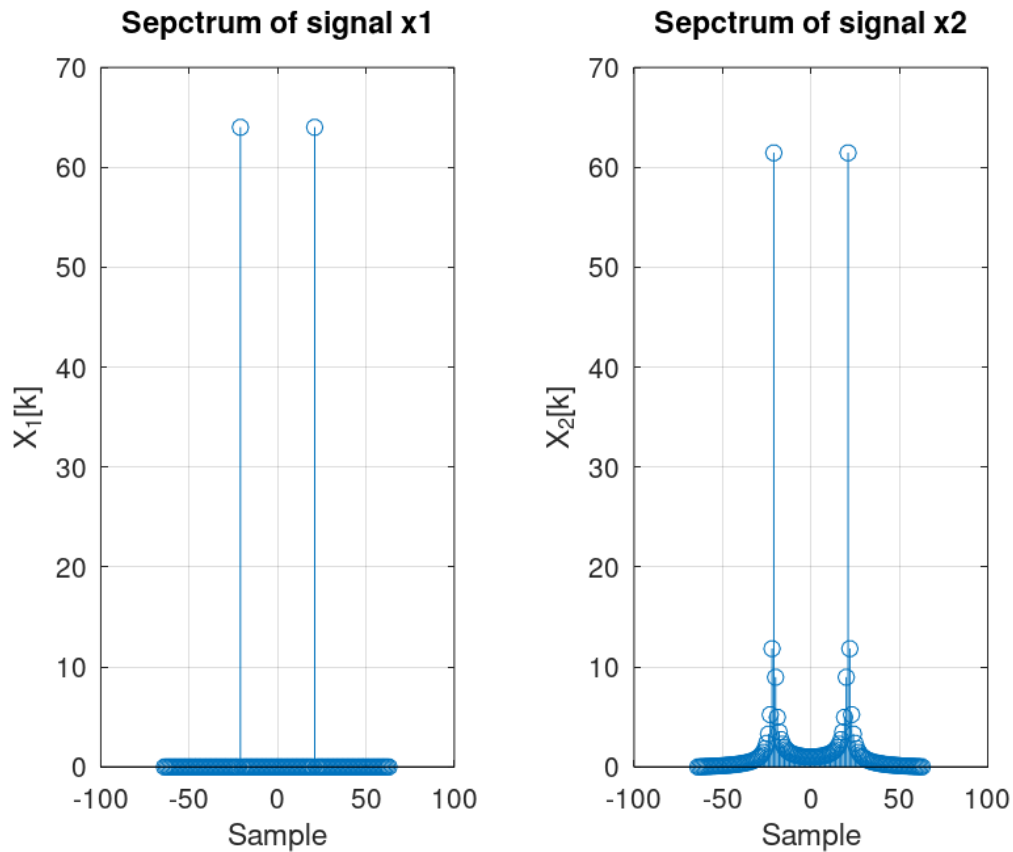
```
N=128;
fo1=21/128;
fo2=21/127;
n=0:N-1;
x1=cos(2*pi*fo1*n);
x2=cos(2*pi*fo2*n);
X1=fft(x1);
X2=fft(x2);

# Compute the dft of X1 using FFT algorithmw
# Compute the dft of X1 using FFT algorithmw

# Graphik
figure( 1, "visible", "off" )
subplot(1,2,1),stem(n-N/2,fftshift(abs(X1))) # Move frequency 0 to the center
grid on;
xlabel("Sample");
ylabel("X_1[k]");
title("Sepctrum of signal x1");
subplot(1,2,2), stem(n-N/2,fftshift(abs(X2)))
grid on;
xlabel("Sample");
ylabel("X_2[k]");
title("Sepctrum of signal x2");

# Org-Mode specific setting
```

```
print -dpng ./image/oct_fft.png;
ans = "./image/oct_fft.png";
```



11.2.1. Homework 4

```
N=64;
n=0:N-1;

x1=ones(N,1);
X1=fft(x1);                                     # Compute the dft of X1 using FFT algorithmw

# Graphik
figure( 1, "visible", "off" )                  # Do not open the graphic window in org

subplot(2,2,[1,2])
plot(x1);
grid on;
#stem(n-N/2,fftshift(x1))

subplot(2,2,3),stem(n-N/2,fftshift(abs(X1)))    # Move frequency 0 to the center
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
```

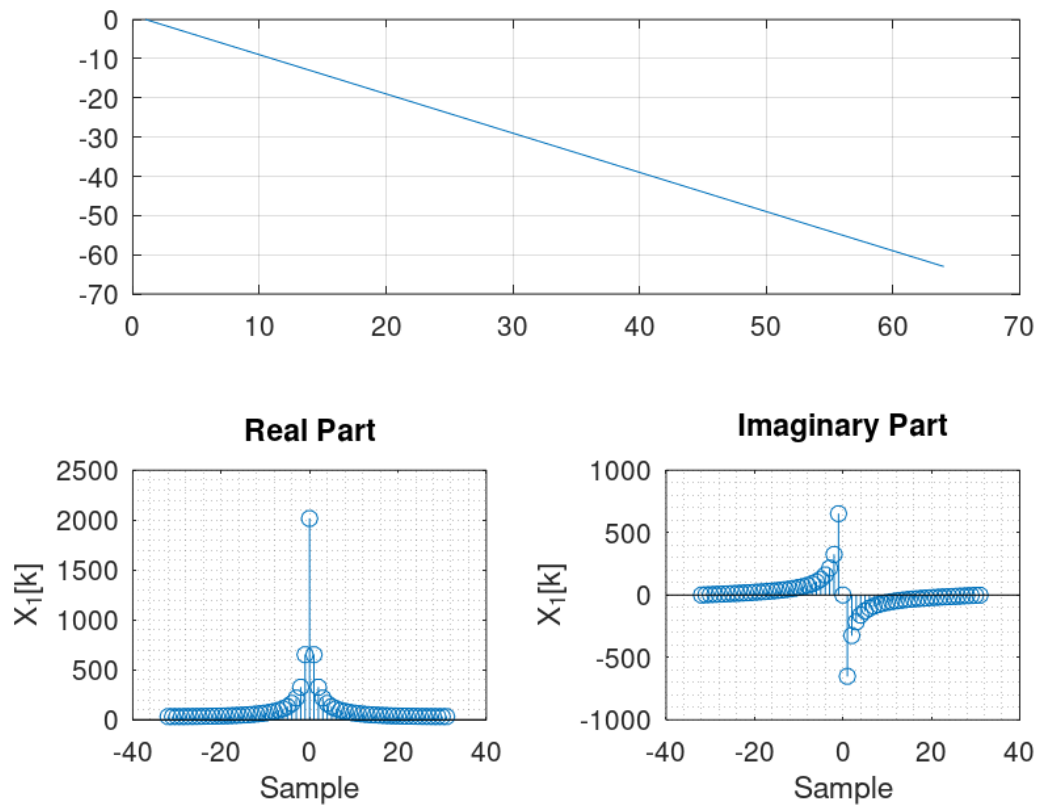


```

xlabel("Sample");
ylabel("X_1[k]");
title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw4a_fft.png;
ans = "./image/hw4a_fft.png";

```



```

x1=[1 2 3 4 5]
X1=fft(x1);
X2=fft(X1);

# Compute the dft of X1 using FFT algorithmw

ans = X2/5;

```

1 5 4 3 2

11.2.2. Homework 6

```

N=64;
fo1=4*60/64;
n=0:N-1;

x1=(-1)
X1=fft(x1);

# Compute the dft of X1 using FFT algorithmw

```

```

# Graphik
figure( 1, "visible", "off" )           # Do not open the graphic window in org

subplot(2,2,[1,2])
plot(x1);
grid on;
#stem(n-N/2,fftshift(x1))

subplot(2,2,3),stem(n-N/2,fftshift(abs(X1))) # Move frequency 0 to the center
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw6a_fft.png;
ans = "./image/hw6a_fft.png";

```

```

N=64;
fo1=8;
n=0:N-1;

x1=0.5*sin(2*pi/N*fo1*n);
X1=fft(x1);           # Compute the dft of X1 using FFT algorithmw

# Graphik
figure( 1, "visible", "off" )           # Do not open the graphic window in org

subplot(2,2,[1,2])
plot(x1);
grid on;
#stem(n-N/2,fftshift(x1))

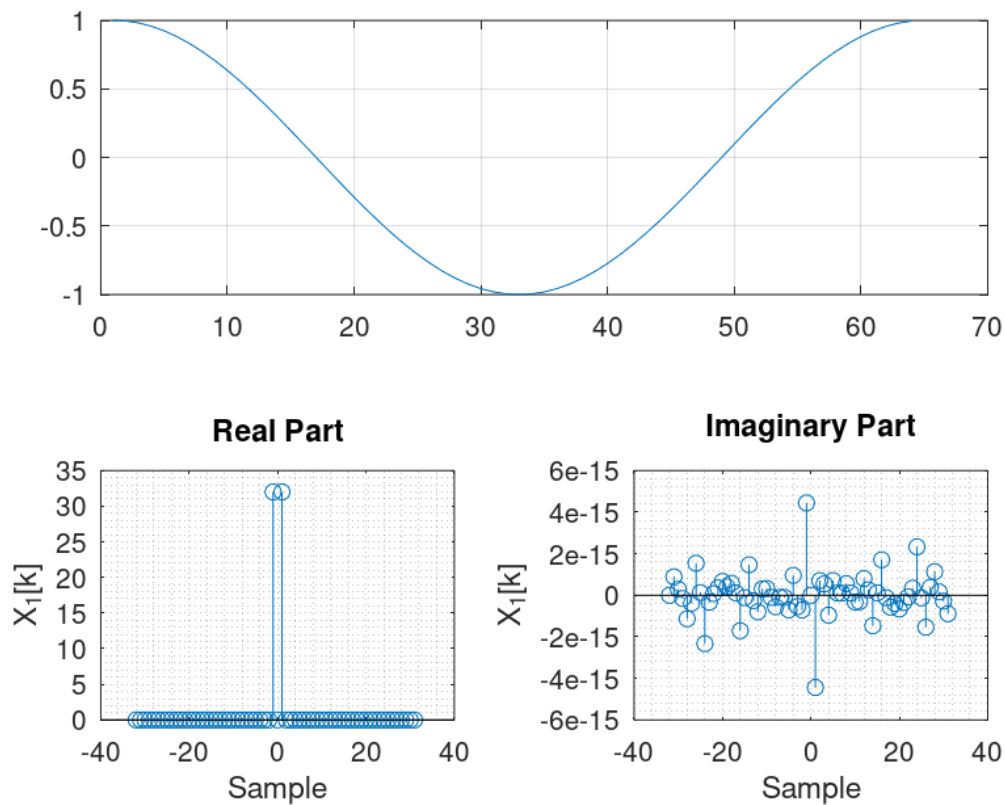
subplot(2,2,3),stem(n-N/2,fftshift(abs(X1))) # Move frequency 0 to the center
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw6b_fft.png;

```

```
ans = "./image/hw6b_fft.png";
```



```
N=64;
fo1=4;
n=0:N-1;

x1=2*cos(2*pi/N*fo1*n);
X1=fft(x1);                                     # Compute the dft of X1 using FFT algorithmw

# Graphik
figure( 1, "visible", "off" )                  # Do not open the graphic window in org

subplot(2,2,[1,2])
plot(x1)
grid on;
#stem(n-N/2,fftshift(x1))

subplot(2,2,3),stem(n-N/2,fftshift(abs(X1)))    # Move frequency 0 to the center
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

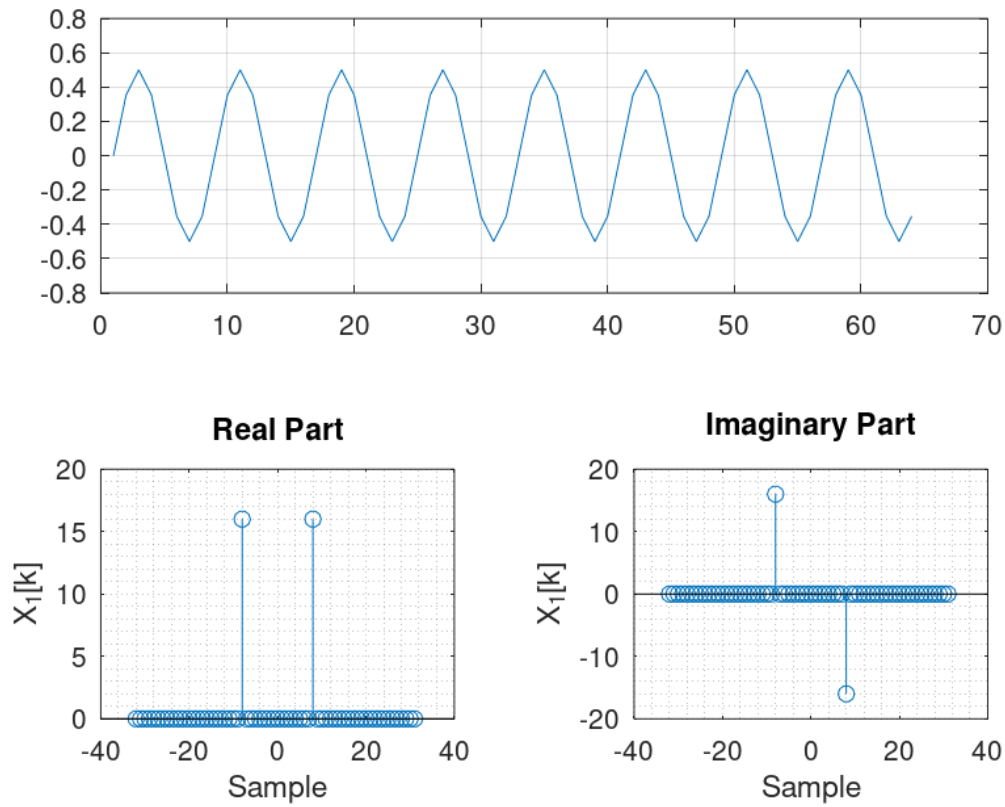
subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
```

```

title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw6d_fft.png;
ans = "./image/hw6d_fft.png";

```



12. Dual-tone multi-frequency (DTMF) signaling

DTMF signaling is the way analog phones send the number dialed by a user over to the central phone office. This was in the day before all-digital networks and cell phones were the norm, but the method is still used for in-call option selection ("press 4 to talk to customer service" ...).

The mechanism is rather clever: the phone's keypad is arranged in a 4x3 grid and each button is associated to two frequencies according to this table:

	1209 Hz	336 Hz	477 Hz
697 Hz	1	2	3
770 Hz	4	5	6
852 Hz	7	8	9
941 Hz	*	0	#

The frequencies in the table have been chosen so that they are "coprime"; in other words, no frequency is a multiple of any other, which reduces the probability of erroneously detecting the received signals due to interference. When a button is pressed, the two corresponding frequencies are generated simultaneously and sent over the line. For instance, if the digit '1' is pressed, the generated signal will be:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j \frac{2\pi}{N} nk}, \quad k = 0, 1, \dots, N-1$$



FFT Module



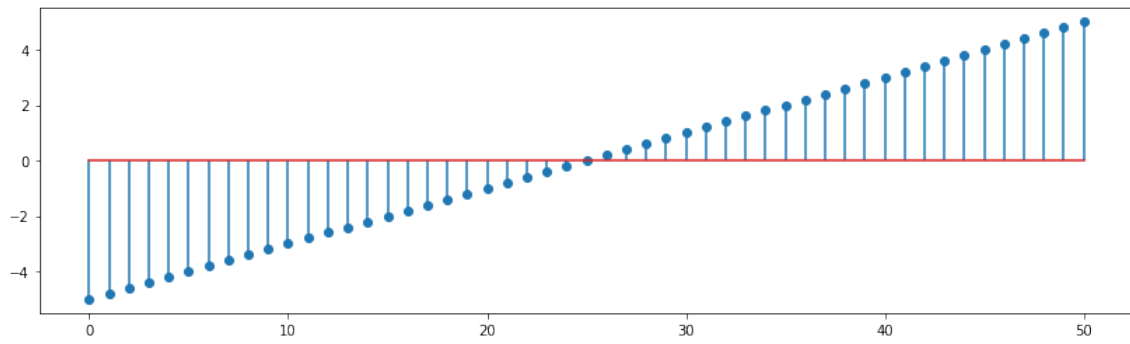
In Python, we will use the `fft` module in Numpy to compute the DFT

```
# First the usual bookkeeping
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import IPython
from scipy.io.wavfile import write
```

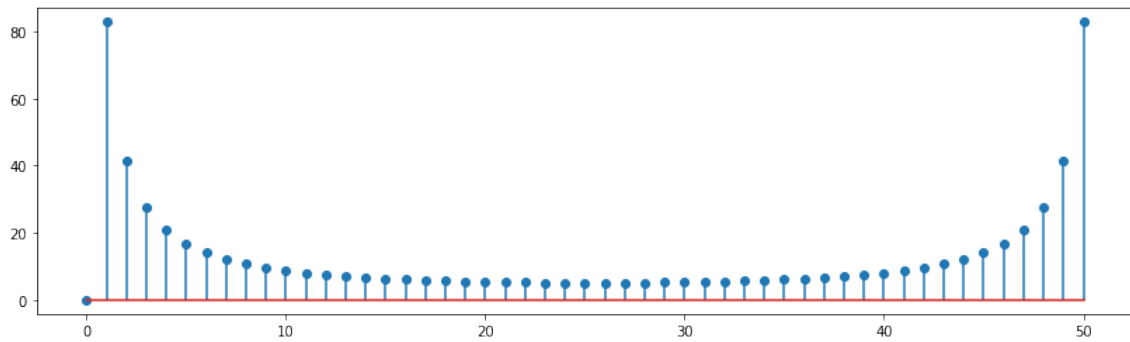
```
# Sets the size of the output plots
plt.rcParams["figure.figsize"] = (14,4)
```

Typically, we will take a vector of data points, compute the DFT and plot the magnitude of the result. For instance, consider the DFT of a linear ramp:

```
x = np.arange(0, 10.2, 0.2) - 5
#draw figure
plt.stem(x);
```



```
X = np.fft.fft(x);  
plt.stem(abs(X));
```



13. Goethe's temperature measurement

- Key Characteristic of a Digital Signal
 1. Series of measurements, taken at regular interval
 2. Each sample has a discrete amplitude
- Moving Average

$$\begin{aligned}y[n] &= \frac{1}{N} \sum_{m=0}^{N-1} x[n-m] \\&= \frac{1}{N} x[n] + \underbrace{\frac{1}{N} \sum_{m=1}^{N-1} x[n-m]}_{y[n-1]} + \frac{1}{N} x[n-N] - \frac{1}{N} x[n-N] \\&= y[n-1] + \frac{1}{N} (x[n] - x[n-N])\end{aligned}$$

- n: average of the last capital N observations
- N: window of observation over which average is computed
- Engineers Scientist Guide Chapter 15

14. Karplus-Strong Algorithm

The Karplus-Strong algorithm is a simple digital feedback loop with an internal buffer of samples. The buffer is filled with a set of initial values and the loop, when running, produces an arbitrarily long output signal. Although elementary, the K-S loop can be used to synthesize interesting musical sounds. Let's start with a basic implementation of K-S loop:

file#NAME: KS1 Algorithm

```
def KS_1(x, N):  
    # given the initial buffer x, produce a N-sample output  
    # by concatenating identical copies of the buffer  
    y = x  
    while len(y) < N:  
        # keep appending until we reach or exceed the required length  
        y = np.append(y, x)  
    # trim the excess  
    y = y[0:N+1]  
    return y
```

First we need to include the necessary Python libraries:

```
%matplotlib inline  
import matplotlib  
import matplotlib.pyplot as plt  
import numpy as np  
import IPython  
from scipy.io.wavfile import write
```

Set the size of the output plots

```
plt.rcParams["figure.figsize"] = (14,4)
```

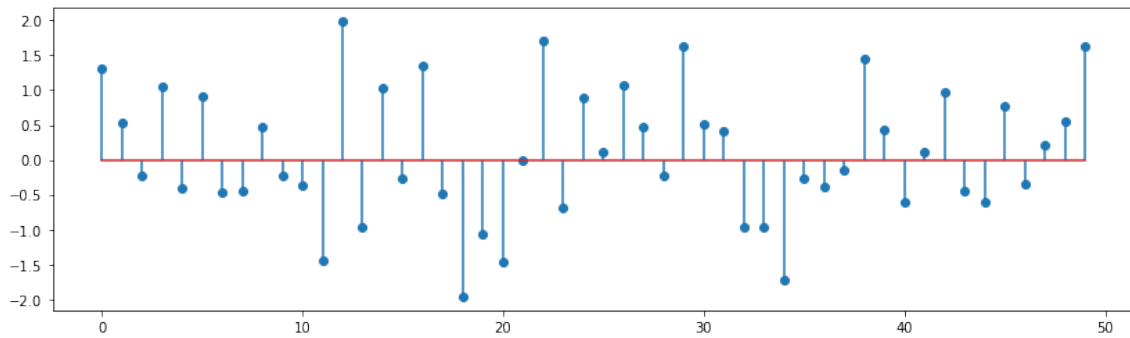
Then, since we're playing audio, we need to set the internal "clock" of the system, aka the sampling rate:

```
Fs = 16000 # 16 KHz sampling rate
```

With this sampling rate, since the period of the generated signal is equal to the length of the initial buffer, we will be able to compute the fundamental frequency of the resulting sound. For instance, if we init the K-S algorithm with a vector of 50 values, the buffer will fit $16000/50=320$ times in a second's worth of samples or, in other words, the resulting frequency will be 320Hz, which corresponds roughly to a E4 on a piano.

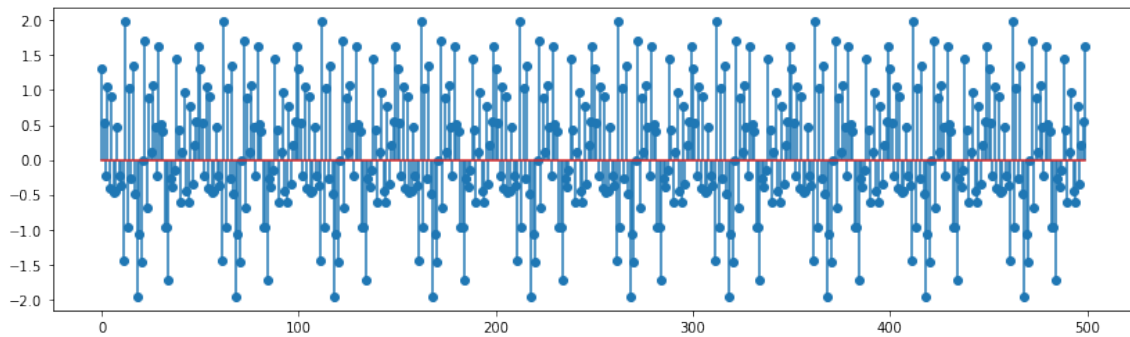
We still haven't talked about what to use as the initial values for the buffer. Well, the cool thing about K-S is that we can use pretty much anything we want; as a matter of fact, using random values will give you a totally fine sound. As a proof, consider this initial data set:

```
b = np.random.randn(50)  
  
#draw figure  
plt.stem(b);
```

Let's now generate a 2-second audio clip:

```
y = KS_1(b, Fs * 2)
# we can look at a few periods:
plt.stem(y[0:500]);
```



```
write('test1.wav', Fs, y)
```

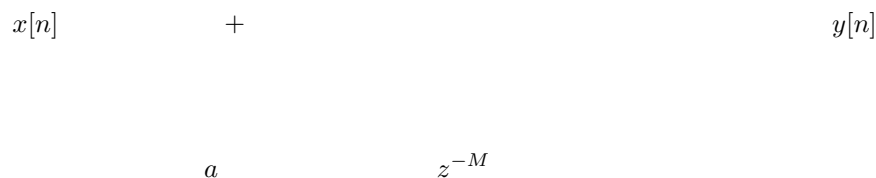
Play wave 1

```
# let's play an octave lower: just double the initial buffer's length
b = np.random.randn(100)
y = KS_1(b, Fs * 2)
write('test2.wav', Fs, y)
```

Play wave 2

The Block Diagram

OK, so the K-S algorithm works! From the signal processing point of view, we can describe the system with the following block diagram.



The output can be expressed as

$$y[n] = x[n] + x[n - M]$$

assuming that the signal is the finite support signal

$$x[n] = \begin{cases} 0 & \text{for } n < 0 \\ b_n & \text{for } 0 \leq n \leq M \\ 0 & \text{for } n \geq M \end{cases}$$

Let's implement the K-S algorithm as a signal processing loop

```
def KS_2(x, N):
    # length of the input
    M = len(x)
    # prepare the output
    y = np.zeros(N)
    # this is NOT an efficient implementation, but it shows the general principle
    # we assume zero initial conditions (y[n]=0 for n < 0)
    for n in range(0, N):
        y[n] = (x[n] if n < M else 0) + (y[n-M] if n-M >= 0 else 0)
    return y
```

```
# let's play an octave lower: just double the initial buffer's length
b = np.random.randn(50)
y = KS_2(b, Fs * 2)
write('test3.wav', Fs, y)
```

Play wave 3

By looking at block diagram we can see a simple modification that adds a lot of realism to the sound: by setting α to a value close to but less than one, we can introduce a decay in the note that produces guitar-like sounds:

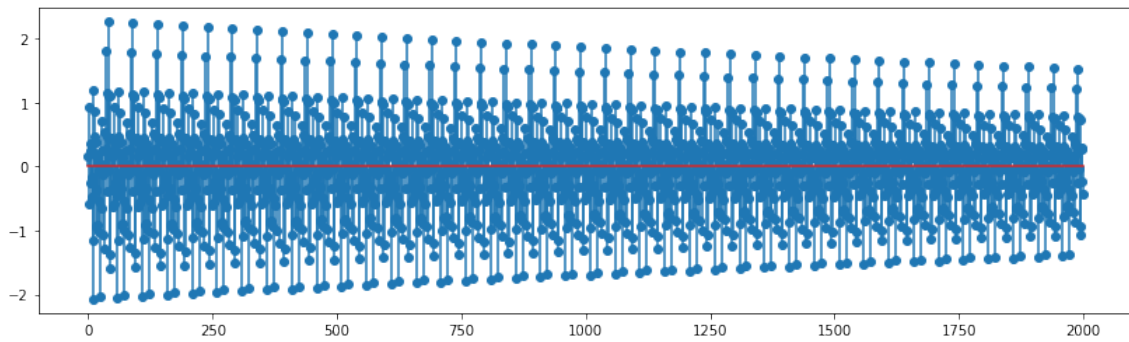
$$y[n] = x[n] + \alpha y[n - M]$$

```
def KS_3(x, N, alpha = 0.99):
    M = len(x)
    y = np.zeros(N)
    #
    for n in range(0, N):
        y[n] = (x[n] if n < M else 0) + alpha * (y[n-M] if n-M >= 0 else 0)
    return y
```

If we now plot the resulting K-S output, we can see the decaying envelope:

```
y = KS_3(b, Fs * 2)

# we can look at a few periods:
plt.stem(y[0:2000]);
```



```
# let's play an octave lower: just double the initial buffer's length
write('test4.wav', Fs, y)
```

Play wave 4

There is just one last detail (the devil's in the details, here as everywhere else). Consider the output of a damped K-S loop; every time the initial buffer goes through the loop, it gets multiplied by α so that we can write

$$y[n] = \alpha^{\frac{n}{M}} x[n] + \alpha y[n - M]$$

(think about it and it will make sense). What that means is that the decay envelope is dependent on both α and M or, in other words, the higher the pitch of the note, the faster its decay. For instance:

```
write('test5.wav', Fs, KS_3(np.random.rand(50), Fs*2))
```

Play wave 5

```
write('test6.wav', Fs, KS_3(np.random.rand(10), Fs*2))
```

Play wave 6

This is no good and therefore we need to compensate so that, if α is the same, the decay rate is the same. This leads us to the last implementation of the K-S algorithm:

```
def KS(x, N, alpha = 0.99):
    # we will adjust alpha so that all notes have a decay
    # comparable to that of a buf len of 50 samples
    REF_LEN = 50
    M = len(x)
    a = alpha ** (float(M) / REF_LEN)
    y = np.zeros(N)
    #
    for n in range(0, N):
        y[n] = (x[n] if n < M else 0) + a * (y[n-M] if n-M >= 0 else 0)
    return y
```

```
write('test7.wav', Fs, KS(np.random.rand(50), Fs*2))
```

Play wave 7

```
write('test8.wav', Fs, KS(np.random.rand(10), Fs*2))
```

Play wave 8

15. Playing Music

Let's now play some cool guitar and, arguably, no guitar chord is as cool as the **opening chord of "A Hard Day's Night"**, by The Beatles



Much has been written about the chord (which, in fact, is made up of 2 guitars, one of which a 12-string, a piano and a bass) but to keep things simple, we will accept the most prevalent thesis which states that the notes are $D_3, F_3, G_3, G_4, A_4, C_5$ and G_5 . To give it a "wider" feeling we will add another D_2 below.

In Western music, where equal temperament is used, A_4 is the reference pitch at a frequency at 440Hz. All other notes can be computed using the formula

$f(n) = A_4 \times 2^{n/12}$ where n is the number of half-tones between A_4 and the desired note. The exponent n is positive if the note is above A_4 and negative otherwise.

Each note is generated using a separate Karplus-Strong algorithm. We try to mix the different "instruments" by assigning a different gain to each note. Also, we sustain Paul's D note on the bass a bit longer by changing the corresponding decay factor.

```
def freq(note):
    # general purpose function to convert a note in standard notation
    # to corresponding frequency
    if len(note) < 2 or len(note) > 3 or \
        note[0] < 'A' or note[0] > 'G':
        return 0
    if len(note) == 3:
        if note[1] == 'b':
            acc = -1
        elif note[1] == '#':
            acc = 1
        else:
            return 0
        octave = int(note[2])
    else:
        acc = 0
        octave = int(note[1])
    SEMITONES = {'A': 0, 'B': 2, 'C': -9, 'D': -7, 'E': -5, 'F': -4, 'G': -2}
    n = 12 * (octave - 4) + SEMITONES[note[0]] + acc
    f = 440 * (2 ** (float(n) / 12.0))
    #print note, f
    return f

def ks_chord(chord, N, alpha):
    y = np.zeros(N)
    # the chord is a dictionary: pitch => gain
    for note, gain in chord.items():
        # create an initial random-filled KS buffer the note
```

```
x = np.random.randn(int(np.round(float(Fs) / freq(note))))
y = y + gain * KS(x, N, alpha)
return y
```

```
# A Hard Day's Night's chord
hdn_chord = {
    'D2' : 2.2,
    'D3' : 3.0,
    'F3' : 1.0,
    'G3' : 3.2,
    'F4' : 1.0,
    'A4' : 1.0,
    'C5' : 1.0,
    'G5' : 3.5,
}

# write('test4.wav', Fs, y)
write('hdn.wav', 2*Fs, ks_chord(hdn_chord, Fs * 4, 0.995))
```

A Hard Day's Night opening chord

16. Homework Module 3

16.1. Excercise 4

```
N=64;
fo1=4*60/64;
n=0:N-1;

x1=(-1)*n
X1=fft(x1);                                # Compute the dft of X1 using FFT algorithmw

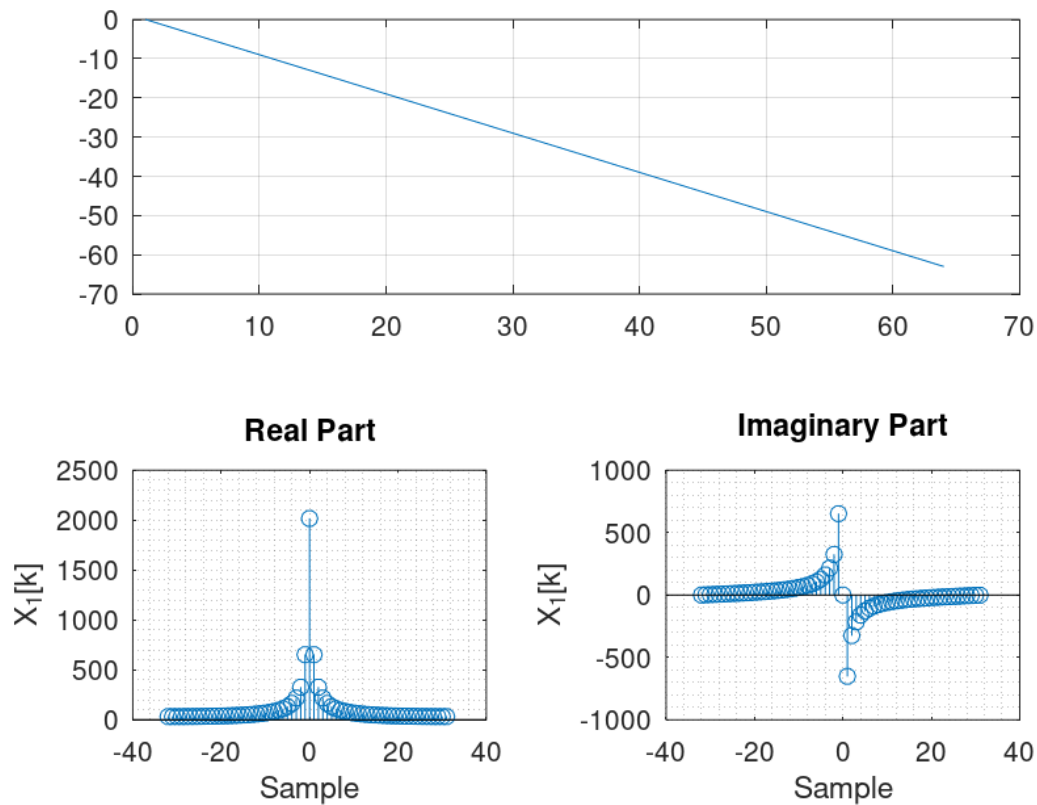
# Graphik
figure( 1, "visible", "off" )              # Do not open the graphic window in org

subplot(2,2,[1,2])
plot(x1);
grid on;
#stem(n-N/2,fftshift(x1))

subplot(2,2,3),stem(n-N/2,fftshift(abs(X1))) # Move frequency 0 to the center
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw4a_fft.png;
ans = "./image/hw4a_fft.png";
```



```
x1=[1 2 3 4 5]
X1=fft(x1);
X2=fft(X1);

ans = X2/5;
```

Compute the dft of X1 using FFT algorithmw

1 5 4 3 2

16.2. Exercice 6

```
N=64;
n=0:N-1;

x1=ones(N,1);
X1=fft(x1);

# Graphik
figure( 1, "visible", "off" )

subplot(2,2,[1,2])
plot(x1);
grid on;
#stem(n-N/2,fftshift(x1))

subplot(2,2,3),stem(n-N/2,fftshift(abs(X1))) # Move frequency 0 to the center
```

Compute the dft of X1 using FFT algorithmw

Do not open the graphic window in org

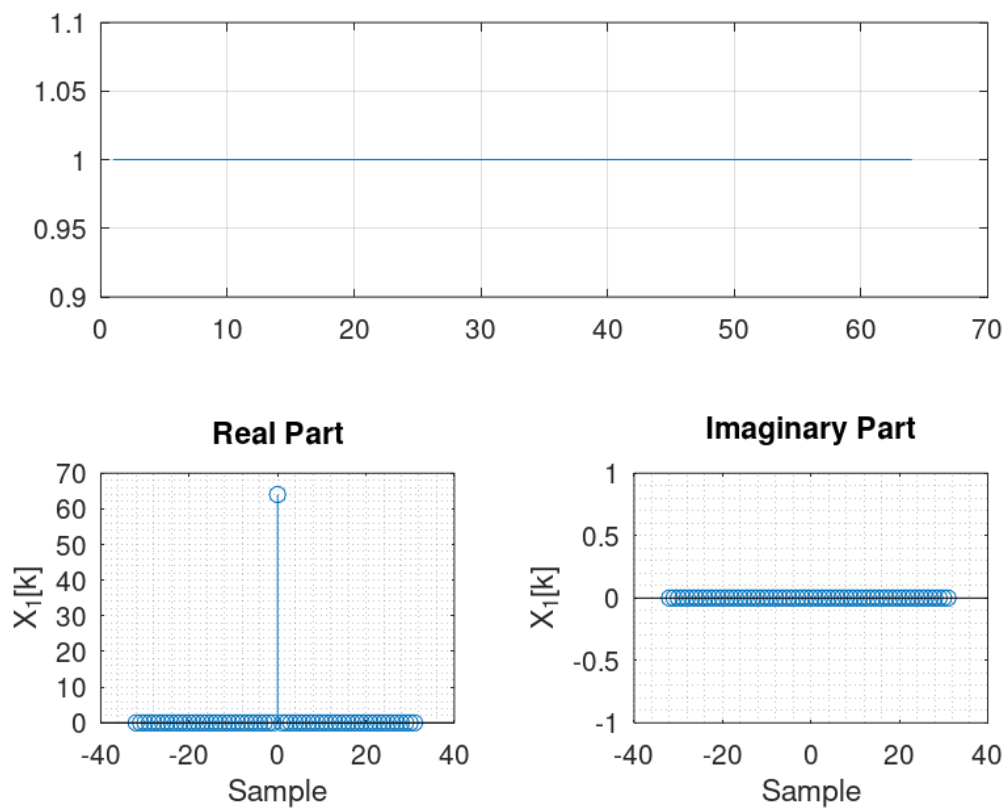
```

grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw6a_fft.png;
ans = "./image/hw6a_fft.png";

```



```

N=64;
fo1=8;
n=0:N-1;

x1=0.5.*sin(2*pi*fo1*n/N);
X1=fft(x1);                                     # Compute the dft of X1 using FFT algorithmw

# Graphik
figure( 1, "visible", "off" )                  # Do not open the graphic window in org

subplot(2,2,[1,2])

```



```

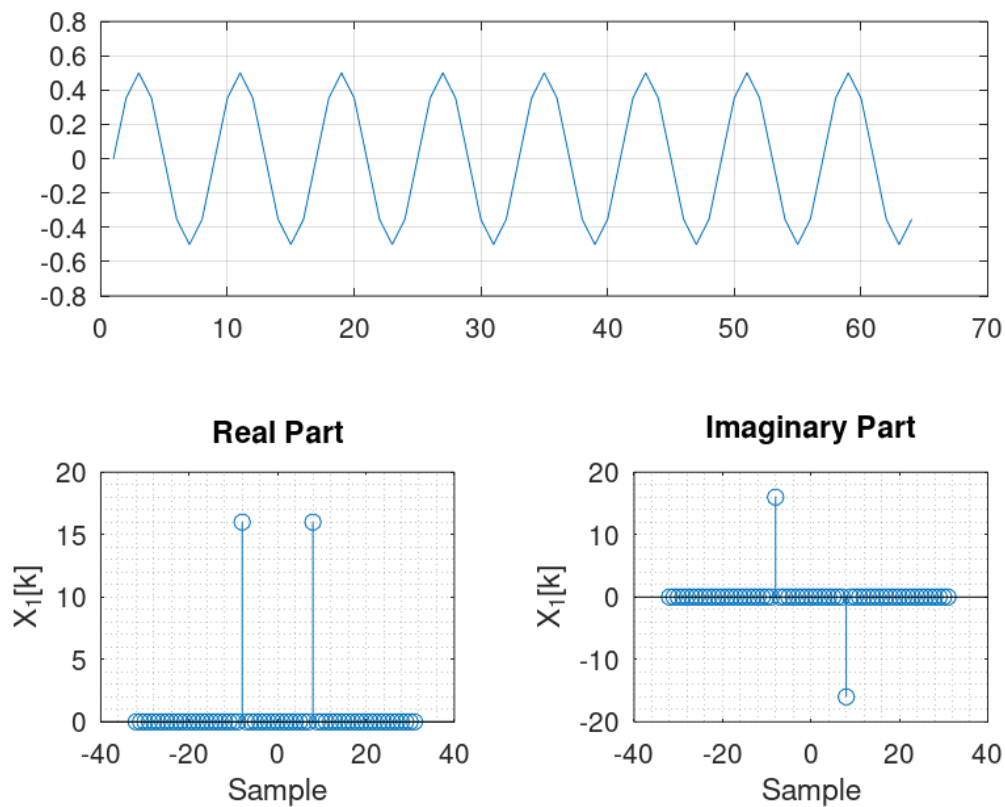
plot(x1)
grid on;
#stem(n-N/2,fftshift(x1))

subplot(2,2,3),stem(n-N/2,fftshift(abs(X1))) # Move frequency 0 to the center
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw6d_fft.png;
ans = "./image/hw6d_fft.png";
#ans = X1'

```



```

N=64;
fo1=8;
n=0:N-1;

x1=0.5*sin(2*pi/N*fo1*n);

```

```

X1=fft(x1);                                     # Compute the dft of X1 using FFT algorithmw

# Graphik
figure( 1, "visible", "off" )                  # Do not open the graphic window in org

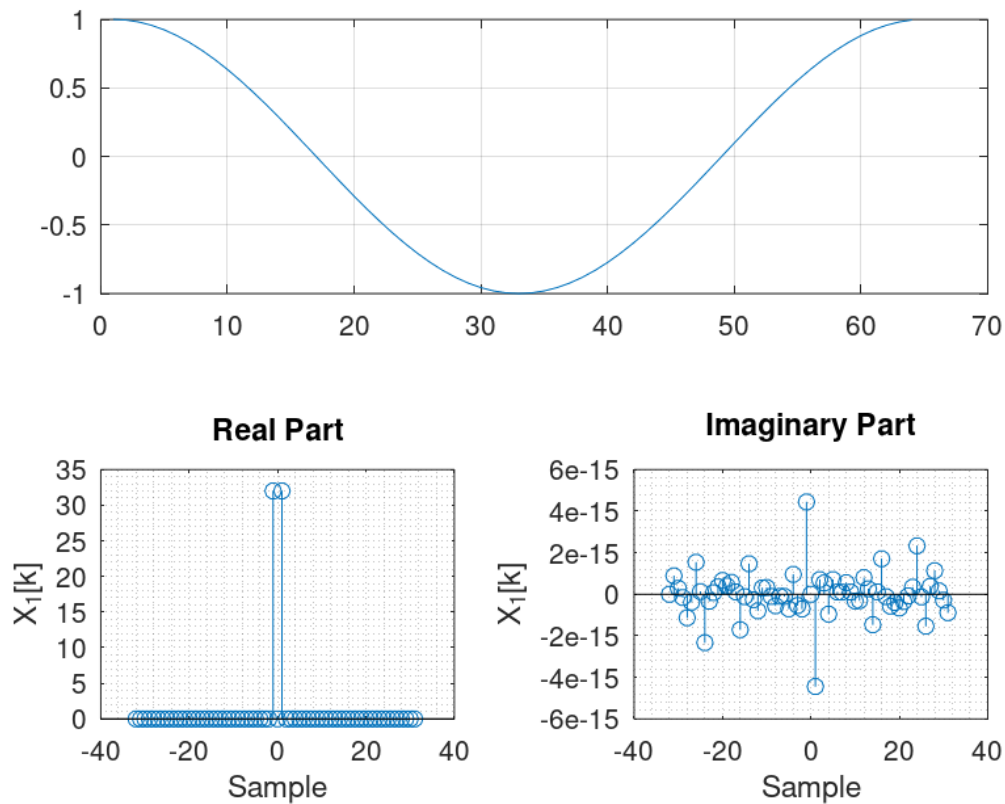
subplot(2,2,[1,2])
plot(x1);
grid on;
#stem(n-N/2,fftshift(x1))

subplot(2,2,3),stem(n-N/2,fftshift(abs(X1)))    # Move frequency 0 to the center
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw6b_fft.png;
ans = "./image/hw6b_fft.png";

```



```

N=64;
fo1=8;
fo2=4;
n=0:N-1;

f1 = @(n) 0.5*sin(2*pi/N*fo1*n);
f2 = @(n) 2*cos(2*pi/N*fo1*n);
f3 = @(n) 1

norm1 = sum( f1([0:63]) .* f1([0:63]));
norm2 = sum( f2([0:63]) .* f2([0:63]));
norm3 = sum( f3([0:63]) .* f2([0:63]));

# ans = norm1;
# ans = norm2;
# ans = norm3;
ans = (norm1 + norm2 + norm3);

```

```

135.99999999999999 135.99999999999999 135.99999999999999 135.99999999999999 511.99999999999997 31.999999999999998
127.99999999999999 8.0000000000000004 32.000000000000001 32

```

```

N=64;
L=8;
M=8;
n=0:N-1;

fo = L/M
x1=cos(2*pi/N*fo*n);
X1=fft(x1);                                     # Compute the dft of X1 using FFT algorithmw

# Graphik
figure( 1, "visible", "off" )                  # Do not open the graphic window in org

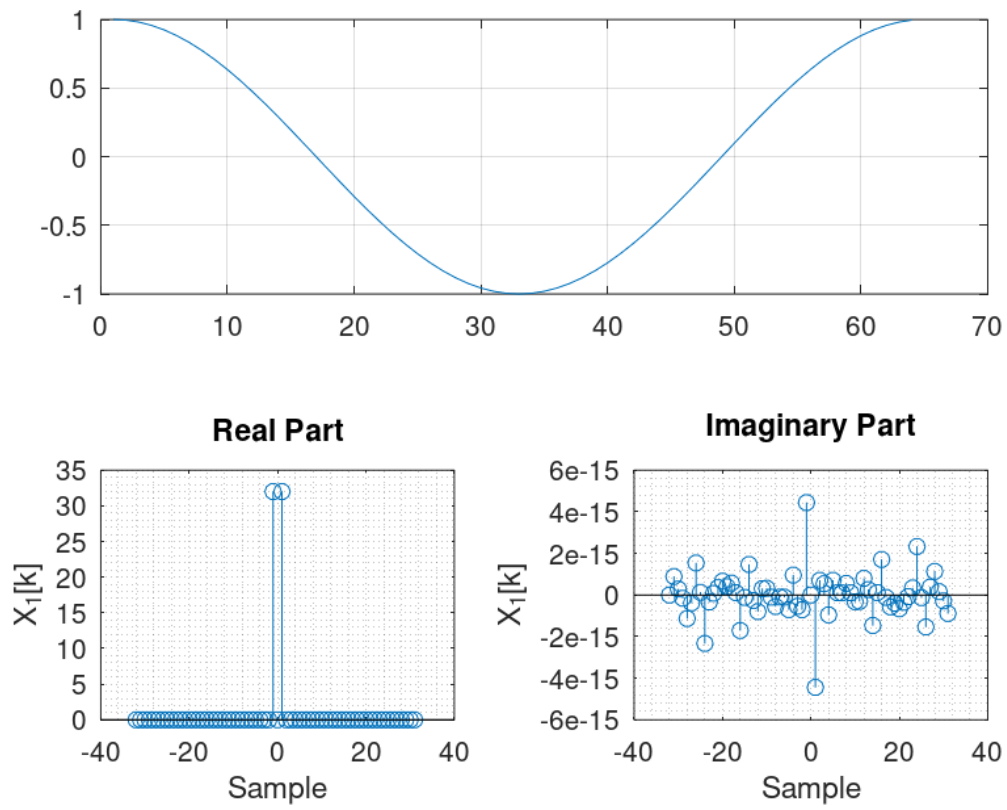
subplot(2,2,[1,2])
plot(x1);
grid on;
#stem(n-N/2,fftshift(x1))

subplot(2,2,3),stem(n-N/2,fftshift(abs(X1)))    # Move frequency 0 to the center
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Real Part");

subplot(2,2,4),stem(n-N/2,fftshift(imag(X1)))
grid minor;
xlabel("Sample");
ylabel("X_1[k]");
title("Imaginary Part");

# Org-Mode specific setting
print -dpng ./image/hw6b_fft.png;
ans = "./image/hw6b_fft.png";

```



17. Links

- [DSP Professor Murugan Pallikonda Rajasekaran](#)
- [Software Defined Radio with HackRF](#)
- [VSB - Modulation \(MVB\)](#)
- [Phase-Shift Method-Based Optical VSB](#)
- [Understanding the "Phasing Method" of Single Sideband Demodulation](#)
- [Einseitenbandmodulation](#)
- [Adam Panagos - Really nice tutorial videos](#)

17.1. All About Circuits

17.1.1. Filter Design

- [Practical FIR Filter Design: Part1 - Design with Octave](#) - see also `m-files/fir-filter.m`
- [Practical FIR Filter Design: Part2 Implementing Your Filter](#)
- [Design of FIR Filters Using the Frequency Sampling Method](#)
- [FIR Filter Design by Windowing: Concepts and the Rectangular Window](#)
- [From Filter Specs to Window Parameters in FIR Filter Design](#)
- [Design Examples of FIR Filters Using the Window Method](#)

17.1.2. Software Defined Radio

- [Practical Guide to Radio-Frequency Analysis and Design](#)
- [Introduction to Software-Defined Radio](#)

17.1.3. Digital Modulation

- [Digital Modulation: Amplitude and Frequency](#)
- [Digital Signal Processing in Scilab: How to Decode an FSK Signal](#)
- [How to Use I/Q Signals to Design a Robust FSK Decoder](#)

18. Books

- Flatland: A Romance of Many Dimensions
- Starting Digital Signal Processing in Telecommunication Engineering A Laboratory-based Course

Emacs 24.3.1 (Org mode 8.2.5h)