Laboratory Report Cover Sheet

SRM Institute of Science and Technology
College of Engineering and Technology
Department of Electronics and Communication Engineering

18ECC204J DIGITAL SIGNAL PROCESSING

Fifth Semester, 2023-24 (Odd semester)

Name :

Register No. :

Day / Session :

Venue :

Title of Experiment :

Date of Conduction :

Date of Submission :

Particulars	Max. Marks	Marks Obtained
Pre lab	10	
Lab Performance	15	
Post lab	10	
Viva	5	
Total	40	

REPORT VERIFICATION

Staff Name :

Signature :

EXP NO 1: GENERATION OF BASIC SIGNALS

AIM

To generate and obtain the output for the basic signals.

SOFTWARE REQUIREMENT

SCI Lab

INTRODUCTION

Signals can be classified as continuous or discrete time. In the mathematical abstraction, the domain of a continuous-time signal is the set of real numbers (or some interval thereof), whereas the domain of a discrete-time (DT) signal is the set of integers (or other subset of real numbers). What these integers represent depends on the nature of the signal; most often it is time.

A continuous-time signal is any function which is defined at every time *t* in an interval, most commonly an infinite interval. A simple source for a discrete-time signal is the sampling of a continuous signal, approximating the signal by a sequence of its values at particular time instants. A signal, of which a sinusoid is only one example, is a sequence of numbers. A continuous-time signal is an infinite and uncountable set of numbers, as are the possible values each number can have between a start and end time, there are infinite possible values for time and instantaneous amplitude.

1. a) Generation of Continuous Signals

Scilab code: Sine wave

```
1 clc ;
2 clf ;
3 clear all;
4 // Caption: Generation of sine wave
5 f =0.2;
6 t =0:0.1:10;
7 x = sin (2* %pi * t * f ) ;
8 plot (t ,x ) ;
9 title ( ' s i n e wave ' ) ;
10 xlabel ( ' t ' ) ;
11 ylabel ( ' x ' ) ;
```

Simulation Output:

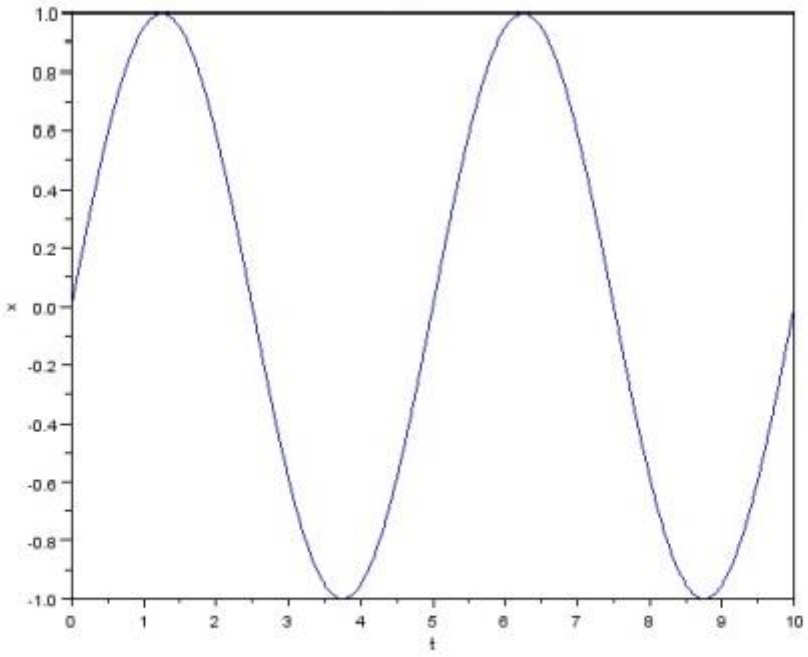


Figure 1.1: sinewave

Scilab code: Cosine wave

```
1 clc ;
2 clf ;
3 clear all;
4 // Caption: Generation of cosine wave
5 f =0.2;
6 t =0:0.1:10;
7 x = cos (2* %pi * t * f ) ;
8 plot (t ,x ) ;
9 title ( ' c o s i n e wave ' ) ;
10 xlabel ( ' t ' ) ;
11 ylabel ( ' x ' ) ;
```

Simulation Output:

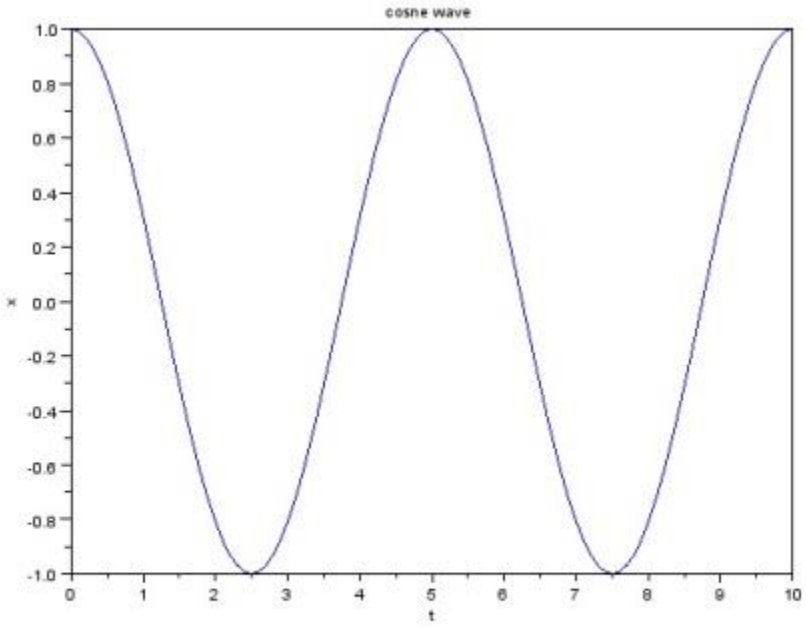


Figure 1.2: cosine wave

Scilab code: Triangular wave

```
1 clc ;
2 clf ;
3 clear all;
4 // Caption: Generation of Triangular wave
5 a =8;
6 t =0:( %pi /4) :(4* %pi ) ;
7 y = a *sin (2* t ) ;
8 a = gca () ;
9 a . x_location =" middle "
10 plot (t ,y ) ;
11 title ('Triangular Wave' ) ;
12 xlabel ( ' t ' ) ;
13 ylabel ( ' y ' ) ;
```

Simulation Output:

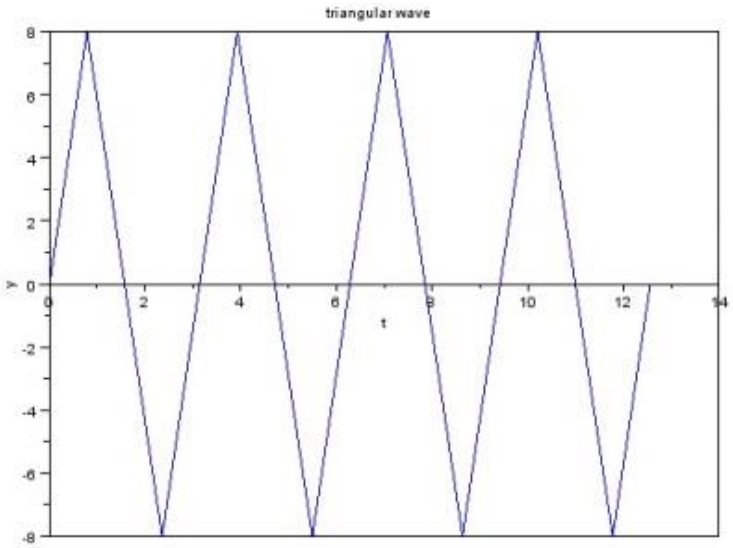


Figure 1.3: triangular wave

Scilab code: Exponential wave

```
1 clc ;
2 clf ;
3 clear all;
4 // Caption: Generation of Exponential wave
5 t = -2:0.1:2;
6 x = exp (t ) ;
7 plot (t ,x ) ;
8 title ( ' e x p o n e n t i a l wave ' ) ;
9 xlabel ( ' t ' ) ;
10 ylabel ( ' x ' ) ;
```

Simulation Output:

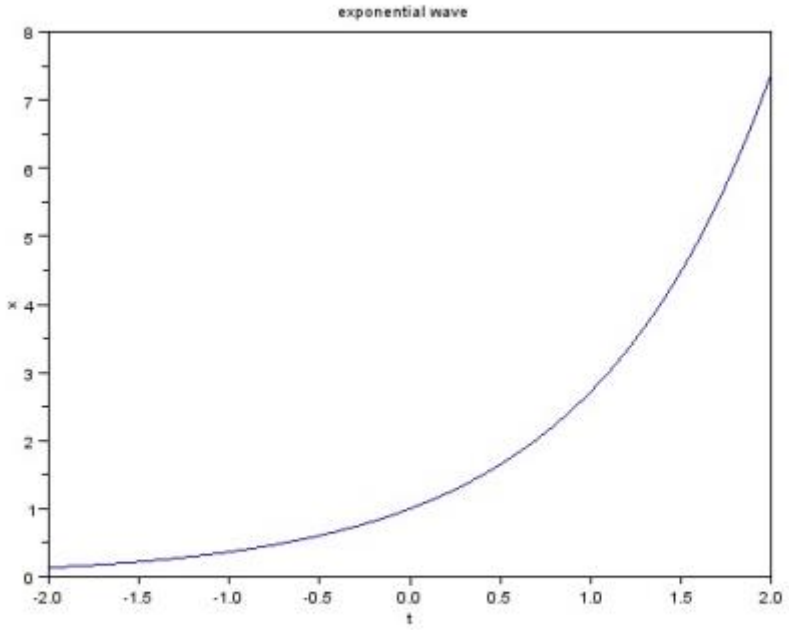


Figure 1.4 : Exponential wave

1. b) Generation of Discrete Signals

Scilab code: Unit impulse signal

```
1 clc ;
2 clf ;
3 clear all;
4 // Unit impulse
5 L =5;
6 n = - L : L;
7 x =[ zeros (1 , L ) ,ones (1 ,1) ,zeros (1 , L ) ];
8 a = gca () ;
9 a . y_location =" middle "
10 plot2d3 (n ,x ) ;
11 title ( 'unit impulse' ) ;
```

Simulation Output:

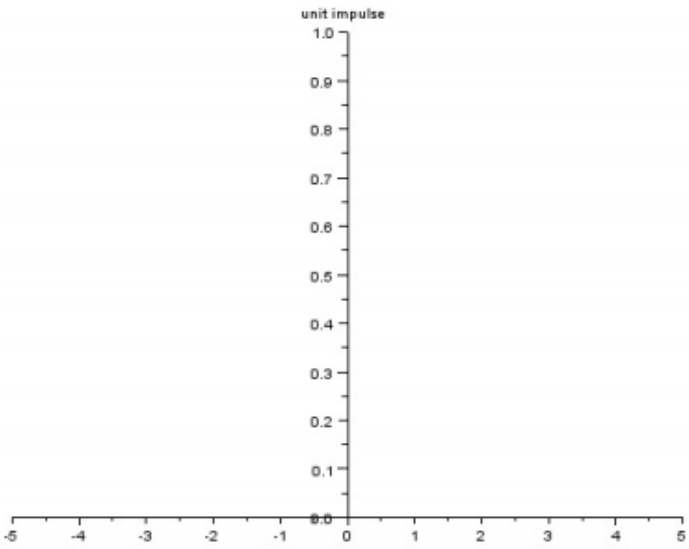


Figure 1.5: unit impulse signal

Scilab code: Unit step signal

```
1 clc ;
 2 clf ;
3 clear all;
4 L =5;
5 n = - L : L;
6 x =[ zeros (1 , L ) ,ones (1 , L +1) ];
7 a = gca () ;
8 a . y_location =" mi d dl e ";
9 plot2d3 (n ,x ) ;
10 title ( ' u n i t s t e p ' ) ;
11 xlabel ( ' n ' ) ;
12 ylabel ( ' x ' ) ;
```

Simulation Output:

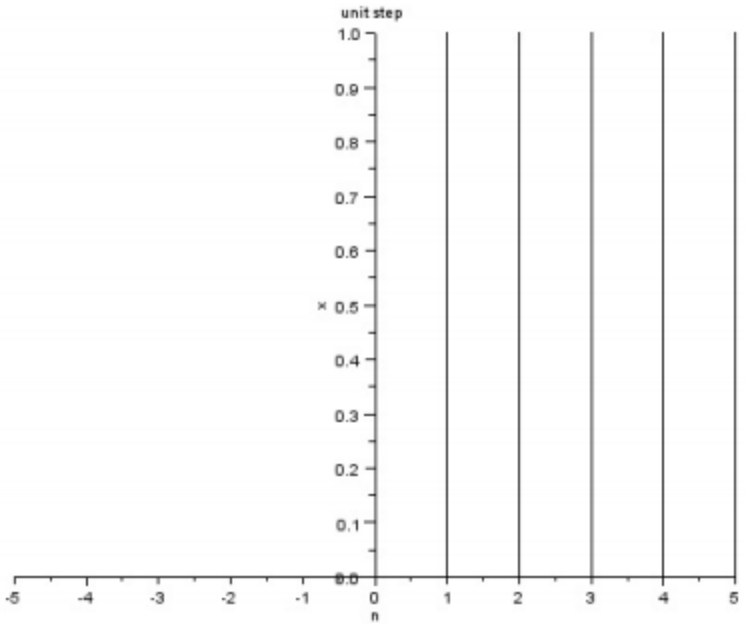


Figure 1.6 : unitstepsignal

Scilab code: Unit ramp signal

```
1 // u n i t ramp
2 clc ;
3 clf ;
4 clear all;
5 L =5;
6 n = - L : L;
7 x =[ zeros (1 , L ) ,0: L ];
8 a = gca () ;
9 a . y_location = ' mi d dl e ' ;
10 plot2d3 (n ,x ) ;
11 xtitle ( ' u n i t ramp s i g n a l ' ) ;
12 xlabel ( '---->n ' ) ;
13 ylabel ( '---->x ( n ) ' ) ;
```

Simulation Output:

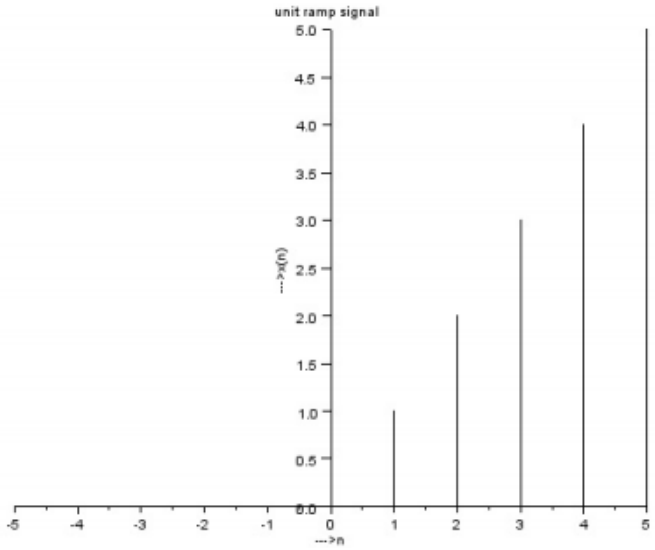


Figure 1.7 : unit ramp

Pre-lab questions:

1. What is continuous signal and discrete signal?
2. What are the properties of a signal?
3. How is a signal generated?
4. What is the difference between analog and digital signals?
5. Which signal is more reliable analog or digital?

Post-Lab questions:

1. Derive the code and show the output for signum function.
2. Derive the code and show the output for sinc function.
3. Derive the code and show the output for discrete exponential wave.

Result:

EXP NO 2: GENERATION OF CONTINUOUS TIME AND DISCRETE TIME SIGNAL

AIM:

To generate the continuous time and discrete time signal using SCI lab

Software Requirement:

SCI Lab

INTRODUCTION:

Signals are represented mathematically as functions of one or more independent variables. Here we focus attention on signals involving a single independent variable. For convenience, this will generally refer to the independent variable as time. There are two types of signals: continuous-time signals and discrete-time signals. Continuous-time signal: the variable of time is continuous. A speech signal as a function of time is a continuous-time signal. Discrete-time signal: the variable of time is discrete.

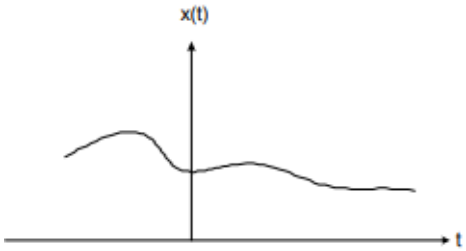


Fig.1. CT signal

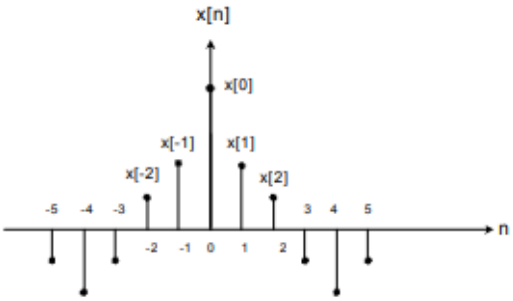


Fig.2 DT signal

To distinguish between continuous-time and discrete-time signals we use symbol t to denote the continuous variable and n to denote the discrete-time variable. And for continuous-time signals we will enclose the independent variable in parentheses (·), for discrete-time signals we will enclose the independent variable in bracket [·].

A discrete-time signal x n][may represent a phenomenon for which the independent variable is inherently discrete. A discrete-time signal x n][may represent successive samples of an underlying phenomenon for which the independent variable is continuous. For example, the

processing of speech on a digital computer requires the use of a discrete time sequence representing the values of the continuous-time speech signal at discrete points of time.

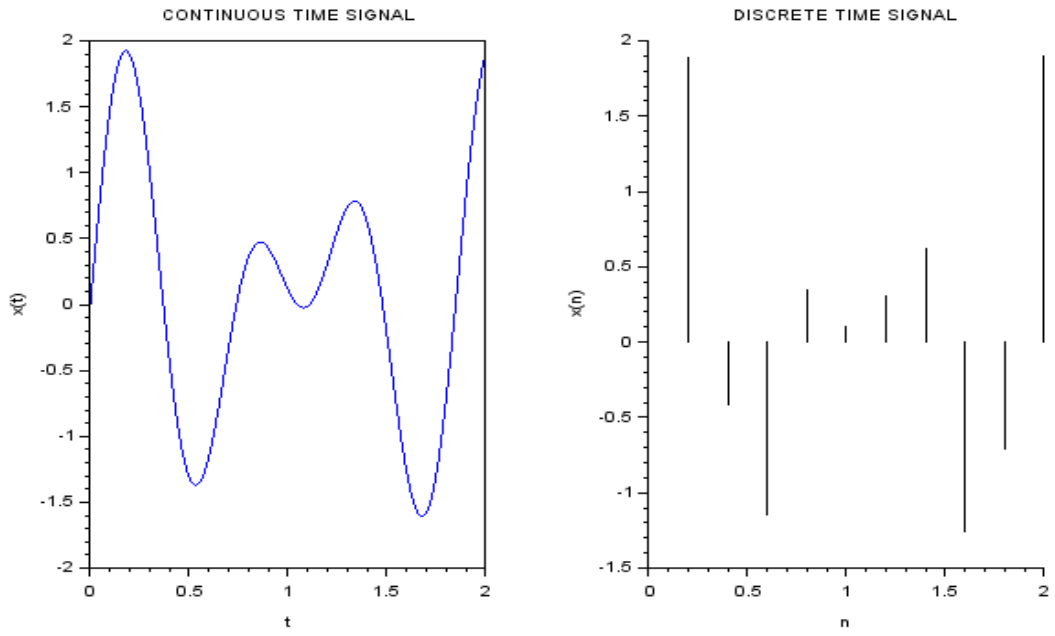
The differences between continuous and discrete-time signals are as follows:

Table 1

S.No.	Continuous-time signal	Discrete-time signal
1	The continuous-time signal is an analog representation of a natural signal.	The discrete-time signal is a digital representation of a continuous-time signal.
2	The continuous-time signal can be converted into discrete-time signal by the Euler's method.	The discrete -time signal can be converted into continuous-time signal by the methods of zero-order hold or first-order hold.
3	The conversion of continuous to discrete-time signal is comparatively easy than the conversion of discrete to continuous-time signals.	The conversion of discrete to continuous-time signals is very complicated and it is done through a sample and hold process.
4	It is defined over a finite or infinite domain of sequence.	It is defined over a finite domain of sequence.
5	The value of the signal can be obtained at any arbitrary point of time.	The value of the signal can be obtained only at sampling instants of time.
6	The continuous-time signals are not used for the processing of digital signals.	The discrete-time signals are used for the processing of digital signals.
7	The continuous-time variable is denoted by a letter t.	The discrete-time variable is denoted by a letter n.
8	The independent variable encloses in the parenthesis $(\bullet)$.	The independent variable encloses in the bracket $[\bullet]$.

```
// GENERATION OF CONTINUOUS TIME SIGNAL AND DISCRETE TIME SIGNAL
clear ;
clc ;
close ;
t =0:0.01:2;
x1 =sin (7* t ) +sin (10* t ) ;
subplot (1 ,2 ,1) ;
plot (t , x1 ) ;
xlabel ( 't' ) ;
ylabel ( 'x(t)') ;
title ( 'CONTINUOUS TIME SIGNAL');
n =0:0.2:2;
x2 =sin (7* n ) +sin (10* n ) ;
subplot (1 ,2 ,2) ;
plot2d3 (n , x2 ) ;
xlabel ( 'n') ;
ylabel ( 'x(n)') ;
title ( 'DISCRETE TIME SIGNAL' ) ;
```

SIMULATION RESULT



Pre-lab questions:

1. Define continuous time signal.
2. How is discrete time signal generated?
3. Draw the graphical representation of continuous time signal and discrete time signal.

Post-Lab questions:

1. Write any three differences between analog signal and digital signal.
2. Write the code for generation of discrete signal for time interval 5μs and 7μs using subplot function.
3. Give the advantages of digital signal over analog signal.

Result:

EXPERIMENT 3
SAMPLING THEOREM & ALIASING EFFECT

Aim: To generate the sampled signal from the analog signal and verify sampling theorem and aliasing effect using SCI lab

Software Requirement: SCI Lab

Theory:

The real life signals that we encounter in our day to day basis are mostly analog signals. These signals are defined continuously in time and have an infinite range of amplitude values. In order to process these signals to obtain meaningful information, they need to be converted to a format which is easily handled by computing resources like microprocessors, computers etc... The first step in this process is to convert the real-time signal into discrete-time signals. Discrete-time signals are defined only at a particular set of time instances. They can thus be represented as a sequence of numbers with a continuous range of values.

The process of converting an analog signal (denoted as x(t)) to a digital signal (denoted as x(n)) is called the analog-to-digital conversion (referred to as digitization), usually performed by an analog-to-digital converter (ADC). Here t is the continuous time variable and n is the sequence order. In many applications after the processing of the digital signal is performed, x(n) needs to be converted back to analog signal x(t) before it is applied to the appropriate analog device. This reverse process is called digital-to-analog conversion and is typically performed using a digital-to-analog converter (DAC).

The typical block diagram of an ADC is shown in Fig. 1 below.

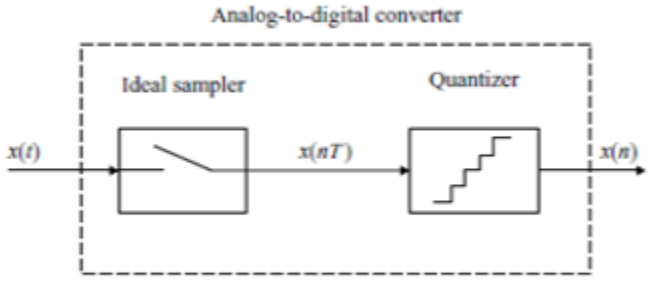


Fig:-1 Block diagram of an ADC

The process of digitization consists of first sampling (digitization in time) and quantization (digitization in amplitude). In this experiment we will study and understand the principle of sampling, while the principle of quantization will be studied in the next experiment. The sampling process depicts an analog signal as a sequence of values. The basic sampling function can be

carried out with an ideal 'sample-and-hold' circuit which maintains the sampled signal until the next sample is taken. An ideal sampler can be considered as a switch that periodically opens and closes every T seconds. The sampling frequency (fs in Hertz) is thus defined as

$$f_s = \frac{1}{T} \ldots . (1)$$

The sampled discrete time signal x(nT) , n=0,1,2,.... of the original continuous time signal x(t) is shown in Fig. 2 below.

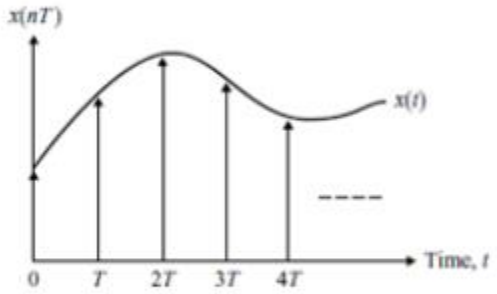


Fig:-2 Digitization of analog signal x(t) into discrete-time signal x(nT)

In order to represent an analog signal x(t) by a discrete-time signal x(nT) accurately, so that the analog signal can be exactly reconstructed back from the discrete-time signal, the sampling frequency fs must be at least twice the maximum frequency component (fM) of the original analog signal. Thus we have,

$$f_s \geq 2f_m \ldots . (2)$$

The minimum sampling rate is called the Nyquist rate and the above Sampling Theorem is called the Shannon's Sampling Theorem. When an analog signal is sampled at fs , frequency components higher than fs/2 fold back into the frequency range [0, fs/2]. This folded frequency components overlap with the original frequency components in the same range and leads to an undesired effect known as aliasing. In this case, the original analog signal cannot be recovered from the sample data.

Consider an analog signal of frequency 1Hz as shown in Fig. 3(a) below. The sampling frequency is 4Hz. The sampled signal is shown in Fig. 3(b), Note that an exact reconstruction of the missing samples is obtained so long as the Shannon's Sampling Theorem is satisfied.

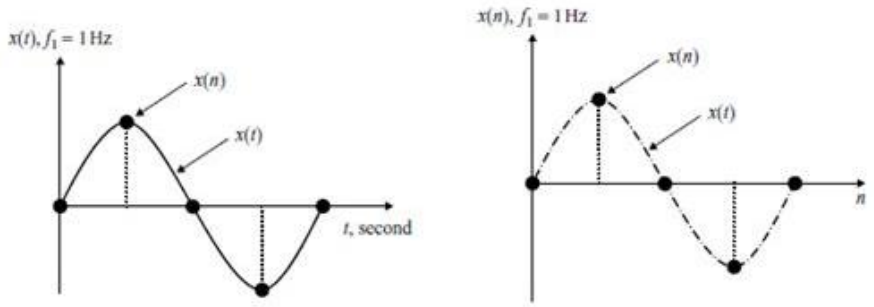


Fig:-3 Sampling of an analog signal *x*(t) into discrete-time signal *x*(nT) (a) and its exact reconstruction (b)

Now let's consider the analog signal of frequency 5Hz as shown in Fig. 4(a) below. The sampling frequency is the same as above, i.e. 4Hz. The sampled signal is shown in Fig. 4(b), Note that the reconstruction of the original analog signal is not possible since the sampling frequency does not satisfy Shannon's Sampling Theorem. In this case the reconstructed signal has a frequency of 1Hz. The signal of 5Hz is folded back as 1Hz, into the range determined by the sampling frequency leading to the problem of aliasing.

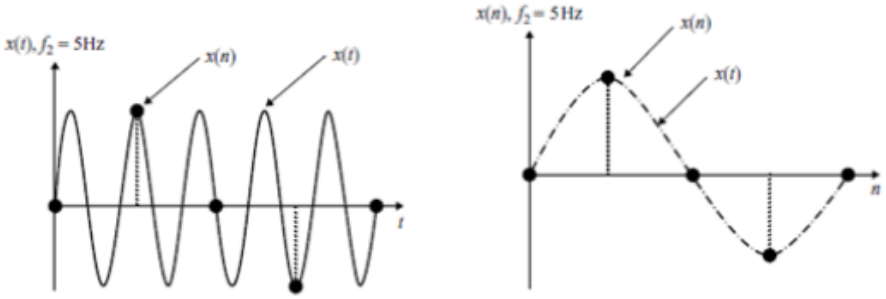


Fig:-4 Sampling of an analog signal *x*(t) into discrete-time signal *x*(nT) (a) and its inaccurate reconstruction (b)

Aliasing – from alias – is an effect that makes different signals indistinguishable when sampled. It also refers to the difference between a signal reconstructed from samples and the original continuous signal, when the resolution is too low. Basically, aliasing depends on the sampling rate and frequency content of the signal.

Sampling Rate and Nyquist Frequency Limit

▪ For a given highest frequency B, we get the lower bound on the sampling frequency : 2B or Nyquist rate. For instance : for a signal whose maximum frequency is 16 KHz, we need a 32 KHz sampling rate.

▪ For a given sampling rate, we get the upper bound for frequency components : B<fs/2, or Nyquist frequency or Fmax. For instance : for a signal whose sampling rate is 48 KHz, we can sample signals up to 24 KHz.

In practice, a signal can never be perfectly bandlimited. Even if an ideal reconstruction could be made, the reconstructed signal would not be exactly the original signal. The error that corresponds to the failure of band limitation is referred to as aliasing.

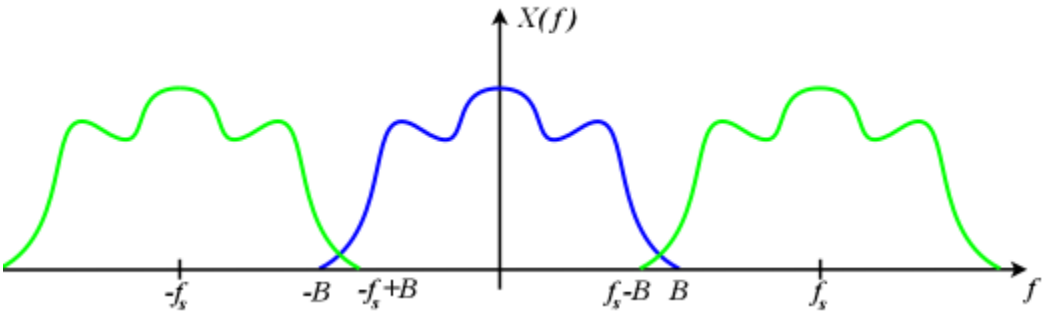


Fig 5: The blue sampled signal is insufficiently bandlimited. The overlapping edges of the green images are added and creating a spectrum

When a signal is sampled, its contents is reduced from real numbers to integer numbers. Values can be rounded to a superior or inferior value. If a signal is sampled with a 32 KHz sampling rate, any frequency components above 16 KHz – Nyquist frequency, create an aliasing.

Any frequency component above fs/2 is indistinguishable from a lower-frequency component, called an alias, associated with one of the copies.The Fourier transform of the signal creates a symmetrical image. The energy above the Nyquist frequency is transferred below this frequency.

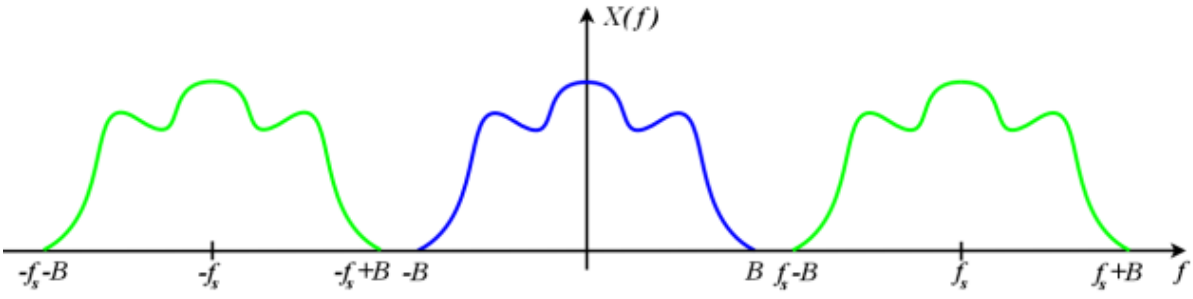
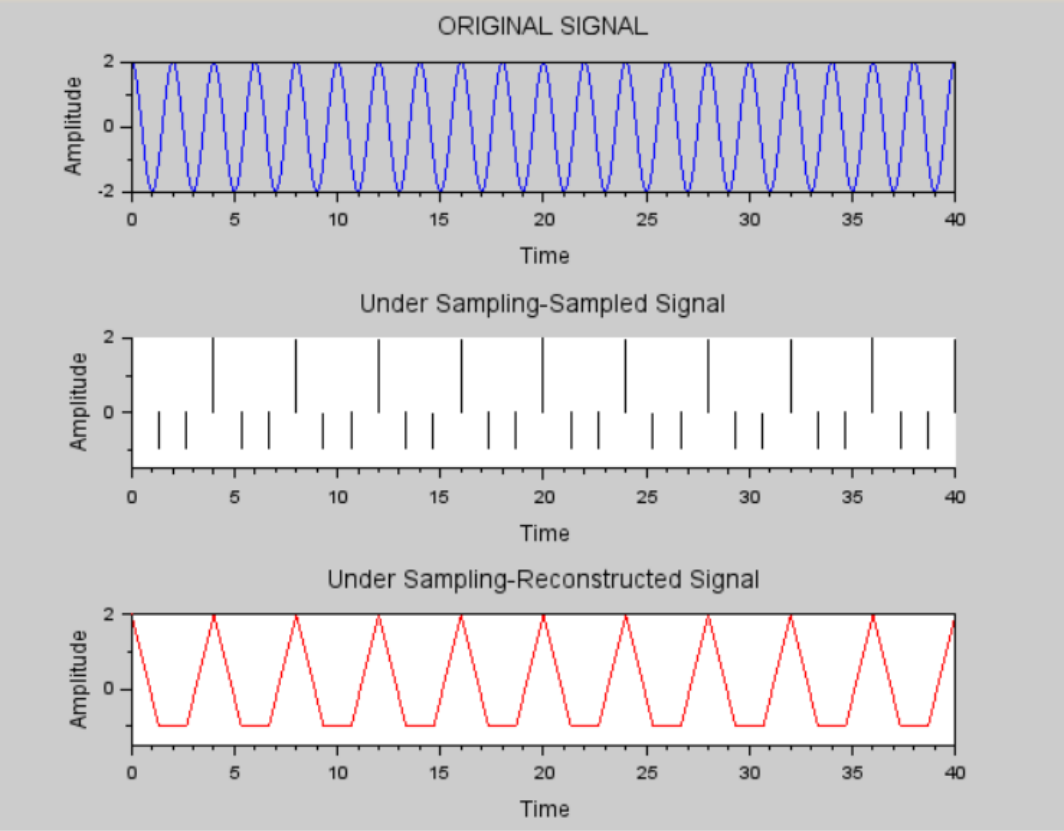


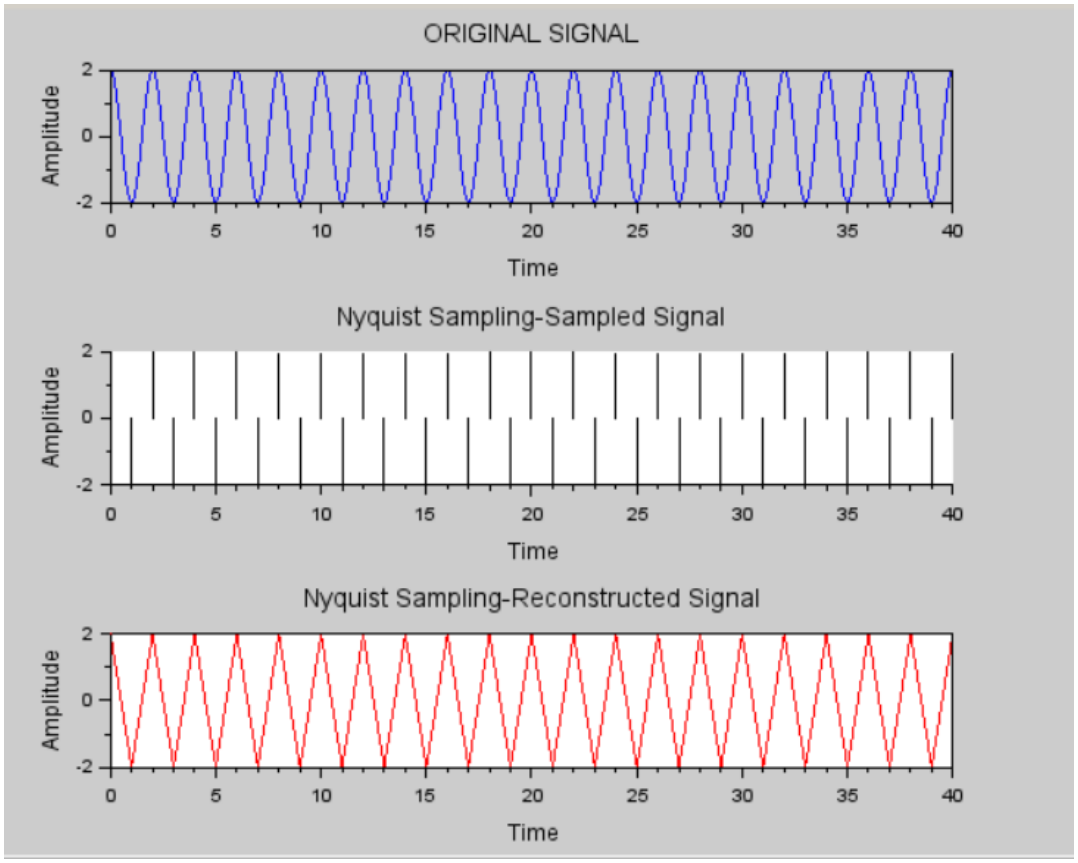
Fig 5 The blue signal is bandlimited and properly sampled. The images do not overlap.

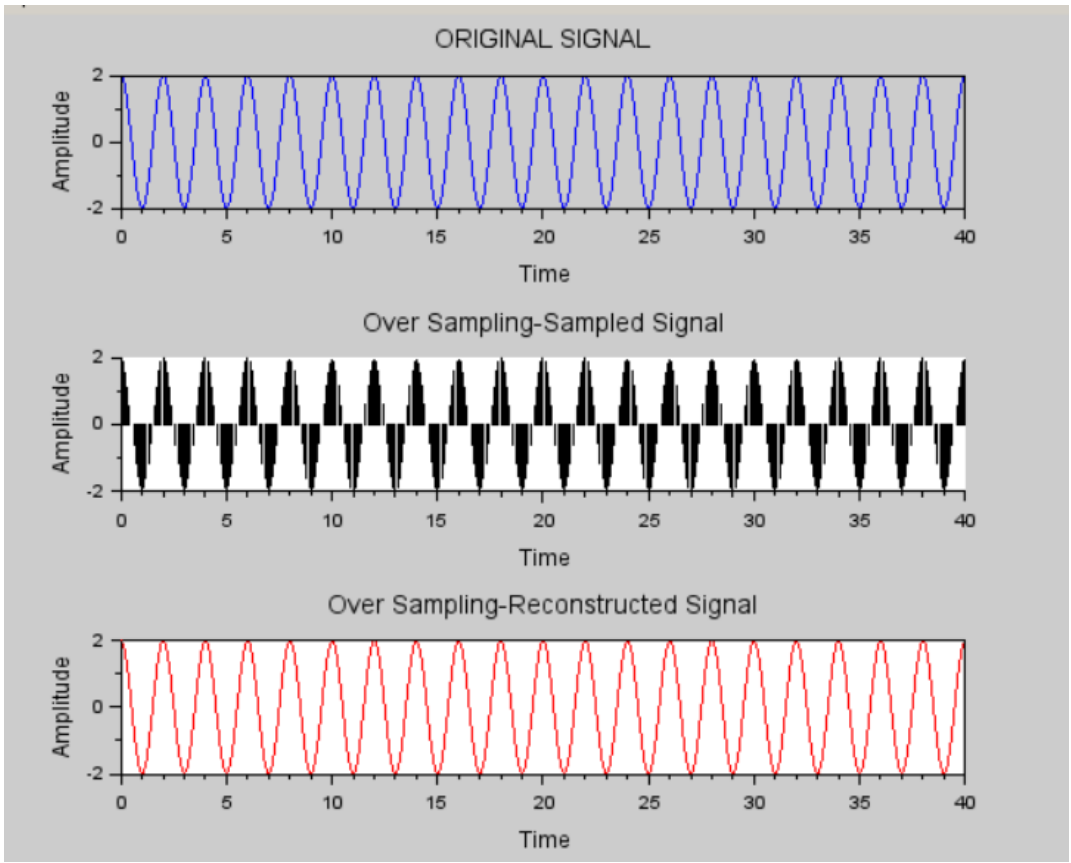
```
clc;
clf;
clear all;
fm =0.5// message frequencyh
k =20//number of cycles in input signal
A = 2//amplitude
//input ("E n t e r t h e am pli t u d e of i n p u t s i g n a l :") ;
tm=0:0.1:k/fm;
x = A*cos(2*%pi*fm*tm) ;
// Sampling Rate ( N y q ui s t Rate )=2∗fm
fnyq =2*fm ;
// UNDER SAMPLING
//xgrid(1)
fs =(3/4)*fnyq ;
n =0:1/fs:k/fm ;
xn = A*cos(2*%pi*fm*n) ;
figure(1) ;
//a = gca() ;
subplot(3,1,1);
plot(tm,x);
title("ORIGINAL SIGNAL");
xlabel("Time");
ylabel("Amplitude");
//a.x_location = ”origin”
//a.y_location = ”origin”
subplot(3,1,2);
plot2d3("gnn",n,xn);
title ("Under Sampling-Sampled Signal") ;
xlabel("Time");
ylabel("Amplitude") ;
subplot(3,1,3);
plot(n,xn,"r");
title ("Under Sampling-Reconstructed Signal") ;
xlabel("Time");
```

```
ylabel("Amplitude") ;
// NYQUIST SAMPLING
//xgrid(1)
fs= fnyq ;
n =0:1/fs:k/fm;
xn=A*cos(2*%pi*fm*n);
figure(2);
//a = gca();
subplot(3,1,1);
plot(tm,x);
title("ORIGINAL SIGNAL");
xlabel("Time");
ylabel("Amplitude");
subplot(3,1,2);
plot2d3("gnn",n,xn);
//plot(n,xn,"r");
title ("Nyquist Sampling-Sampled Signal") ;
xlabel("Time");
ylabel("Amplitude") ;
subplot(3,1,3);
//plot2d3("gnn",n,xn);
plot(n,xn,"r");
title ("Nyquist Sampling-Reconstructed Signal") ;
xlabel("Time");
ylabel("Amplitude") ;
//xgrid(1)
//OVER SAMPLING
fs=fnyq*10;
n=0:1/fs:k/fm;
xn=A*cos(2*%pi*fm*n);
figure (3);
//a = gca ();
subplot(3,1,1);
plot(tm,x);
```

```
title("ORIGINAL SIGNAL");
xlabel("Time");
ylabel("Amplitude");
subplot(3,1,2);
plot2d3("gnn",n,xn);
title ("Over Sampling-Sampled Signal") ;
xlabel("Time");
ylabel("Amplitude") ;
subplot(3,1,3);
plot(n,xn,"r");
title ("Over Sampling-Reconstructed Signal") ;
xlabel("Time");
ylabel("Amplitude") ;
//xgrid(1)
```




ORIGINAL SIGNAL
Amplitude
Time
Nyquist Sampling-Sampled Signal
Amplitude
Time
Nyquist Sampling-Reconstructed Signal
Amplitude
Time


ORIGINAL SIGNAL
Amplitude
Time
Over Sampling-Sampled Signal
Amplitude
Time
Over Sampling-Reconstructed Signal
Amplitude
Time

Pre-lab questions:

1. Define Sampling rate
2. Why is signal to be sampled?
3. Define : sampling theorem
4. What is aliasing? When is aliasing occurred?
5. How to avoid aliasing?

Post-Lab questions:

1. If signal x(t)= 5sin(800Πt) is sampled what is the minimum sampling rate required to avoid aliasing ? Determine the discrete time signal after sampled
2. Define Alias frequency with an example
3. What will be the graphical representation of discrete time signal of x(t) for the following cases a) $f_s=f_m$ b) $f_s=2f_m$ c) $f_s<f_m$ d) $f_s>2f_m$

Result:

Sampling Theorem and Aliasing effect are verified using SciLab

EXP No:4 Linear Convolution and Circular Convolution

Aim: To obtain linear and circular convolution of two input sequence using scilab

A linear system has the property that the response to a linear combination of inputs is the same linear combination of the individual responses. The property of time invariance states that, in effect, the system is not sensitive to the time origin. More specifically, if the input is shifted in time by some amount, then the output is simply shifted by the same amount. The importance of linearity derives from the basic notion that for a linear system if the system inputs can be decomposed as a linear combination of some basic inputs and the system response is known for each of the basic inputs, then the response can be constructed as the same linear combination of the responses to each of the basic inputs. Signals (or functions) can be decomposed as a linear combination of basic signals in a wide variety of ways. For systems that are both linear and time-invariant, there are two particularly useful choices for these basic signals: delayed impulses and complex exponentials. The representation of both continuous time and discrete-time signals as a linear combination of delayed impulses and the consequences for representing linear, time-invariant systems. The resulting representation is referred to as convolution.

```
// Program for LINEAR CONVOLUTION
clc;
clf;
clear all;
 x = input("Enter the first sequence: ");
h = input("Enter the second sequence: ");
y = conv(x, h);
disp(conv(x, h), "Convolution = ");
```

OUTPUT:

```
Enter the first sequence: [1 2 3 4 5 6 7 8 ]
Enter the second sequence: [ 5 4 5 2 1]
  "Convolution = "
   5.   14.   28.   44.   61.   78.   95.   112.   84.   60.   23.   8.
```

// program for circular convolution using concentric circle method

```
clc ;
clf ;
clear all;
g=input("enter the first sequence");
h=input("enter the second sequence");
N1=length (g);
N2=length(h);
N=max(N1,N2) ;
N3=N1-N2;
if(N3>=0)then
h =[h,zeros(1,N3)];
else
g =[g,zeros(1,- N3)];
end
for n=1:N
y(n)=0;
for i=1:N
j=n - i+1;
if(j<=0)
j= N + j;
end
y(n)=y(n)+g(i)*h(j);
end
end
disp(' sequence y =');
disp(y);
plot2d3(y);
```

Output

```
enter the first sequence[2 1 2 1]
enter the second sequence[ 1 2 3 4]
```

" sequence y ="

14. 16. 14. 16.

```
// Program for Circular convolution using DFT computation
clc ;
close ;
x1=[2 ,1 ,2 ,1];
x2=[1 ,2 ,3 ,4];
//DFT Compu tation
X1 =fft(x1,-1);
X2=fft(x2,-1);
X3=X1 .* X2 ;
//IDFT Computation
x3 =fft( X3 ,1);
// D i s p l a y s e q u e n c e x3 [ n ] i n command window
disp(x3);
```

Output

14. 16. 14. 16.

Pre lab

1. Define linear convolution
2. Define circular convolution
3. what is convolution property of DFT

Post lab

1.Find the linear convolution of two sequence manual and check your answer with scilab
x(n)={3,-1,0,1,3,2,0,1,2,1}h(n)={1,1,1}

2.Find the linear convolution of two sequence manual and check your answer with scilab
x(n)={3,2,1,2}h(n)={1,2,1,2}

3.Find the circular convolution of two sequence manual and check your answer with scilab
x_1(n)={3,2,1,2}x2(n)={1,2,3,1}

RESULT:

Laboratory Report Cover Sheet

SRM Institute of Science and Technology
College of Engineering and Technology
Department of Electronics and Communication Engineering

18ECC204J DIGITAL SIGNAL PROCESSING
Fifth Semester, 2023-24 (Odd semester)

Name :

Register No. :

Day / Session :

Venue :

Title of Experiment :

Date of Conduction :

Date of Submission :

Particulars	Max. Marks	Marks Obtained
Pre lab	10	
Lab Performance	15	
Post Lab	10	
Viva	05	
Total	40	

REPORT VERIFICATION

Staff Name :

Signature :

EXPERIMENT 5

Experiment 5a: Auto correlation and cross correlation

Aim: To obtain correlation of two input sequences using Scilab

(i) Auto correlation

(ii) Cross correlation.

Software Requirement:

SCI Lab

Introduction

Auto correlation is the convolution of a time series with its time-reversed self. The Fourier transform of an autocorrelation is proportional to the Power Spectral Density of time series. The cross correlation of two sequences x[n] and y[n] = x[n-k] shows a peak at the value of k. Hence cross correlation is employed to compute the exact value of the delay k between the two signals. Used in radar and sonar applications, where the received signal reflected from the target is the delayed version of the transmitted signal (measure delay to determine the distance of the target)

//program for cross correlation

```
clc;
clr;
clear all;
x = input("Enter First Sequence: ");
h = input("Enter Second Sequence: ");
y = xcorr(x, h);
disp(y, "Cross correlation = ");
```

Output:

Enter First Sequence: [1 2 3 4]

Enter Second Sequence: [3 4 5 6]

"Cross correlation = "

6. 17. 32. 50. 38. 25. 12.

//program for Auto correlation

```
clc;
clr;
clear all;
x = input("Enter First Sequence: ");
//h = input("Enter Second Sequence: ");
y = xcorr(x);
disp(y, "Auto correlation  = ");
```

Output:

Enter First Sequence: [1 2 3 4]

"Autocorrelation = “

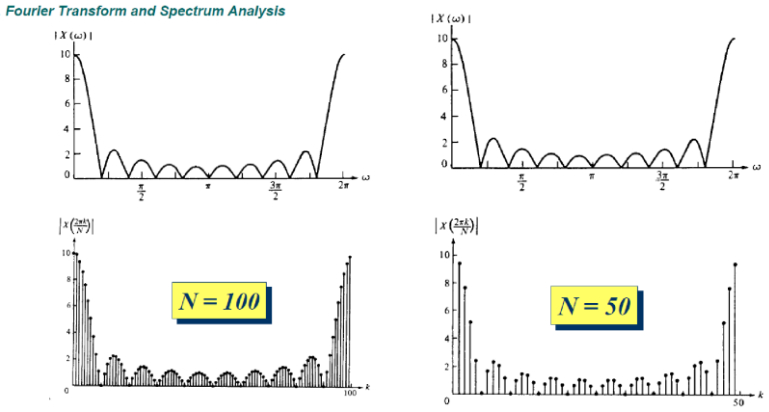
4. 11. 20. 30. 20. 11. 4.

Experiment 5b. Spectrum Analysis using DFT

Aim: To analyze the spectrum of a signal using DFT in Scilab platform

Discrete Fourier Transform:

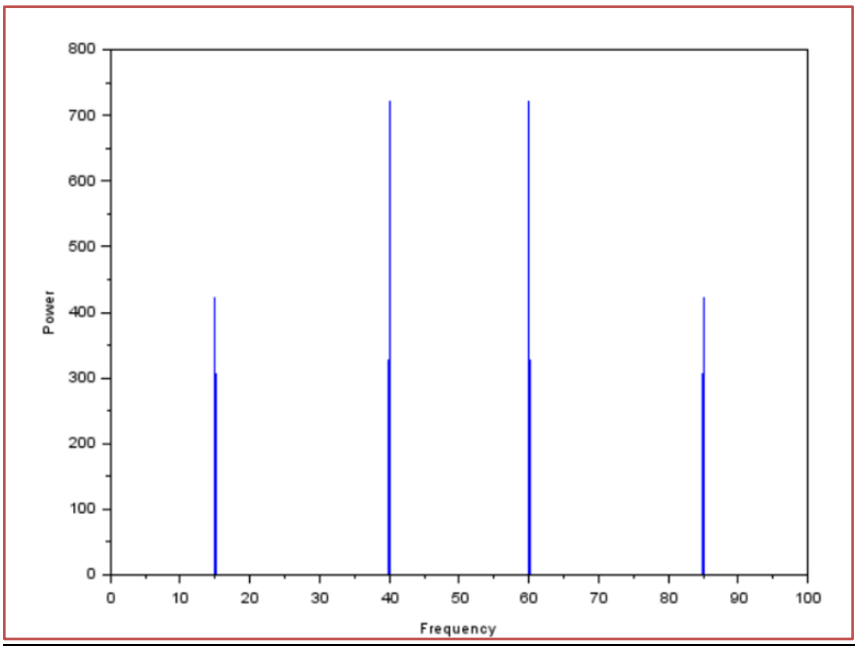
Spectrum of aperiodic discrete-time signals is periodic and continuous and it is difficult to handle by computer. Since the spectrum is periodic, there's no point to keep all periods – one period is enough. Computer cannot handle continuous data, we can only keep some samples of the spectrum. Interestingly enough, such requirements lead to a very simple way to find the spectrum of signal is Discrete Fourier Transform. Discrete Fourier Transform (DFT) is exactly the output of the Fourier Transform of an aperiodic sequence at some particular frequencies.



//Spectrum analysis using DFT

```
clc;
clr;
clear all;
fs=100;
t = 0:1/fs:10-1/fs;
x = ((1.3)*sin(2*%pi*15*t)+ (1.7)*sin(2*%pi*40*(t-2)))
y=fft(x)
n = length(x);
f = (0:n-1)*(fs/n);
power = abs(y).^2/n;
plot(f,power)
xlabel('Frequency')
ylabel('Power')
```

OUTPUT:



Pre lab

1. Define correlation.
2. Define auto correlation.
3. State the properties of autocorrelation.
4. Draw the spectrum of periodic and aperiodic signal.

Post lab

1. List the differences between Auto correlation and convolution.
2. List the difference between Auto correlation and cross correlation.
3. What is the length of the resultant sequence of auto correlation?
4. List a few applications of correlation.

RESULT:

Lab 6 : Efficient computation of DFT and IDFT using FFT

Aim: To obtain the efficient computation of DFT and IDFT using FFT

Software Requirement: SCI Lab

Theory:

DFT:

Discrete Fourier Transform (DFT) is used for performing frequency analysis of discrete time signals. DFT gives a discrete frequency domain representation whereas the other transforms are continuous in frequency domain. The N point DFT of discrete time signal x[n] is given by the equation

$X(k) = \sum_{n=0}^{N-1} \quad x(n)e^{\frac{-j2\pi kn}{N}}$ for k=0,1,2,…N-1

The inverse DFT allows us to recover the sequence x[n] from the frequency samples

$x(n) = \frac{1}{N}\sum_{k=0}^{N-1} \quad X(k)e^{\frac{-j2\pi kn}{N}}$ for n=0,1,2,…N-1

FFT:

A fast Fourier transform (FFT) is an efficient algorithm to compute the discrete Fourier transform (DFT) and its inverse. FFTs are of great importance to a wide variety of applications, from digital signal processing and solving partial differential equations to algorithms for quick multiplication of large integers. Evaluating the sums of DFT directly would take $O(N^2)$ arithmetical operations. An FFT is an algorithm to compute the same result in only O(N log N) operations. In general, such algorithms depend upon the factorization of N, but there are FFTs with O(N log N) complexity for all N, even for prime N. Since the inverse DFT is the same as the DFT, but with the opposite sign in the exponent and a 1/N factor, any FFT algorithm can easily be adapted for it as well.

Algorithm:

1) Get the input sequence
2) Find the FFT of the input sequence using SciLAB function.
3) Find the IFFT of the input sequence using SciLAB function.
4) Display the above outputs.

Program:

```
// program for calculation of FFT of a signal
clc ;
clf ;
clear all;
N = input('Enter the value of N');
x = input ('enter input sequence');
y = fft(x);
A = real(y);
B = imag(y);
mag = abs(y);
x1 = atan(imag(y),real(y));
phase = x1 *(180/ %pi ) ;
disp ('the resultant FFT sequence is ' ) ;
disp (y);
disp ('the magnitude response is ') ;
disp ( mag ) ;
disp ('the phase response is') ;
disp (phase) ;
z = ifft ( y ) ;
disp ('the resultant IFFT sequence is') ;
disp ( z );
subplot (3 ,2 ,1) ;
plot2d3 ( x );
title ( 'input sequence') ;
subplot (3 ,2 ,2) ;
plot2d3 ( A );
title ( 'FFT real sequence ' ) ;
subplot (3 ,2 ,3) ;
plot2d3 ( B );
title ('FFT imaginary sequence ' ) ;
subplot (3 ,2 ,4) ;
plot2d3 ( mag ) ;
title ( 'magnitude response ' ) ;
subplot (3 ,2 ,5) ;
plot2d3 ( phase ) ;
title ( 'phase response ') ;
subplot (3 ,2 ,6) ;
plot2d3 ( x );
```

title ('IFFT sequence ') ;

Results:

Enter the value of N 8

enter input sequence [1 2 3 4 5 6 7 8]

"the resultant FFT sequence is "

column 1 to 5

36. + 0.i -4. + 9.6568542i -4. + 4.i -4. + 1.6568542i -4. + 0.i

column 6 to 8

-4. - 1.6568542i -4. - 4.i -4. - 9.6568542i

"the magnitude response is "

column 1 to 7

36. 10.452504 5.6568542 4.3295688 4. 4.3295688 5.6568542

column 8

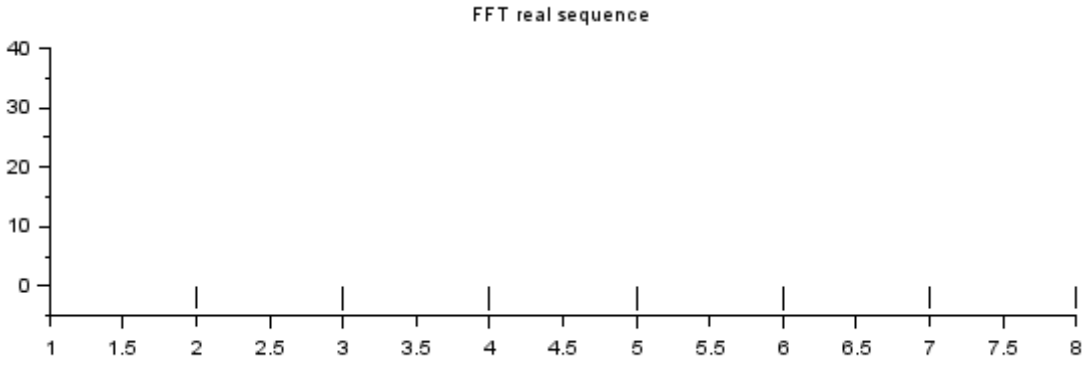
10.452504

"the phase response is"

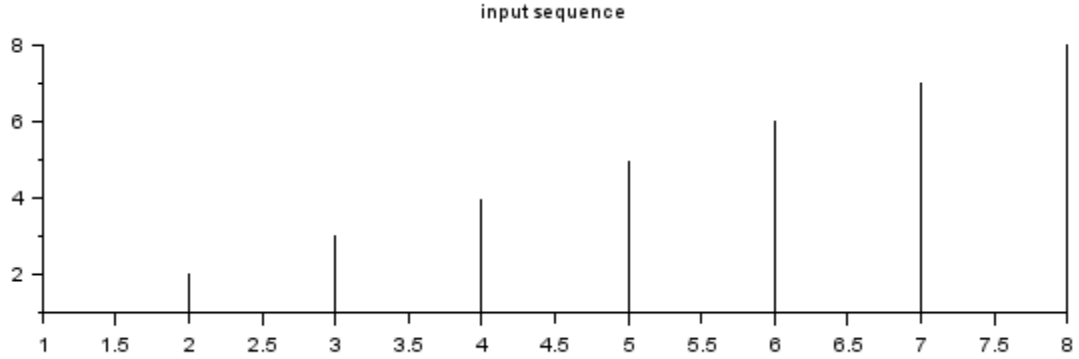
0. 112.5 135. 157.5 180. -157.5 -135. -112.5

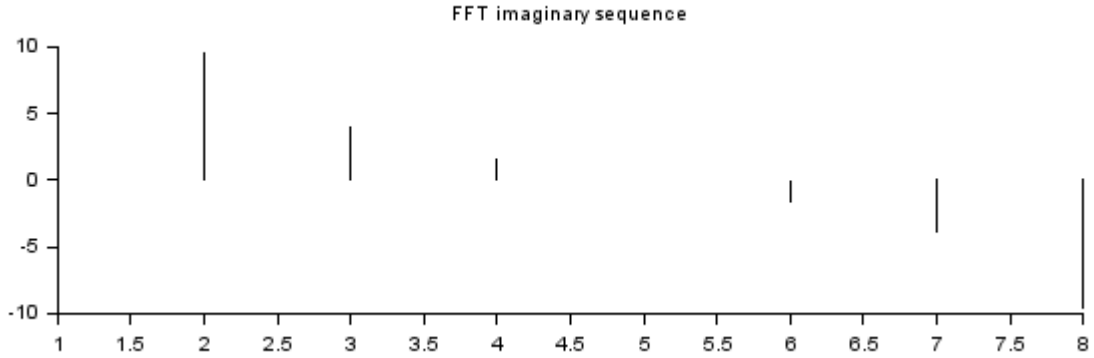
"the resultant IFFT sequence is"

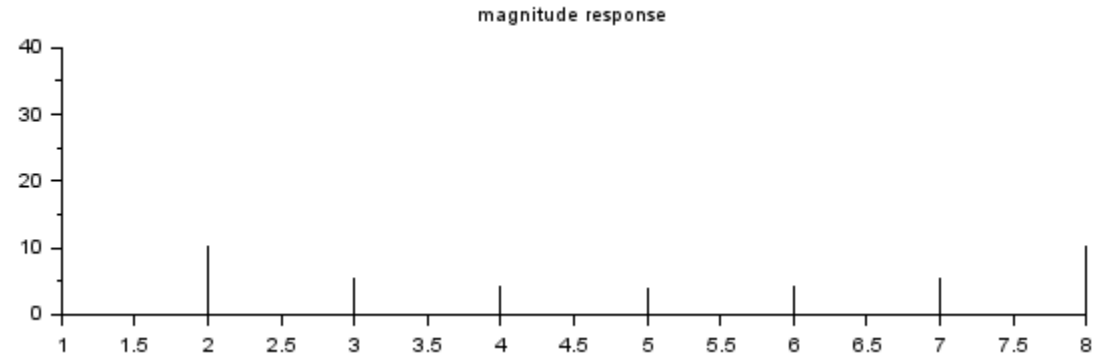
1. 2. 3. 4. 5. 6. 7. 8.


FFT real sequence
40
30
20
10
0
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8

:


input sequence
8
6
4
2
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8


FFT imaginary sequence
10
5
0
-5
-10
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8


magnitude response
40
30
20
10
0
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6
6.5
7
7.5
8

Pre-lab questions:

1. Why do we need Fourier transform in DSP?
2. What is the need of FFT ?
3. What's the difference between FFT and DFT?
4. What is "decimation-in-time" versus "decimation-in-frequency"?

Post-Lab questions:

1. Compute the 8-point FFT of the sequence x (n) = [1 2 1 2 3 4 3 4] using DIT-FFT and DIF-FFT and verify the result using Sci Code.

Result:

Lab 7: Design of digital FIR Low Pass, High Pass, Band Pass, band Stop filter using rectangular window

Aim: Design and implementation of FIR Filter (LP /HP /BP /BS) to meet given specifications using Windowing technique

a. Rectangular window

Software Requirement: SCI Lab

Theory:

FIR filters are digital filters with finite impulse response. They are also known as non-recursive digital filters as they do not have the feedback.

An FIR filter has two important advantages over an IIR design:

 Firstly, there is no feedback loop in the structure of an FIR filter. Due to not having a feedback loop, an FIR filter is inherently stable. Meanwhile, for an IIR filter, we need to check the stability.

 Secondly, an FIR filter can provide a linear-phase response. As a matter of fact, a linear-phase response is the main advantage of an FIR filter over an IIR design otherwise, for the same filtering specifications; an IIR filter will lead to a lower order.

FIR FILTER DESIGN

An FIR filter is designed by finding the coefficients and filter order that meet certain specifications, which can be in the time-domain (e.g. a matched filter) and/or the frequency domain (most common). Matched filters perform a cross-correlation between the input signal and a known pulse-shape. The FIR convolution is a cross-correlation between the input signal and a time-reversed copy of the impulse-response. Therefore, the matched-filter's impulse response is "designed" by sampling the known pulse-shape and using those samples in reverse order as the coefficients of the filter. When a particular frequency response is desired, several different design methods are common:

1. Window design method

WINDOW DESIGN METHOD

In the window design method, one first designs an ideal IIR filter and then truncates the infinite impulse response by multiplying it with a finite length window function. The result is a finite impulse response filter whose frequency response is modified from that of the IIR filter.

Algorithm:

1) Get the input analog cut off frequency.
2) Get the input sampling frequency.
3) Get the filter order.
4) Find the digital cut off frequency.
5) Normalize the digital cut off frequency.
6) Using built in filter function find the time domain filter coefficients, frequency domain filter response and Frequency grid for LPF,HPF,BPF and BSF.
7) Plot the magnitude response of the filter with respect to Normalized Digital Frequency and Analog Frequency.

Program(a)Low pass filter

```
// To Design a Low Pass FIR Filter
// F i l t e r Length =5 , Order = 4
//Window = Rectangular Window
clc ;
clear ;
xdel(winsid());
fc=input('Enter Analog cutoff freq.in Hz=')
fs=input('Enter Analog sampling freq.in Hz=')
M=input('Enter order of filter =')
w=(2*%pi)*(fc/fs);
disp(w,'Digital cut off frequency in radians,cycles/samples');
wc=w/%pi;
disp(wc,'Normalized digital cut off frequency in cycles/samples');
```

```
[wft,wfm,fr]=wfir('lp',M+1,[wc/2,0],'re',[0,0]);
disp(wft,'Impulse Response of LPF FIR Filter:h[n]=');
// Pl o t t i n g the Magnitude Response of LPF FIR Filter
subplot(2,1,1);
plot(2*fr,wfm);
xlabel('Normalized Digital Frequency w--->')
ylabel('Magnitude |H(w)|=')
title('Magnitude Response of FIR LPF')
xgrid(1)
subplot(2,1,2)
plot(fr*fs,wfm)
xlabel('Analog Frequency in Hz f--->')
ylabel('Magnitude|H(w)|=')
title('Magnitude Response of FIR LPF')
xgrid(1)
```

Results

Enter Analog cutoff freq.in Hz=250

Enter Analog sampling freq.in Hz=2000

Enter order of filter =4

0.7853982

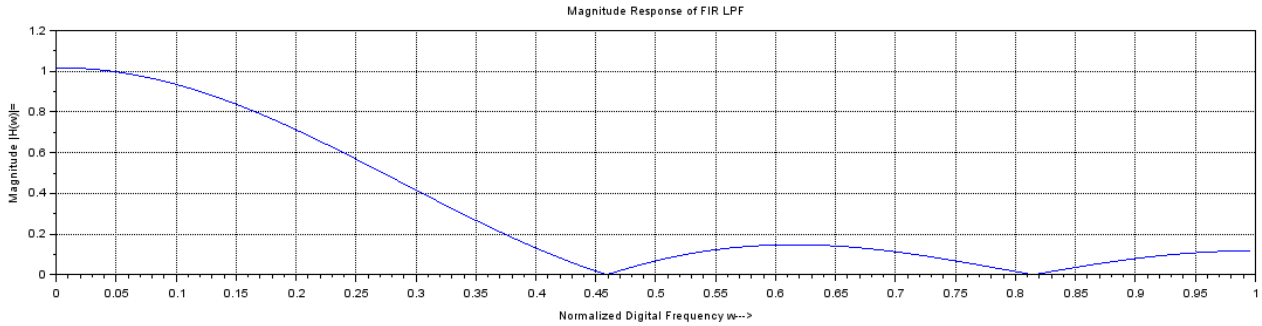
"Digital cut off frequency in radians,cycles/samples"

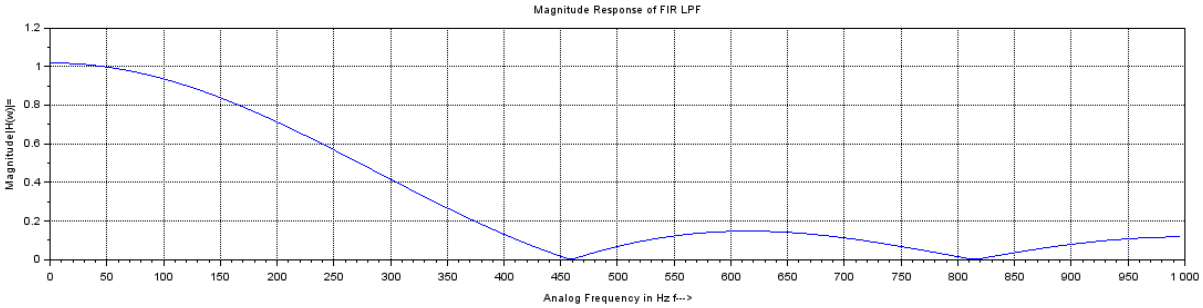
0.25

"Normalized digital cut off frequency in cycles/samples"

0.1591549 0.2250791 0.25 0.2250791 0.1591549

"Impulse Response of LPF FIR Filter:h[n]="





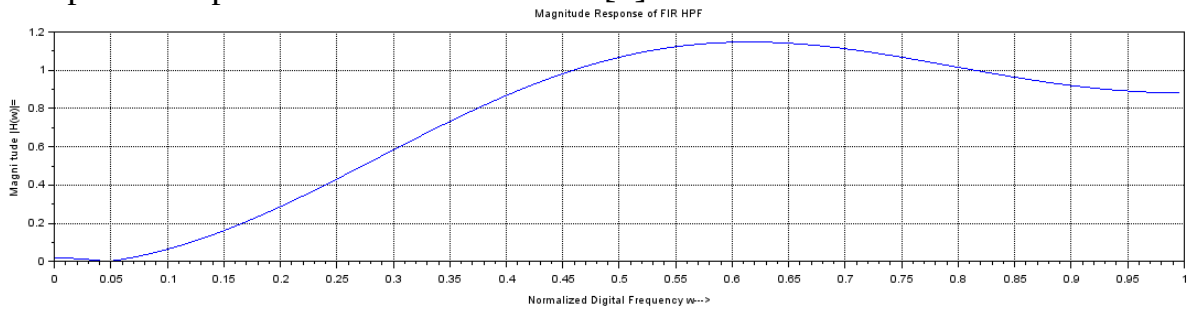
Program:(b) High pass filter

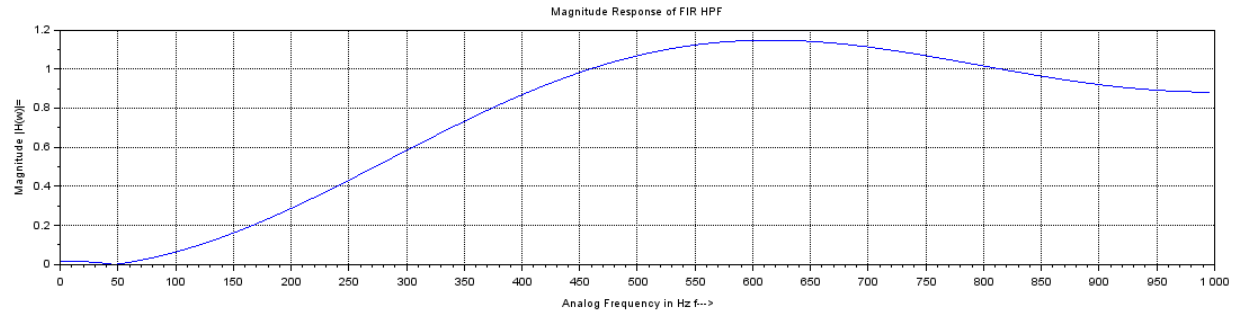
```
// To De s ign an High Pas s FIR F i l t e r
// Filter Length =5 , Order = 4
//Window = Rectangular Window
clc;
clear;
xdel(winsid());
fc=input('Enter Analog cut off freq in Hz=')// 250
fs=input('Enter Analog sampling freq in Hz=')//2000
M=input('Enter order of filter =')//4
w=(2*%pi)*(fc/fs);
disp(w,'Digital cut off frequency in radians cycles/samples');
wc=w/%pi;
disp(wc,'Normalized digital cut off frequency in cycles/samples');
[wft,wfm,fr]=wfir('hp',M+1,[wc/2,0],'re',[0,0]);
disp(wft,'Impulse Response of HPF FIR Filter:h[n]=');
// Pl o t t i n g the Magni tude Re spons e o f HPF FIR F i l t e r
subplot(2,1,1)
plot(2*fr,wfm)
xlabel('Normalized Digital Frequency w--->')
```

```
ylabel('Magni tude |H(w)|=')
title('Magnitude Response of FIR HPF')
xgrid(1)
subplot(2,1,2)
plot(fr*fs,wfm)
xlabel('Analog Frequency in Hz f--->')
ylabel ('Magnitude |H(w)|=')
title('Magnitude Response of FIR HPF')
xgrid(1)
```

Results:

```
Enter Analog cut off freq in Hz=250
Enter Analog sampling freq in Hz=2000
Enter order of filter =4
  0.7853982
 "Digital cut off frequency in radians cycles/samples"
  0.25
 "Normalized digital cut off frequency in cycles/samples"
 -0.1591549  -0.2250791   0.75  -0.2250791  -0.1591549
 "Impulse Response of HPF FIR Filter:h[n]="
```





Program:(c) Band pass filter

```
// To Design a Band Pass FIR Filter
// F i l t e r Length =5, Order = 4
//Window = Rectangular Window
clc ;
clear;
xdel( winsid());
fc1=input('Enter Analog lower cut off freq.in Hz=') // 250
fc2=input('Enter Analog higher cut off freq. in Hz=') // 600
fs=input('Enter Analog sampling freq.in Hz=')//2000
M=input('Enter order of filter =')//4
w1=(2*%pi)*(fc1/fs);
w2=(2*%pi)*(fc2/fs);
disp(w1,'Digital lower cut off frequency in radians cycles/samples');
disp(w2,'Digital higher cut off frequency in radians cycles/samples');
wc1=w1/%pi;
wc2= w2/%pi;
disp(wc1,'Normalized digital lower cut off frequency in cycles/ samples');
disp(wc2,'Normalized digital higher cut off frequency in cycles / samples');
[wft,wfm,fr]=wfir('bp' ,M+1,[wc1/2,wc2/2],'re',[0,0]);
disp(wft,'Impulse Response of BPF FIR Filter : h[ n]= ');
// Pl o t t i n g the Magni tude Re sponse of HPF FIR Filter
subplot(2,1,1)
plot(2*fr,wfm)
xlabel('Normalized Digital Frequency w--->' )
ylabel('Magnitude|H(w)|=')
title('Magnitude Response of FIR BPF')
xgrid(1)
subplot(2,1,2)
plot(fr*fs,wfm)
xlabel('Analog Frequency in Hz f --->' )
ylabel('Magnitude |H(w)|= ')
title ('Magnitude Response of FIR BPF')
xgrid(1)
```

Results:
Enter Analog lower cut off freq.in Hz=250

Enter Analog higher cut off freq. in Hz=600

Enter Analog sampling freq.in Hz=2000

Enter order of filter =4

0.7853982

"Digital lower cut off frequency in radians cycles/samples"

1.8849556

"Digital higher cut off frequency in radians cycles/samples"

0.25

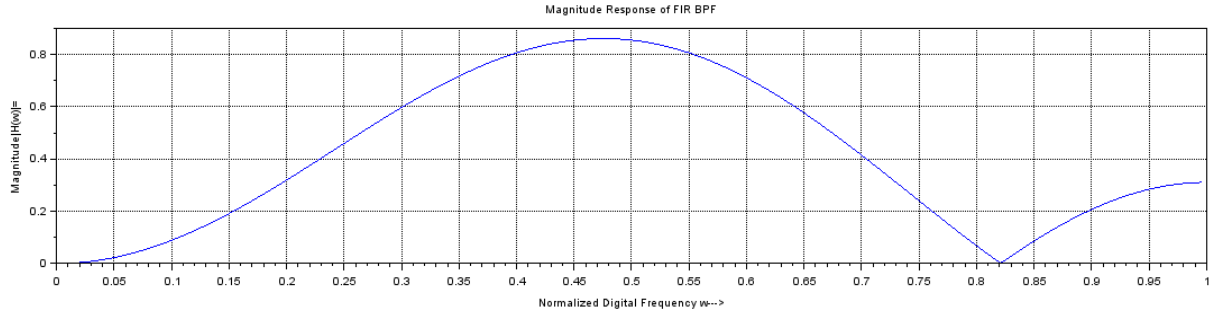
"Normalized digital lower cut off frequency in cycles/ samples"

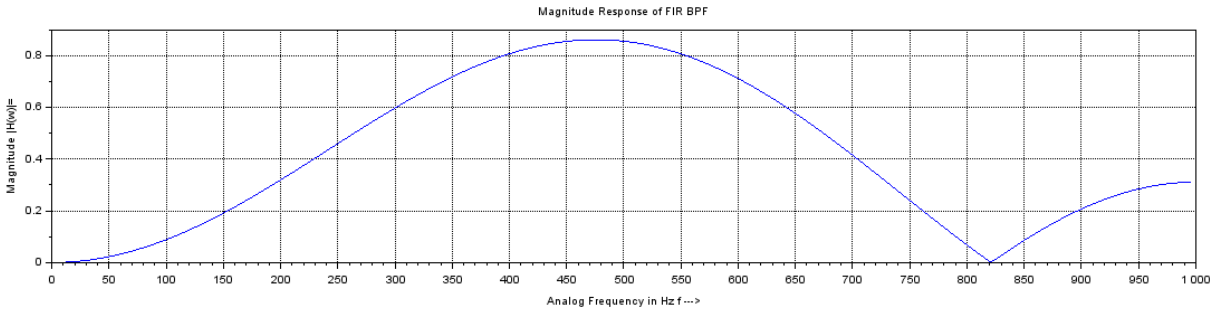
0.6

"Normalized digital higher cut off frequency in cycles / samples"

-0.2527039 0.0776516 0.35 0.0776516 -0.2527039

"Impulse Response of BPF FIR Filter : h[n]= "





Program:(d) Band stop filter

```
// Filter Length =5, Order = 4
//Window = Rectangular Window
clc ;
clear ;
xdel ( winsid ());
fc1 = input ('Enter Analog lower cut off freq in Hz=') // 250
fc2 = input ('Enter Analog higher cut off freq in Hz=') // 600
fs = input ('Enter Analog sampling freq in Hz=') //2000
M = input ('Enter order of filter =') // 4
w1 = (2* %pi )*( fc1/fs);
w2 = (2* %pi )*( fc2/fs);
disp (w1,'Digital lower cut off frequency in radians cycles/samples' );
disp(w2 , 'Digital higher cut off frequency in radians.cycles/samples ' );
wc1 = w1/%pi;
wc2 = w2/%pi;
disp (wc1 , 'Normalized digital lower cut off frequency in cycles / samples
' );
disp (wc2 , 'Normalized digital higher cut off frequency in cycles / samples
' );
[wft,wfm,fr]= wfir('sb',M+1,[wc1/2,wc2/2],'re',[0,0]);
disp (wft , 'Impulse Response of BSF FIR Filter : h [ n]= ' );
// Pl o t t i n g the Magni tude Re spons e o f HPF FIR F i l t e r
subplot (2 ,1 ,1)
plot (2*fr , wfm )
 xlabel ( ' Normalized Digital Frequency w--->' )
ylabel ( 'Magnitude |H(w)|= ' )
```

```
title ( 'Magnitude Response of FIR BSF ' )
xgrid (1)
subplot (2 ,1 ,2)
plot (fr*fs , wfm )
xlabel ( ' Analog Frequency in Hz f --->')
ylabel ('Magnitude |H(w) |= ')
title ('Magnitude Response of FIR BSF')
xgrid (1)
```

Results:

Enter Analog lower cut off freq in Hz=250

Enter Analog higher cut off freq in Hz=600

Enter Analog sampling freq in Hz=2000

Enter order of filter =4

0.7853982

"Digital lower cut off frequency in radians cycles/samples"

1.8849556

"Digital higher cut off frequency in radians.cycles/samples "

0.25

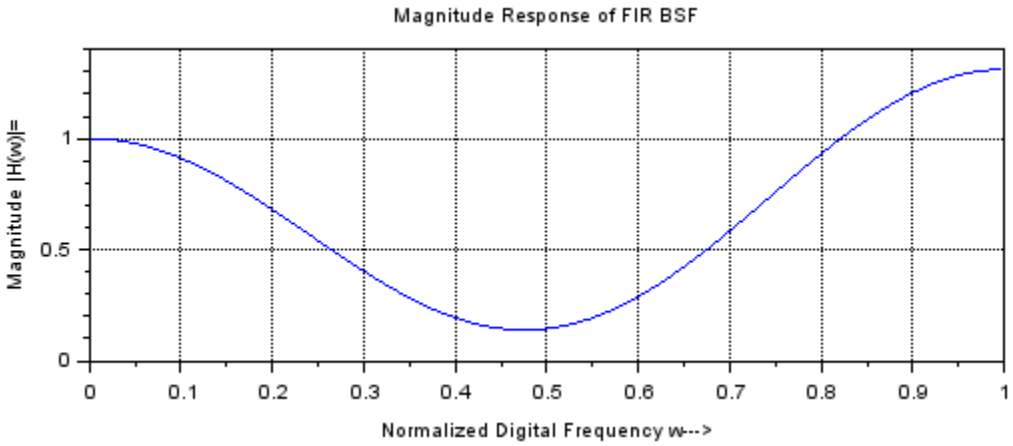
"Normalized digital lower cut off frequency in cycles / samples "

0.6

"Normalized digital higher cut off frequency in cycles / samples "

0.2527039 -0.0776516 0.65 -0.0776516 0.2527039

"Impulse Response of BSF FIR Filter : h [n]= "


Magnitude Response of FIR BSF
Magnitude |H(w)|=
1
0.5
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Normalized Digital Frequency w--->
Magnitude Response of FIR BSF
Magnitude |H(w) |=
1
0.5
0
0
100
200
300
400
500
600
700
800
900
1 000
Analog Frequency in Hz f --->
Magnitude Response of FIR BSF

8. Design of digital FIR Low Pass and High Pass filter using Hanning and Hamming window

Theory

Finite Impulse Response (FIR) Filter

FIR filters are digital filters with finite impulse response. They are also known as non-recursive digital filters as they do not have the feedback (a recursive part of a filter), even though recursive algorithms can be used for FIR filter realization. Hence it is an all zero filter. Therefore, input and output difference equation for FIR filter is given by

$$y(n)=b_0x(n)+b_1x(n-1)+b_2x(n-2)+...+b_{M-1}x(n-N+1)$$

Where b0, b1, b2 ... b(M-1) are filter coefficients. FIR filters are particularly useful for applications where exact linear phase response is required. The FIR filter is generally implemented in a non-recursive way which guarantees a stable filter.

FIR filters can be designed using different methods, but most of them are based on ideal filter approximation. The objective is not to achieve ideal characteristics, as it is impossible anyway, but to achieve sufficiently good characteristics of a filter. The transfer function of FIR filter approaches the ideal as the filter order increases, thus increasing the complexity and amount of time needed for processing input samples of a signal being filtered.

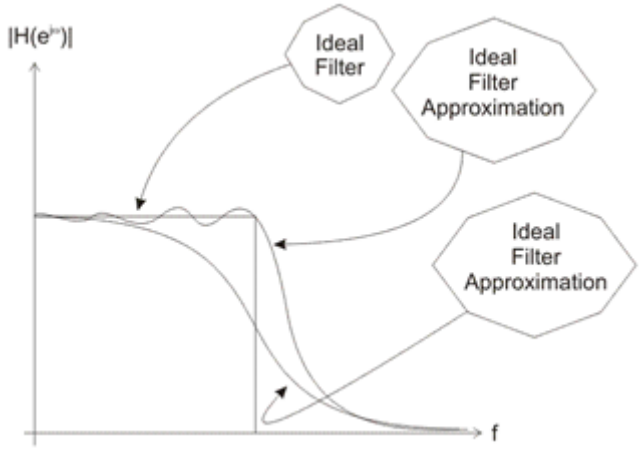


Fig-1

FIR filters can have linear phase characteristic, which is not like IIR filters. Obviously, in such cases when it is necessary to have a linear phase characteristic, FIR filters are the only option available. If the linear phase characteristic is not necessary, as is the case with processing speech signals, FIR filters are not good solution at all.

A number of delay lines contained in a filter, i.e. a number of input samples that should be saved for the purpose of computing the output sample, determines the order of a filter. For example, if the filter is assumed to be of order 10, it means that it is necessary to save 10 input

samples preceding the current sample. All eleven samples will affect the output sample of FIR filter

The transform function of a typical FIR filter can be expressed as a polynomial of a complex variable z^-1. All the poles of the transfer function are located at the origin. For this reason, FIR filters are guaranteed to be stable, whereas IIR filters have potential to become unstable

Basic concepts and FIR filter specification

Most FIR filter design methods are based on ideal filter approximation. The resulting filter approximates the ideal characteristic as the filter order increases, thus making the filter and its implementation more complex.

Figure 2.a and 2.b illustrates a low-pass digital filter specification. The word specification actually refers to the frequency response specification

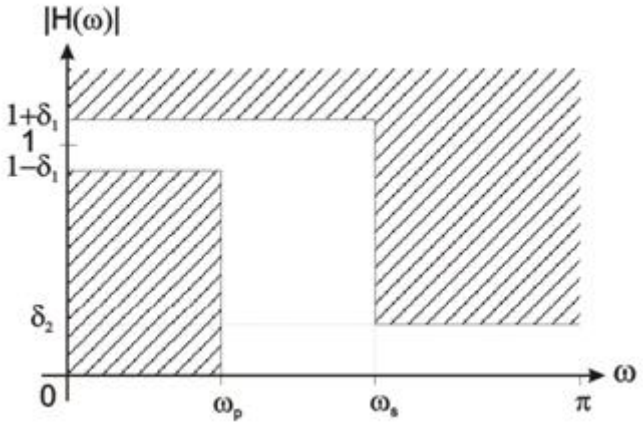


Figure 2.a: Low-pass digital filter specification

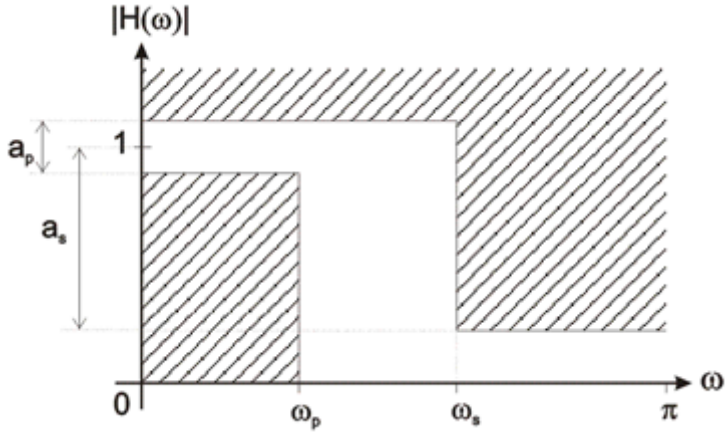


Figure 2.b: Low-pass digital filter specification

ω_p -normalized cut-off frequency in the passband;
ω_s- normalized cut-off frequency in the stopband;
δ_1 -maximum ripples in the passband
δ_2 - minimum attenuation in the stopband [dB]
a_p - maximum ripples in the passband; and

a_s - minimum attenuation in the stopband [dB].

$$a_p = 20\log_{10}(1+\delta_1 / 1-\delta_1)$$

$$a_s = -20\log_{10}\delta_1$$

Frequency normalization can be expressed as follows:

$$\omega = (2\pi f / f_s)$$

where:

f_s - is a sampling frequency;

f -is a frequency to normalize; and

ω - is normalized frequency.

Specifications for high-pass, band-pass and band-stop filters are defined almost the same way as those for low-pass filters. Figure 3.a and 3.b illustrates a high-pass filter specification

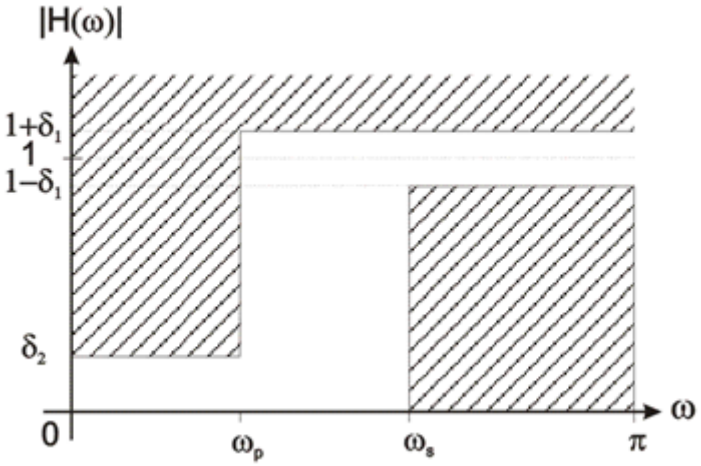


Figure 3.b: High-pass digital filter specification

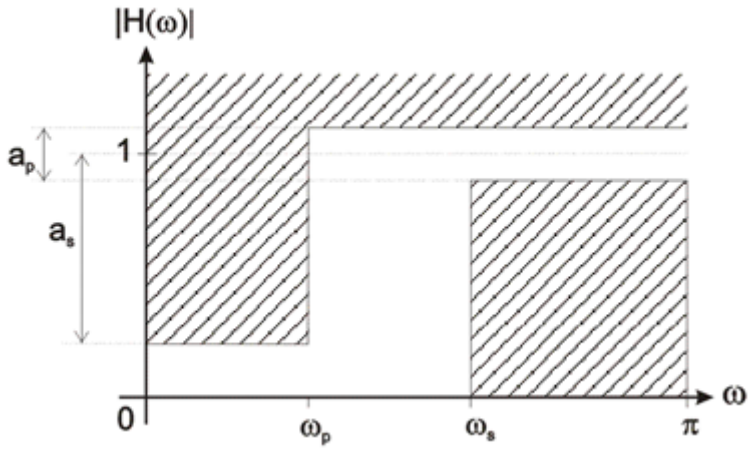


Figure 3.b: High-pass digital filter specification

Comparing these two figures 2.a, 2.b and 3.a, 3.b, it is obvious that low-pass and high-pass filters have similar specifications. The same values are defined in both cases with the difference that in the latter case the pass band is substituted by the stop band and vice versa.

Finite impulse response (FIR) filter design methods

The filter design process starts with specifications and requirements of the desirable FIR filter. Which method is to be used in the filter design process depends on the filter specifications and implementation?

There are essentially three well-known methods for FIR filter design namely:

1.The window method.

2.The frequency sampling technique.

3.Optimal filter design methods

Each of the given methods has its advantages and disadvantages. Thus, it is very important to carefully choose the right method for FIR filter design. Due to its simplicity and efficiency, the window method is most commonly used method for designing filters. The sampling frequency method is easy to use, but filters designed this way have small attenuation in the stop band.

Out of these three techniques we are going to discuss about window method only

Ideal filter approximation

The ideal filter frequency response is used when designing FIR filters using window functions. The objective is to compute the ideal filter samples. FIR filters have finite impulse response, which means the ideal filter frequency sampling must be performed in a finite number of points. As the ideal filter frequency response is infinite, it is easy to produce sampling errors. The error

is less as the filter order increases. Figure 4.a and 4.b illustrates the transfer functions of two standard ideal filters

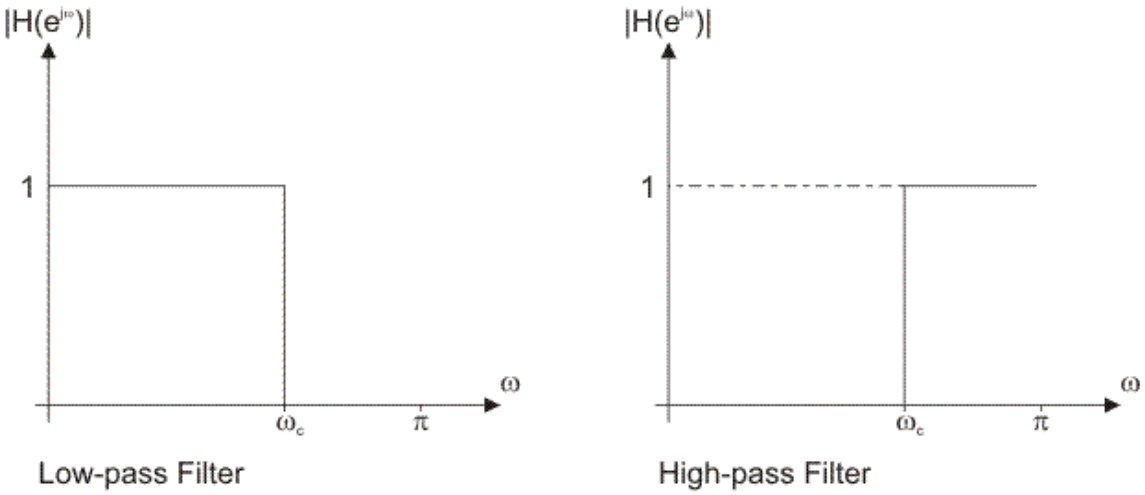


Figure 4.a and 4.b: Transfer functions of two standard ideal filters

The ideal filter frequency response can be computed via inverse Fourier transform. The two standard ideal filters frequency responses are contained in the table 1 below.

Type of filter	Frequency response $h_d[n]$
low-pass filter	$h_d[n] = \begin{cases} \frac{\sin[\omega_c(n-M)]}{\pi(n-M)}; & n \neq M \\ \frac{\omega_c}{\pi}; & n = M \end{cases}$
high-pass filter	$h_d[n] = \begin{cases} 1-\frac{\omega_c}{\pi}; & n \neq M \\ -\frac{\sin(\omega_c(n-M))}{\pi(n-M)}; & n = M \end{cases}$

Table 1: The frequency responses of two standard ideal filters

The value of variable n ranges between 0 and N, where N is the filter order. A constant M can be expressed as M = N / 2. Equivalently, N can be expressed as N = 2M

The constant M is an integer if the filter order N is even, which is not the case with odd order filters. If M is an integer (even filter order), the ideal filter frequency response is symmetric about its Mth sample which is found via expression shown in the table 1 above. If M is not an integer, the ideal filter frequency response is still symmetric, but not about some frequency response sample

Since the variable n ranges between 0 and N, the ideal filter frequency response has N+1 sample

If it is needed to find frequency response of a non-standard ideal filter, the expression for inverse Fourier transform must be used:

$$h_d[n] = 1/\pi \int_0^{\pi} e^{j\omega(n-M)} d\omega$$

Non-standard filters are rarely used. However, if there is a need to use some of them, the integral above must be computed via various numerical methods

FIR filter design using window functions

The FIR filter design process via window functions can be split into several steps:

1.Defining filter specifications;

2.Specifying a window function according to the filter specifications;

3.Computing the filter order required for a given set of specifications;

4.Computing the window function coefficients;

5.Computing the ideal filter coefficients according to the filter order;

6.Computing FIR filter coefficients according to the obtained window function and ideal filter coefficients

7.If the resulting filter has too wide or too narrow transition region, it is necessary to change the filter order by increasing or decreasing it according to needs, and after that steps 4, 5 and 6 are iterated as many times as needed

The final objective of defining filter specifications is to find the desired normalized frequencies, transition width and stopband attenuation. The window function and filter order are both specified according to these parameters. Accordingly, the selected window function must satisfy the given specifications.

After this step, that is, when the window function is known, we can compute the filter order required for a given set of specifications.

When both the window function and filter order are known, it is possible to calculate the window function coefficients w[n] using the formula for the specified window function

After estimating the window function coefficients, it is necessary to find the ideal filter frequency samples. The final objective of this step is to obtain the coefficients $h_d[n]$. Two sequences w[n] and $h_d[n]$ have the same number of elements.

The next step is to compute the frequency response of designed filter h[n] using the following expression:

$$h[n] = w[n] . hd[n]$$

Lastly, the transfer function of designed filter will be found by transforming impulse response via Fourier transform:

$$H(e^{jw}) = \sum_{n=0}^{N} h(n).e^{-jnw}$$

If the transition region of designed filter is wider than needed, it is necessary to increase the filter order, reestimate the window function coefficients and ideal filter frequency samples, multiply them in order to obtain the frequency response of designed filter and reestimate the transfer function as well. If the transition region is narrower than needed, the filter order can be decreased for the purpose of optimizing hardware and/or software resources. It is also necessary to reestimate the filter frequency coefficients after that. For the sake of precise estimates, the filter order should be decreased or increased by 1.

Window functions

The window method is most commonly used method for designing FIR filters. The simplicity of design process makes this method very popular.

A window is a finite array consisting of coefficients selected to satisfy the desirable requirements. This chapter provides a few methods for estimating coefficients and basic characteristics of the window itself as well as the result filters designed using these coefficients. The point is to find these coefficients denoted by w[n].

When designing digital FIR filters using window functions it is necessary to specify:

A window function to be used; and

The filter order according to the required specifications (selectivity and stop band attenuation).

These two requirements are interrelated. Each function is a kind of compromise between the two following requirements:

The higher the selectivity, i.e. the narrower the transition region; and

The higher suppression of undesirable spectrum, i.e. the higher the stop band attenuation.

Table 2 below contains all window functions mentioned in this chapter and briefly compares their selectivity and stop band attenuation

These two requirements are interrelated. Each function is a kind of compromise between the two following requirements:

The higher the selectivity, i.e. the narrower the transition region; and

The higher suppression of undesirable spectrum, i.e. the higher the stop band attenuation.

Table 2 below contains all window functions mentioned in this chapter and briefly compares their selectivity and stop band attenuation.

Special attention should be paid to the fact that minimum attenuation of window function and that of the filter designed using that function are different in most cases. The difference, i.e. additional attenuation occurs under the process of designing a filter using window functions. This affects the stop band attenuation to become additionally higher, which is very desirable.

However, a drawback of this method is that the minimum stop band attenuation is fixed for each function. The following concepts such as the main lobe, main lobe width, side lobes, transition region, minimum stopband attenuation of window function and minimum stopband attenuation of designed filter are described in more detail in Figure 5

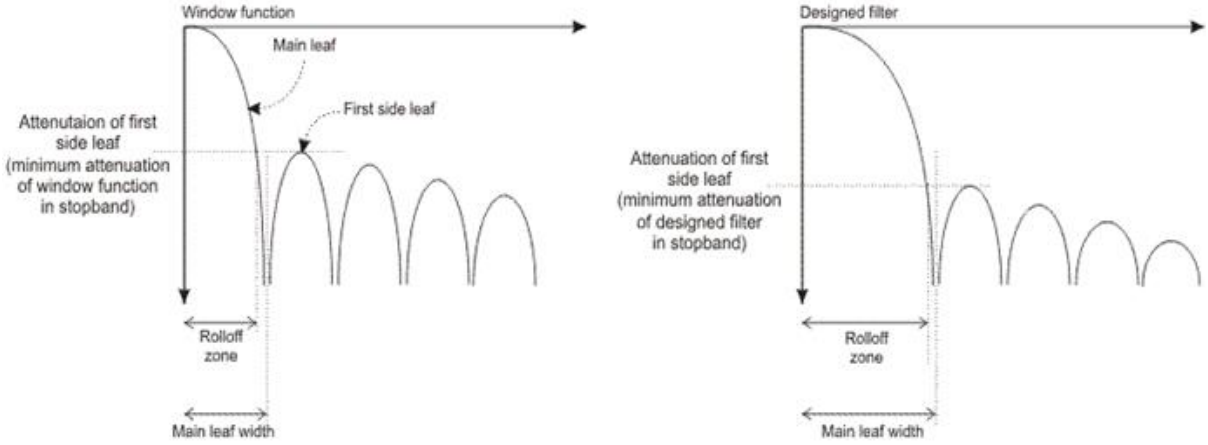
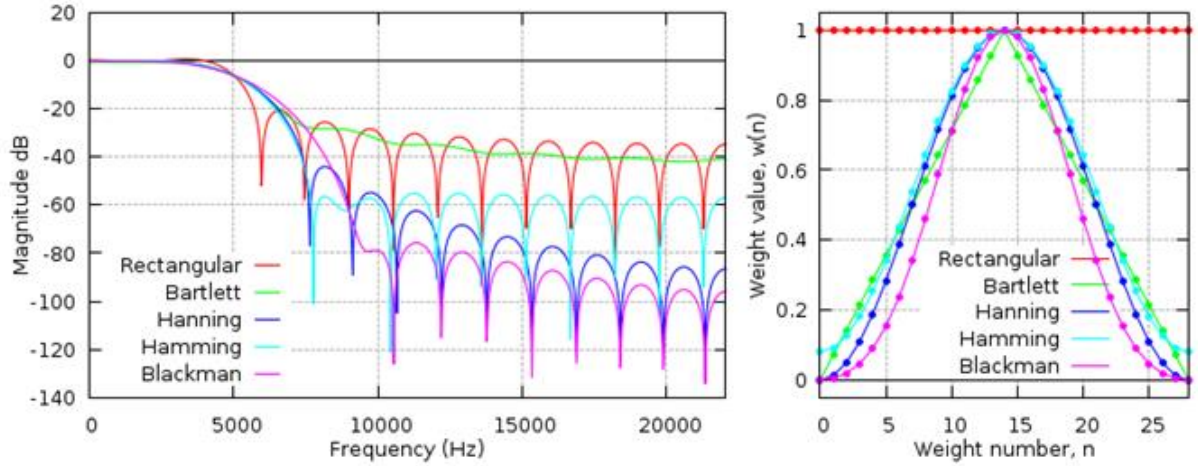


Figure 5: Main lobe, main lobe width, side lobes, transition region

As can be seen in the table 2 above, the stopband attenuation of these windows is not adjustable. It is only possible to affect the transition region by increasing the filter order. For this reason, it is preferable to start design process by specifying the appropriate window function on the basis of the stopband attenuation. It is most preferable to specify a window with the least stopband attenuation that satisfies the given requirements. This enables the designed filter to have the narrowest transition region

Name of Window	Time-domain sequence of window w(n) , 0 ≤ n ≤ N-1
Rectangular Window	1
Barlett (triangular) window	$1 - \frac{2\lvert n - \frac{N-1}{2} \rvert}{N-1}$
Blackman Window	$0.42 - 0.5cos\frac{2\pi n}{N-1} + 0.08cos\frac{4\pi n}{N-1}$
Hamming Window	$0.54 - 0.46cos\frac{2\pi n}{N-1}$
Hanning Window	$\frac{1}{2}(1 - cos\frac{2\pi n}{N-1})$
Kaiser Window $I_0(x)$ is the zeroth order Besselfunction.	$\frac{I_0[\alpha\sqrt{\left(\frac{N-1}{2}\right)^2 - \left(n - \frac{N-1}{2}\right)^2}]}{I_0\left[\alpha\left(\frac{N-1}{2}\right)\right]}$

Frequency Response and Weight Values of different windows types



Design an ideal high pass filter with a frequency response

$H_d e^{(jw)}$ = 1 for $\pi/4 \leq |\omega| \leq \pi$

= 0 for $|\omega| \leq \pi/4$. Find the values of h(n) for N= 11. Find H(z). Plot the magnitude response using Hanning window and Hamming window.

Formula for Hanning window

The rectangular window (no window function):

$$w_R(n) = 1 \qquad 0 \leq n \leq N-1$$

The triangular window:

$$w_{tri}(n) = 1 - \frac{|2n - N + 1|}{N - 1}, \; 0 \leq n \leq N-1$$

The Hamming window:

$$w_{hm}(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right), \; 0 \leq n \leq N-1$$

The Hanning window:

$$w_{hn}(n) = 0.5 - 0.5\cos\left(\frac{2\pi n}{N-1}\right), \; 0 \leq n \leq N-1$$

//PROGRAM 1: Design of HPF using Hanning window

```
clear;
clc;
close;
N =11;
U =6;
h_hann=window('hn',N);
for n=-5+U:1:5+U
if n==6
hd(n)=0.75;
else
hd(n)=(sin(%pi*(n-U))-sin(%pi*(n-U)/4))/(%pi*(n-U));
end
h(n)=h_hann(n)*hd(n);
```

```
end
[hzm,fr]=frmag(h,256);
hzm_dB=20*log10(hzm)./max(hzm);
figure
plot(2*fr,hzm_dB)
a=gca();
xlabel("Frequency");
ylabel("Magnitude in dB") ;
title("Frequency Response of FIR HPF with N =11 Using Hanning Window") ;
xgrid(2);
```

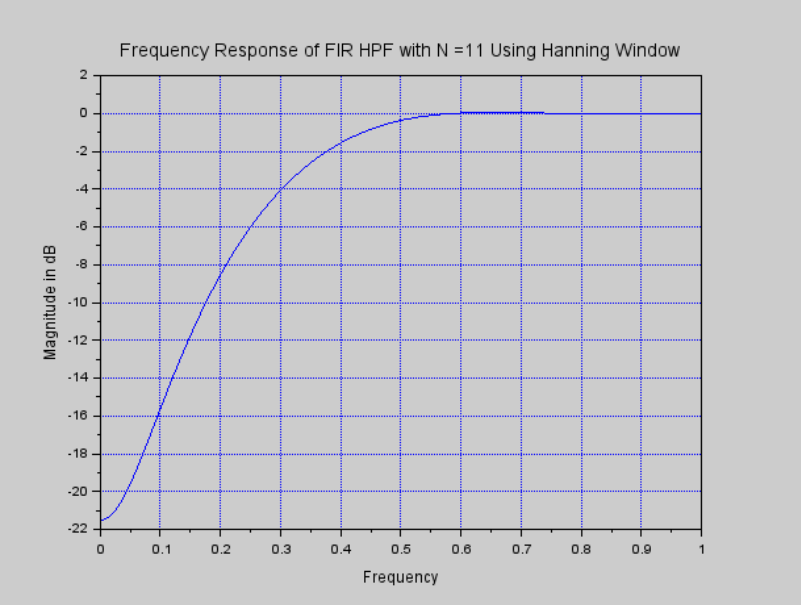


Fig.1: Magnitude response of HPF using Hanning Window

- ✓ *In the bellow figure the hanning window coefficients are computed in h_hann(-5), h_hann(-4), h_hann(-3), h_hann(-2), h_hann(-1), h_hann(0), h_hann(1), h_hann(2), h_hann(3), h_hann(4), h_hann(5) as a total of 11 values (N=11).*

- ✓ *And then the $h_d(n)$ followed by h(n) (Multiplying h_hann(n) * $h_d(n)$).*

```
--> N =11;

--> U =6;

--> h_hann = window ( 'hn',N )
 h_hann  =

   0.   0.0954915   0.3454915   0.6545085   0.9045085   1.   0.9045085   0.6545085   0.3454915   0.0954915   0.

--> for n = -5+ U :1:5+ U
  > if n ==6
  > hd ( n) =0.75;
  > else
  > hd ( n) =( sin ( %pi *( n - U ) ) -sin( %pi *( n - U ) /4) ) /( %pi *( n - U ) ) ;
  > end
  > h ( n ) = h_hann ( n ) * hd ( n ) ;
  > end

--> [ hzm , fr ]= frmag ( h ,256) ;

-->
```

```
--> [ hzm , fr ]= frmag ( h ,256)
 hzm  =

         column 1 to 15

    0.0826497   0.0827782   0.0831637   0.0838059   0.0847044   0.0858585   0.0872675   0.0889303   0.0908457   0.0930125   0.0954291   0.0980939   0.101005   0.1041603   0.1075576

         column 16 to 30

    0.1111947   0.115069   0.1191777   0.1235181   0.1280872   0.1328818   0.1378986   0.1431342   0.1485849   0.1542471   0.1601169   0.1661903   0.1724632   0.1789313   0.1855903

         column 31 to 45

    0.1924357   0.1994628   0.206667   0.2140435   0.2215874   0.2292936   0.2371571   0.2451728   0.2533353   0.2616393   0.2700795   0.2786504   0.2873464   0.296162   0.3050916

         column 46 to 60

    0.3141295   0.3232701   0.3325074   0.3418359   0.3512496   0.3607429   0.3703098   0.3799446   0.3896414   0.3993944   0.4091977   0.4190456   0.4289322   0.4388518   0.4487987

         column 61 to 75

    0.4587672   0.4687515   0.4787461   0.4887454   0.4987438   0.5087359   0.5187162   0.5286795   0.5386205   0.5485338   0.5584146   0.5682575   0.5780578   0.5878106   0.5975111

         column 76 to 90

    0.6071545   0.6167364   0.6262522   0.6356976   0.6450683   0.6543602   0.6635692   0.6726914   0.6817231   0.6906605   0.6995001   0.7082384   0.7168723   0.7253984   0.7338138

         column 91 to 105

-> hzm_dB = 20* log10 ( hzm ) ./ max ( hzm )
hzm_dB  =

       column 1 to 15

 -21.52367  -21.510254  -21.470141  -21.403728  -21.311665  -21.19483  -21.05431  -20.891363  -20.707389  -20.503893  -20.282454  -20.044686  -19.792216  -19.526651  -19.249561

       column 16 to 30

 -18.962457  -18.666782  -18.363896  -18.05507  -17.741485  -17.424229  -17.104296  -16.782592  -16.459935  -16.137061  -15.814627  -15.493221  -15.173361  -14.855505  -14.540055

       column 31 to 45

 -14.22736  -13.917725  -13.611411  -13.308643  -13.009612  -12.714476  -12.42337  -12.136402  -11.853661  -11.575216  -11.301118  -11.031406  -10.766104  -10.505226  -10.248774

       column 46 to 60

 -9.9967445  -9.7491237  -9.5058924  -9.2670258  -9.0324938  -8.8022625  -8.5762942  -8.3545483  -8.1369816  -7.9235489  -7.7142031  -7.5088959  -7.3075777  -7.1101982  -6.9167064

       column 61 to 75

 -6.7270508  -6.5411797  -6.3590412  -6.1805835  -6.005755  -5.8345039  -5.6667791  -5.5025298  -5.3417053  -5.1842557  -5.0301315  -4.8792836  -4.7316637  -4.5872238  -4.4459167
```

Similarly Using Hamming Window we can obtain the HPF response

//PROGRAM 2: Design of HPF using Hamming window

```
clear;
clc;
close;
N =11;
U =6;
h_hamm=window('hm',N);
for n=-5+U:1:5+U
if n==6
hd(n)=0.75;
else
hd(n)=(sin(%pi*(n-U))-sin(%pi*(n-U)/4))/(%pi*(n-U));
end
```

```
h(n)=h_hamm(n)*hd(n);
end
[hzm,fr]=frmag(h,256);
hzm_dB=20*log10(hzm)./max(hzm);
figure
plot(2*fr,hzm_dB)
a=gca();
xlabel("Frequency");
ylabel("Magnitude in dB") ;
title("Frequency Response of FIR HPF with N =11 Using Hamming Window") ;
xgrid(2);
```

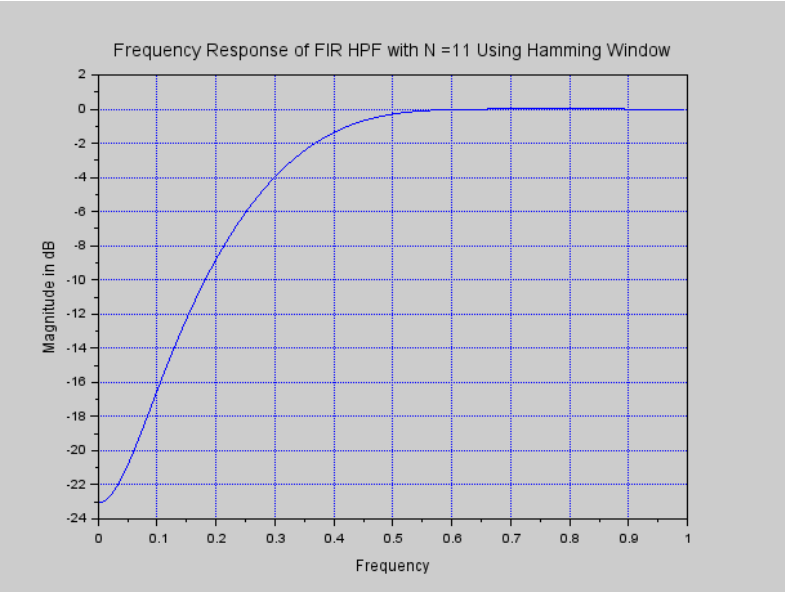


Fig.2: Magnitude response of HPF using Hamming Window

Design an LPF filter with

$H_d e^{(jw)} = e^{-j3w}$ *for* $-\pi/4 \leq \omega \leq \pi$

$= 0$ *for* $\pi/4 \leq |\omega| \leq \pi$. *Find the values of h(n) for N=7. Find H(z). Plot the magnitude response using Hamming window and Hanning window techniques.*

Scilab code for both Hanning and Hamming window Techniques

```
//PROGRAM 3: Design of LPF using Hanning window
clear all;
clc;
close;
N=11;
alpha=3;
U=1;
h_hann=window('hn',N);
for n=0+U:1:6+U
if n==4
hd (n)=0.25;
else
//hd(n)=(sin(%pi*(n-U-alpha)/4))/(%pi*(n-U-alpha)) ;
hd(n)=(sin(%pi*(n-U-alpha)/4))/(%pi*(n-U-alpha)) ;
```

```
end
h(n)=hd(n)*h_hann(n);
end
[hzm,fr]=frmag(h,256);
hzm_dB=20*log10(hzm)./max(hzm);
figure
plot(2*fr,hzm_dB)
a=gca();
xlabel("Frequency");
ylabel("Magnitude in dB");
title("Frequency response of given LPF with N=11 using Hanning window");
xgrid(2);
```

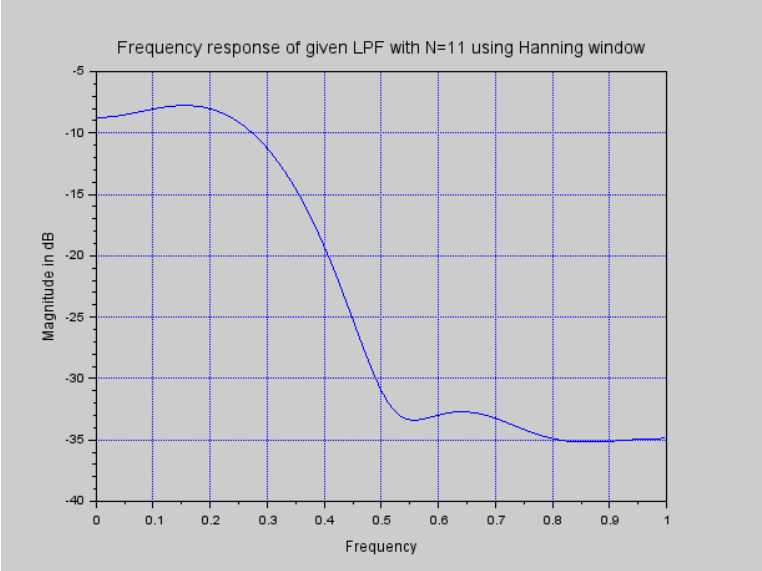


Fig.3: Magnitude response of LPF filter using Hanning Window

//PROGRAM 4: Design of LPF using Hamming window

```
clear all;
clc;
close;
N=11;
alpha=3;
U=1;
h_hamm=window('hm',N);
for n=0+U:1:6+U
if n==4
hd (n)=0.25;
else
hd(n)=(sin(%pi*(n-U-alpha)/4))/(%pi*(n-U-alpha)) ;
end
h(n)=hd(n)*h_hamm(n);
end
[hzm,fr]=frmag(h,256);
```

```
hzm_dB=20*log10(hzm)./max(hzm);
figure
plot(2*fr,hzm_dB)
a=gca();
xlabel("Frequency");
ylabel("Magnitude in dB");
title("Frequency response of given LPF with N=11 using Hamming window");
```

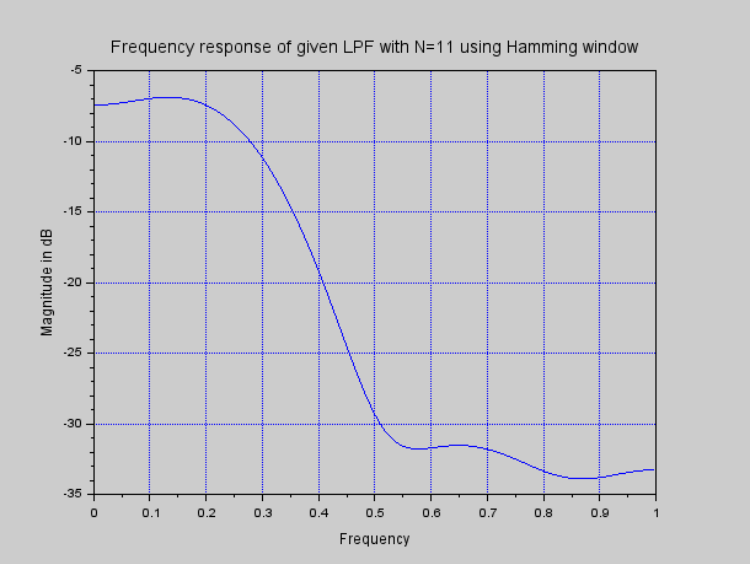


Fig.4: Magnitude response of LPF filter using Hamming Window

Pre-lab questions:

1. What are the different methods used for the design of FIR filters?
2. Write the procedure for design of FIR filter using windowing technique.
3. Draw the spectrum of LPF, BPF, HPF, BSF.

Post-Lab questions:

1. Design a digital FIR HPF filter using Hamming window for N=15 using sci lab.

Result:

Exp 9: Design of digital FIR filter using frequency sampling method.

Theory:

An FIR filter has no feedback loop and is inherently stable. An FIR filter can easily provide a linear-phase response, which is crucial in phase-sensitive applications such as data communications, seismology, etc.

The frequency sampling method is used to design recursive and non-recursive FIR filters for both standard frequency selective filters and with arbitrary frequency response. The main idea of the frequency sampling design method is that a desired frequency response can be approximated by sampling it at N evenly spaced points and then obtaining N-point filter response.

A continuous frequency response is then calculated as an interpolation of the sampled frequency response. The approximation error would then be exactly zero at the sampling frequencies and would be finite in frequencies between them. The smoother the frequency response being approximated; the smaller will be the error of interpolation between the sample points.

There are two distinct types of Non-Recursive Frequency Sampling method of FIR filter design, depending on where the initial frequency sample occurred.

Determine the filter coefficients h(n) obtained by sampling.

$$H_d e^{(jw)} = e^{-j(N-1)w/2} \text{ for } 0 \leq |\omega| \leq \pi/2$$

$$= 0 \text{ for } \pi/2 \leq |\omega| \leq \pi. \text{ For } N=7.$$

```
clear ;

clc ;

close ;

N =7;

U =1; // Zero Adjust

for n =0+ U :1: N -1+ U

h ( n ) =(1+2* cos (2* %pi *( n -U -3) /7) ) / N

end

disp (h ," Filter Coefficients , h(n)=")
```

```
--> close ;

--> N =7;

--> U =1; // Z e ro A dj u s t

--> for n =0+ U :1: N -1+ U
  > h ( n ) =(1+2* cos (2* %pi *( n -U -3) /7) ) / N
  > end
 h  =

  -0.1145625
 h  =

  -0.1145625
   0.0792797
 h  =

  -0.1145625
   0.0792797
   0.3209971
 h  =

  -0.1145625
   0.0792797
   0.3209971
   0.4285714
```

It computes its cofficients like in the iteration: 1 h(0)
iteration:2 h(0) and h(1)
iteration:2 h(0) , h(1) and h(2) goes on till h(6)

```
--> disp (h ,"Filter Coefficients, h(n)=")

  -0.1145625
   0.0792797
   0.3209971
   0.4285714
   0.3209971
   0.0792797
  -0.1145625

  "Filter Coefficients, h(n)="
```

BY using "disp" comment we get all the 7 coefficients alone shown in the console.

Pre-lab question

1. What is the general formula to find the values of H(k), θ(k) and h(n) using frequency sampling method?
2. List the steps in defining the “k” values of frequency sampling method.

Post-lab Question

1. $H_d e^{(jw)} = e^{-j(N-1)w/2}$ *for* $0 \leq |\omega| \leq \pi/2$

   $= 0$ *for* $\pi/2 \leq |\omega| \leq \pi$. *For N=7.*

   Find the values of h(n) for N=11

Result:

Experiment 10(a) Design of Analog Butterworth filter

Aim: To Design and analyze the function of an analog Butterworth filter

Software Requirement: SCI Lab

Theory: The signal processing filter which is having a flat frequency response in the passband can be termed as Butterworth filter and is also called as a maximally flat magnitude filter. In 1930 physicist and the British engineer Stephen Butterworth described about a Butterworth filter in his "on the theory of filter amplifiers" paper for the first time. Hence, this type of filter named as Butterworth filter. There are various types of Butterworth filters such as low pass Butterworth filter and digital Butterworth filter. The frequency response of the nth order Butterworth filter is given as

$$H_{(j\omega)} = \frac{1}{\sqrt{1+\varepsilon^2\left(\frac{\omega}{\omega_p}\right)^{2n}}}$$

Where 'n' indicates the filter order, 'ω' = $2\pi f$, Epsilon ε is maximum pass band gain, (Amax).

Algorithm:

Step 1: For the given Cutoff frequency, band ripple and stopband ripple find the order of the filter

Step 2: Round the order of the filter to the next higher order integer

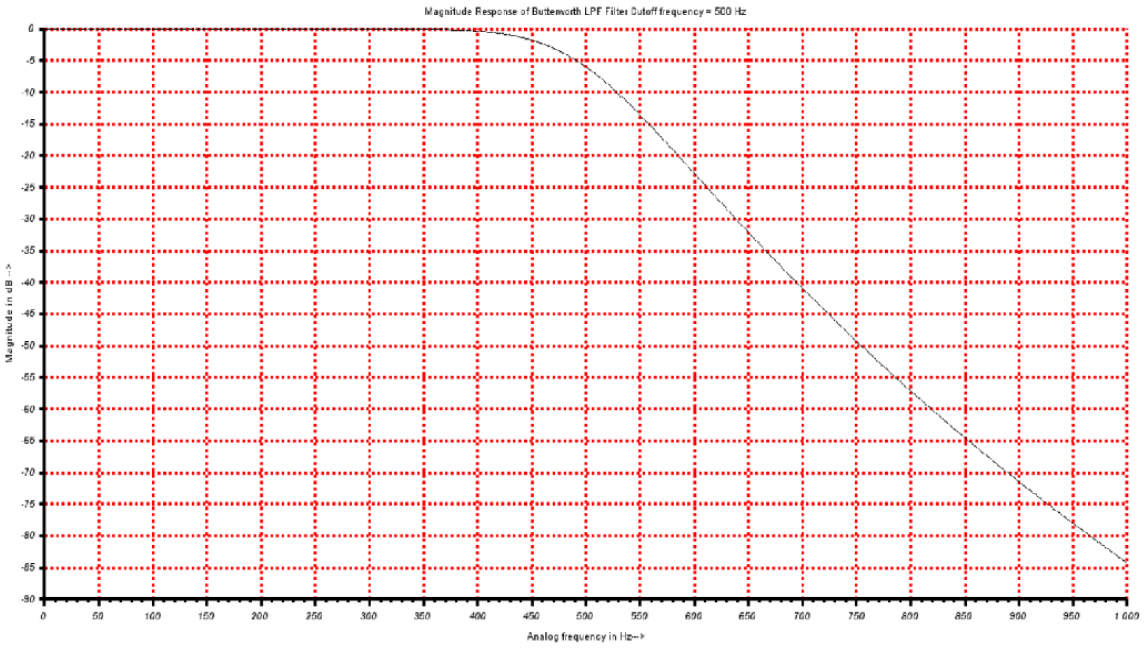
Step 3: Determine the magnitude and phase response of the analog Butterworth filter to Plot

Program:

```
// To Design an Analog Butterworth Filter
//For the given cutoff frequency and filter order
//Wc = 500 Hz
omegap =  500; //pass band edge frequency
omegas =  1000;//stop band edge frequency
delta1_in_dB = -3;//PassBand Ripple in dB
delta2_in_dB = -40;//StopBand Ripple in dB
delta1 = 10^(delta1_in_dB/20)
delta2 = 10^(delta2_in_dB/20)
```

```
 //Caculation of filter order
N = log10((1/(delta2^2))-1)/(2*log10(omegas/omegap))
N = ceil(N) //Rounding off nearest integer
omegac = omegap;
h=buttmag(N,omegac,1:1000);//Analog Butterworth filter magnitude response
mag=20*log10(h);//Magntitude Response in dB
plot2d((1:1000),mag,[0,-180,1000,20]);
a=gca();
a.thickness = 3;
a.foreground = 1;
a.font_style = 9;
xgrid(5)
xtitle('Magnitude Response of Butterworth LPF Filter Cutoff frequency = 500 Hz','Analog frequency in Hz--->','Magnitude in dB -->');
```

Simulation Output:



Experiment 10(b) Design of Analog Chebyshev filter

Aim: To Design and analyze the function of an analog Chebyshev filter

Software Requirement: SCI Lab

Theory: Chebyshev filters are used for distinct frequencies of one band from another. They cannot match the windows-sink filter's performance and they are suitable for many applications. The main feature of Chebyshev filter is their speed, normally faster than the windowed-sinc. Because these filters are carried out by recursion rather than convolution. The designing of the Chebyshev and Windowed-Sinc filters depends on a mathematical technique called as the Z-transform. Types of Chebyshev Filters

Chebyshev filters are classified into two types, namely type-I Chebyshev filter and type-II Chebyshev filter.

Type-I Chebyshev Filters

This type of filter is the basic type of Chebyshev filter. The amplitude or the gain response is an angular frequency function of the nth order of the LPF (low pass filter) is equal to the total value of the transfer function Hn (jw)

Gn(w)=|Hn (jω)|=1√(1+ϵ2Tn2() ω/ωo)

Where,ε=ripple factor

ωo= cutoff frequency

Tn= Chebyshev polynomial of the nth order

$$s_{pm}^{\pm} = \pm \sinh\left(\frac{1}{n}\operatorname{arsinh}\left(\frac{1}{\varepsilon}\right)\right)\sin(\theta_m)$$
$$+j\cosh\left(\frac{1}{n}\operatorname{arsinh}\left(\frac{1}{\varepsilon}\right)\right)\cos(\theta_m)$$

Here m= 1,2,3,.....n

$$\theta_m = \frac{\pi}{2}\frac{2m-1}{n}.$$

The above equation produces the poles of the gain G. For each pole, there is the complex conjugate, & for each and every pair of conjugate there are two more negatives of the pair. The TF should be stable, transfer function (TF) is given by

$$H(s) = \frac{1}{2^{n-1}\varepsilon}\prod_{m=1}^{n}\frac{1}{(s - s_{pm}^{-})}$$

Algorithm:

Step 1: Convert the given analog frequencies to digital domain

Step 2: Prewarp the frequency components and find the prewarping frequency

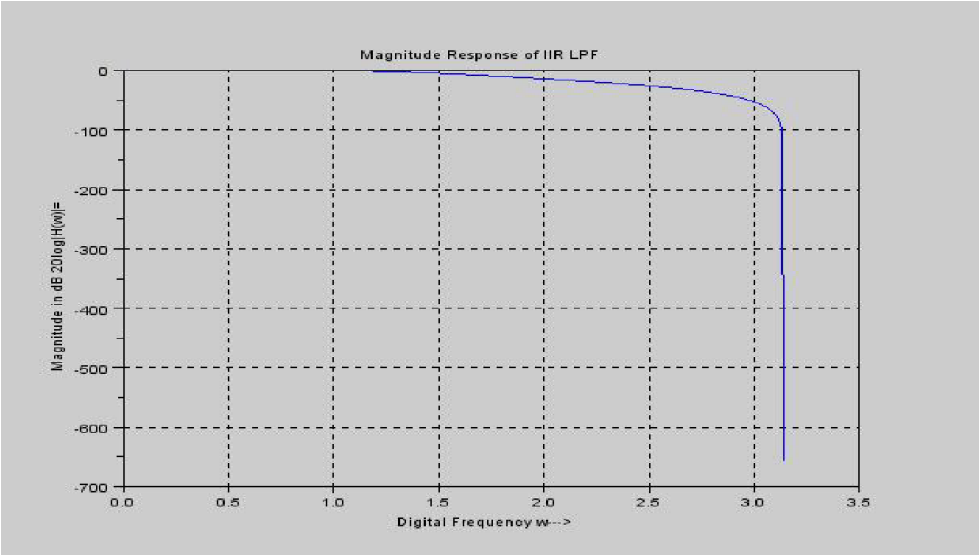
Step 3: Determine the order of the filter and round to next higher order integer

Step 4: Convert the analog transfer function to digital by using Bilinear transformation technique and plot the magnitude and frequency response

Program:

```
// Capt ion : To o b t a i n Di g i t a l I IR Chebyshev low pa s s
f i l t e r
// Fr equency r e s p o n s e
 clc ;
 clear ;
 close ;
 fp= input ( ' Enter the pass band edge (Hz ) = ' );
 fs= input ( ' Enter the stop band edge (Hz ) = ' );
 kp= input ( ' Enter the pass band attenuation (dB) = ' );
 ks= input ( ' Enter the stop band attenuation (dB) = ' );
Fs= input ( ' Enter the sampling rate samples / s e c = ' );
d1 = 10^( kp /20) ;
d2 = 10^( ks /20) ;
d = sqrt ((1/( d2 ^2)) -1);
E = sqrt ((1/( d1 ^2)) -1);
// Di g i t a l f i l t e r s p e c i f i c a t i o n s ( rad / s ampl e s )
 wp =2* %pi *fp *1/ Fs;
 ws =2* %pi *fs *1/ Fs;
// Pre warping
 op =2* Fs* tan (wp /2);
 os =2* Fs* tan (ws /2);
N = acosh (d/E)/ acosh (os/op);
oc = op /(( E ^2) ^(1/(2* N)));
N = ceil (N); // rounded to n e a r e s t i n t e g e r
disp (N, ' I IR F i l t e r o r d e r N =' );
disp (oc , ' Cu t o f f Fr equency i n rad / s e c o n d s OC = ' )
[pols ,gn] = zpch1 (N,E,op);
 HS = poly (gn , ' s ' , ' c o e f f ' )/ real ( poly (pols , ' s ' ));
 z = poly(0,'z')
 Hz = horner (HS ,(2* Fs *(z -1) /(z +1) ))
 num = coeff (Hz (2) )
 den = coeff (Hz (3) )
 Hz (2)= Hz (2) ./ den (3) ;
 Hz (3) = Hz (3) ./ den (3) ;
 disp (Hz , ' Tr a n s f e r f u n c t i o n o f Di g i t l a I IR Chebyshev LPF H(Z)=' )
 [Hw ,w] = frmag (Hz ,256) ;
 figure (1)
 plot (2*w*%pi ,20* log10 ( abs (Hw)));
 xlabel ( ' Di g i t a l Fr equency W>' )
 ylabel ( 'Magni tude i n dB 20 l o g jH(w) j= ' )
 title ( 'Magni tude Re spons e o f I IR LPF ' )
 xgrid (1)
```

Simulation Output



Prelab Questions:

1. List the differences between butterworth and Chebyshev filter
2. Define the term Prewarping and mention its importance
3. To design a Discrete time Low pass filter the specifications are
   Passband F_p = 4 KHz with 0.8 dB ripple
   Stopband F_p = 4.5 KHz with 50 dB attenuation
   Sampling frequency F_s = 22 KHz
   (i) Determine the passband and stopband frequencies (ii) Determine the maximum and minimum values of $|H(\omega)|$ in the pass band and stopband

Postlab Questions:

1. List the properties of Chebyshev filter
2. In your CD the data is sampled at 44.1kHz, and we want to have a good sound quality upto 21kHz. If you had to use an analog butterworth filter as reconstruction filter, What would be the order of the filter?
3. Give the Normalized Low pass Butterworth Denominator polynomials for N=8,9,10.

Exp.11(a): Design of Digital Butterworth filter using Bilinear Transformation

Aim: To Design a digital Butterworth filter using Bilinear Transformation method

Software Requirement : Scilab

Theory: Butterworth filters are optimal in the sense of having a *maximally flat amplitude response*, as measured using a Taylor series expansion .The trivial filter H(Z)=1 has a perfectly flat amplitude response, but that's an all pass, not a low pass filter. Therefore, to constrain the optimization to the space of low pass filters, we need *constraints* on the design, such as H(1)=1 and H(-1)=0. That is, we may require the dc gain to be 1, and the gain at half the sampling rate to be 0.

It turns out Butterworth filters are much easier to design as *analog filters* which are then converted to digital filters. This means carrying out the design over the s plane instead of the z plane, where the s plane is the complex plane over which analog filter transfer functions are defined. The analog transfer function $H_a(s)$ is very much like the digital transfer function H(z), except that it is interpreted relative to the analog frequency axis $s = jw_a$ (the ``$jw$ axis") instead of the digital frequency axis $z = e^{j\omega_d T}$ (the ``unit circle"). In particular, analog filter poles are stable if and only if they are all in the *left-half* of the s plane, *i.e.*, their real parts are *negative*.

Digital Butterworth Filter using Bilinear Transformation

The bilinear -transform is a mathematical transformation from the -domain to the -domain which preserves the frequency characteristics and is defined by:

$$s = \frac{2}{T}\frac{1 - z^{-1}}{1 + z^{-1}} \quad \text{where } T = \text{ sampling period}$$

The bilinear transformation gives a non-linear relationship between analog ω_a frequency and digital frequency ω_d

$$\omega_a = \frac{2}{T}\tan\frac{\omega_d T}{2}$$

Algorithm:

Step 1: From the given specifications, find prewarping analog frequencies, using the formula

$$\omega_a = \frac{2}{T}\tan\frac{\omega_d T}{2}$$

Step2: Using the analog frequencies, find Ha(s) of the analog filter.

Step3:Select the sampling rate of the digital filter, Call it 'T' seconds per sample.

Step 4: Substitute

$$s = \frac{2}{T}\frac{1-z^{-1}}{1+z^{-1}} \quad \text{where } T = \text{ sampling period}$$

into the transfer function found in step 2.

Program:

Using Bilinear transformation, design a high pass filter, monotonic in pass band with cutoff frequency of 1000 and down 10dB at 350 Hz. The sampling frequency is 5000Hz.

```
//To design digital Butterworth filter using bilinear transformation

clear all;
clc;
close;
ap=input('enter the value of ap in dB');
as=input('enter the value of as in dB Hz');
fp=input('enter the value of fp in Hz');
fs=input('enter the value of fs in Hz');
f=input('enter the value of f ');

T=1/f;
wp=2*%pi*fp;
ws=2*%pi*fs;
op=2/T*tan(wp*T/2);
os=2/T*tan(ws*T/2);
N=log(sqrt((10^(0.1*as)-1)/(10^(0.1*ap)-1)))/log(op/os);
disp(ceil(N));
s=%s;
HS=1/(s+1);
oc=op;
HS1=horner(HS,oc/s);
```

```
disp(HS1,'Normalized transfer function,H(s)=');
z=%z;
HZ=horner(HS,(2/T)*(z-1)/(z+1));
disp(HZ,'H(z)=');
```

Simulation Output:

enter the value of ap in dB 3

enter the value of as in dB Hz 10

enter the value of fp in Hz 1000

enter the value of fs in Hz 350

enter the value of f 5000

1.

```
      s
 ------------
 7265.4253 +s

"Normalized transfer function, H(s)="


    1 +z
 -------------
 -9999 +10001z

"H(z)="
```

Exp.11(b): Design of digital Butterworth Filter using Impulse Invariant Method

Aim: To design of digital Butterworth Filter using Impulse Invariant Method

Software Requirement: Scilab

Theory: **Design procedure using impulse invariance:**

Using the impulse invariance design procedure, the relation between frequency in the continuous-time and discrete-time domains is

$$\Omega_p = \omega_p / T$$

$$\Omega_s = \omega_s / T$$

Express the analog transfer function as the sum of single pole filters:

$$H(s) = \sum_{k=1}^{N} \frac{A_k}{(s - s_k)}$$

Compute the z-transform of the digital filter by using the formula

$$H(z) = \sum_{k=1}^{N} \frac{A_k}{\left(1 - e^{s_k T} z^{-1}\right)}$$

Algorithm:

Step 1: From the given specifications, find prewarping analog frequencies, using the formula

$$\Omega_p = \omega_p / T$$

$$\Omega_s = \omega_s / T$$

Step2: Using the analog frequencies, find Ha(s) of the analog filter.

Step3: Select the sampling rate of the digital filter, Call it ‘T’ seconds per sample.

Step4: Express the analog transfer function as the sum of single pole filters:

$$H(s) = \sum_{k=1}^{N} \frac{A_k}{(s - s_k)}$$

Step5: Compute the z-transform of the digital filter by using the formula

$$H(z) = \sum_{k=1}^{N} \frac{A_k}{\left(1 - e^{s_k T} z^{-1}\right)}$$

Program:

```
clear all;
clc ;
 close ;
 s=%s;
 T =1;
HS =(2) /(s ^2+3* s +2) ;
 elts = pfss (HS);
disp (elts , ' Fa c t o r i z e d HS=' );

//The poles associated are -2 and -1
 p1 = -2;
 p2 = -1;

 z=%z;
 HZ =(2/(1 - %e ^( p2*T)*z^( -1))) -(2/(1 - %e ^( p1*T)*z^( -1)));

 disp (HZ , 'HZ=' );
```

Prelab Questions:

1. What are the properties that are maintained same in the transfer of analog filter into a digital filter?
2. What is meant by impulse invariant method of designing IIR filter?
3. What are the properties of the bilinear transformation?

Postlab Questions:

1. An analog filter has a transfer function H(s)= $\frac{10}{s^2+7s+10}$. Design a digital filter equivalent tom this using impulse invariant method for T=0.2 sec.
2. For the analog transfer fuction, H(s)= $\frac{2}{s^2+3s+2}$,determine H(z) using bilinear transformation if (a) T=1 second (b) T=0.1 second.

Experiment 12: Chebyshev filter design using Bilinear and Impulse Invariance Method

Aim: To design Chebyshev filter using bilinear transformation and impulse invariance method

Theory:

Chebyshev filters are a class of analog and digital filters used in signal processing and electronic circuits. They are known for their ability to achieve a sharper roll-off between the passband and stopband compared to other filter designs. Chebyshev filters are defined by a specific ripple level in the passband, making them a valuable choice for applications where stringent requirements on passband flatness are necessary. Both the Bilinear Transformation and the Impulse Invariance Method are fundamental techniques in signal processing used to convert continuous-time (analog) filters to discrete-time (digital) filters. These transformations are vital in preserving the critical characteristics of the analog filter while ensuring its applicability in a digital signal processing context.

To design an analog Chebyshev filter, we need to define the desired filter characteristics, which typically include the passband ripple (ε), stopband attenuation (α_s), and cutoff frequency (ω_c).
Design Steps:

1. Calculate the degree of the Chebyshev polynomial (N) based on the desired passband ripple (ε) and stopband attenuation (As).
2. Determine the pole locations (s-terms) for the analog Chebyshev filter using the inverse hyperbolic cosine function.
3. Normalize the pole locations to the desired cutoff frequency (ωc).
4. Formulate the analog Chebyshev filter transfer function using the normalized pole locations.

By following these steps, you will obtain the transfer function of the analog Chebyshev filter prototype based on the specified filter characteristics. The resulting transfer function can then be further analyzed and used as a basis for the transformation to a digital filter using the Bilinear Transformation or the Impulse Invariance Method.

Bilinear Transformation:

The Bilinear Transformation is a widely used technique for mapping continuous-time transfer functions (analog filters) to discrete-time transfer functions (digital filters). The transformation is based on approximating the Laplace transform (s-domain) of an analog filter to the z-transform (z-domain) of a digital filter. The mapping is achieved using the bilinear mapping function:

$$s = \frac{2}{T}\frac{1-z^{-1}}{1+z^{-1}}$$

Where s is the Laplace variable in the analog domain, z is the Z-transform variable in the digital domain, and T is the sampling period. The continuous-time transfer function H (s) is transformed

into a discrete-time transfer function H(z) using this mapping. The advantages of the Bilinear Transformation include preserving stability and mapping the entire s-plane to the unit circle in the z-plane.

Impulse Invariance Method:

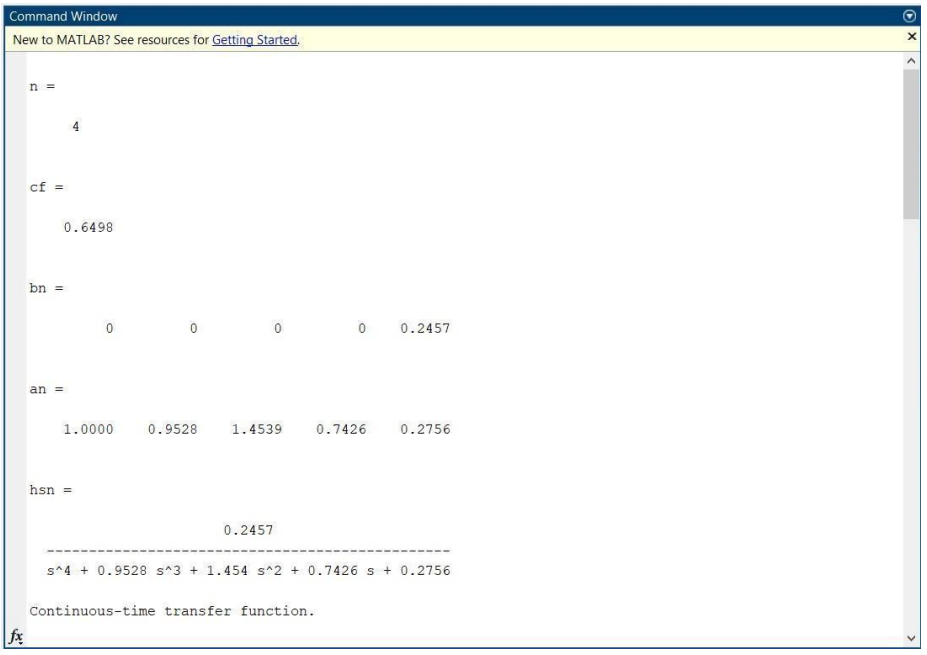
The Impulse Invariance Method is another widely used technique to convert analog filters to digital filters. In this method, the impulse response of the analog filter is used to obtain the impulse response of the corresponding digital filter. The impulse response of the analog filter is sampled at regular intervals (determined by the desired sampling rate) to generate the impulse response of the digital filter.

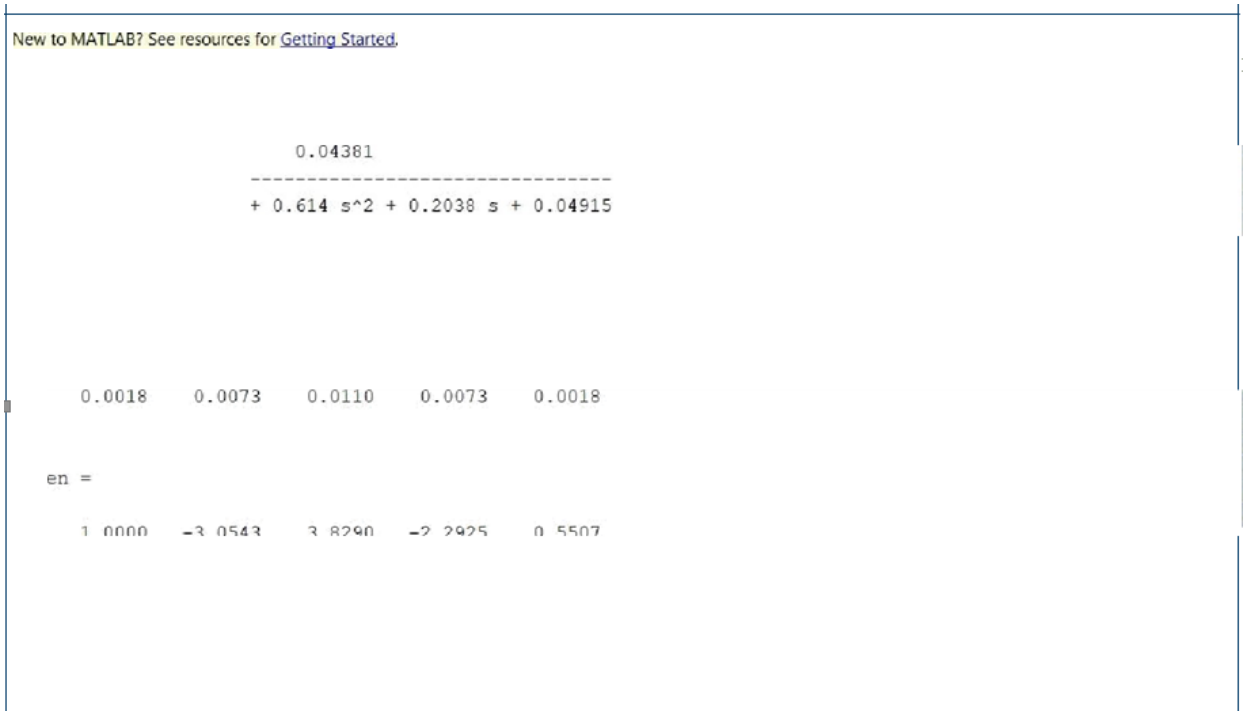
The method is based on the idea that sampling an impulse in the time domain corresponds to sampling the impulse response in the frequency domain. The transfer function of the analog filter H (s) is transformed into a discrete-time transfer function H(z) by using the sampled impulse response.

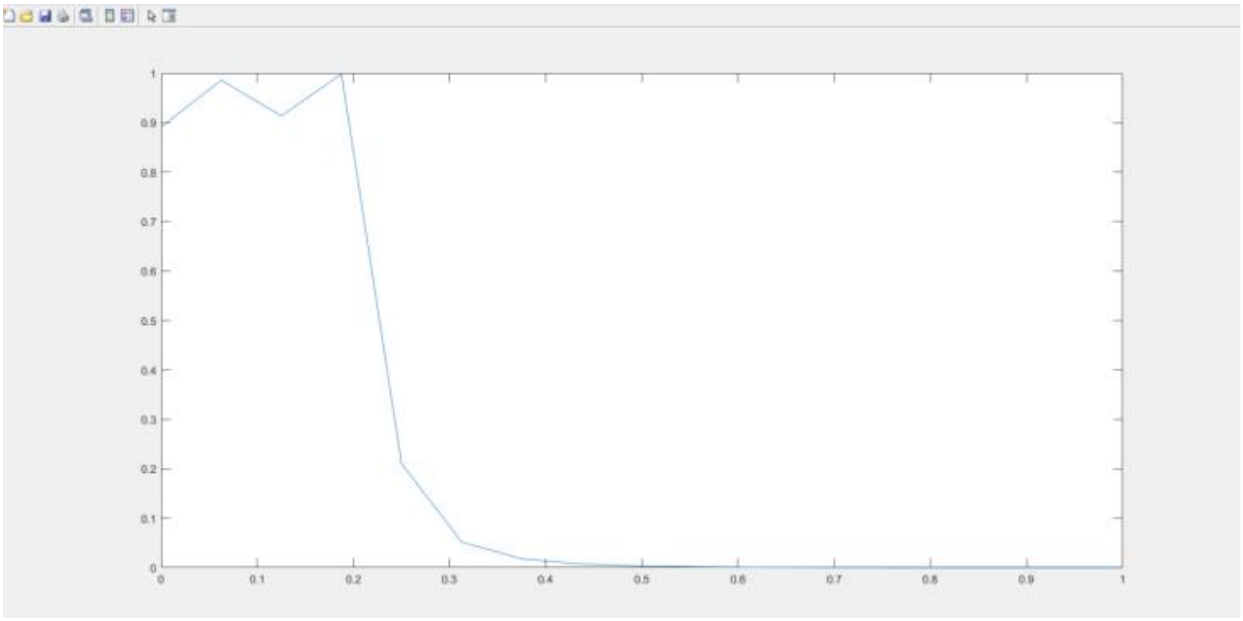
PROGRAM

```
clear all;
clc;
ap= 1;
as= 15;
wp= 0.2*pi;
ws= 0.3*pi;
t=1;
op=(2/t)*tan(wp/2);
os=(2/t)*tan(ws/2);
[n,cf]=cheb1ord(op,os,ap,as,'s')
[bn,an]= cheby1(n,ap,1,'s')
hsn=tf(bn,an)
[b,a]= cheby1(n,ap,cf,'s')
hs=tf(b,a)
[num,den]=bilinear(b,a,1/t)
hz=tf(num,den,t)
w=0:pi/16:pi
hw=freqz(num,den,w)
hw_mag=abs(hw)
plot(w/pi,hw_mag)
```

Output :


Command Window
New to MATLAB? See resources for Getting Started.
n =
4
cf =
0.6498
bn =
0 0 0 0 0.2457
an =
1.0000 0.9528 1.4539 0.7426 0.2756
hsn =
0.2457
s^4 + 0.9528 s^3 + 1.454 s^2 + 0.7426 s + 0.2756
Continuous-time transfer function.


New to MATLAB? See resources for Getting Started.
0.04381
+ 0.614 s^2 + 0.2038 s + 0.04915
0.0018 0.0073 0.0110 0.0073 0.0018
en =
1.0000 -3.0543 3.8290 -2.2925 0.5507

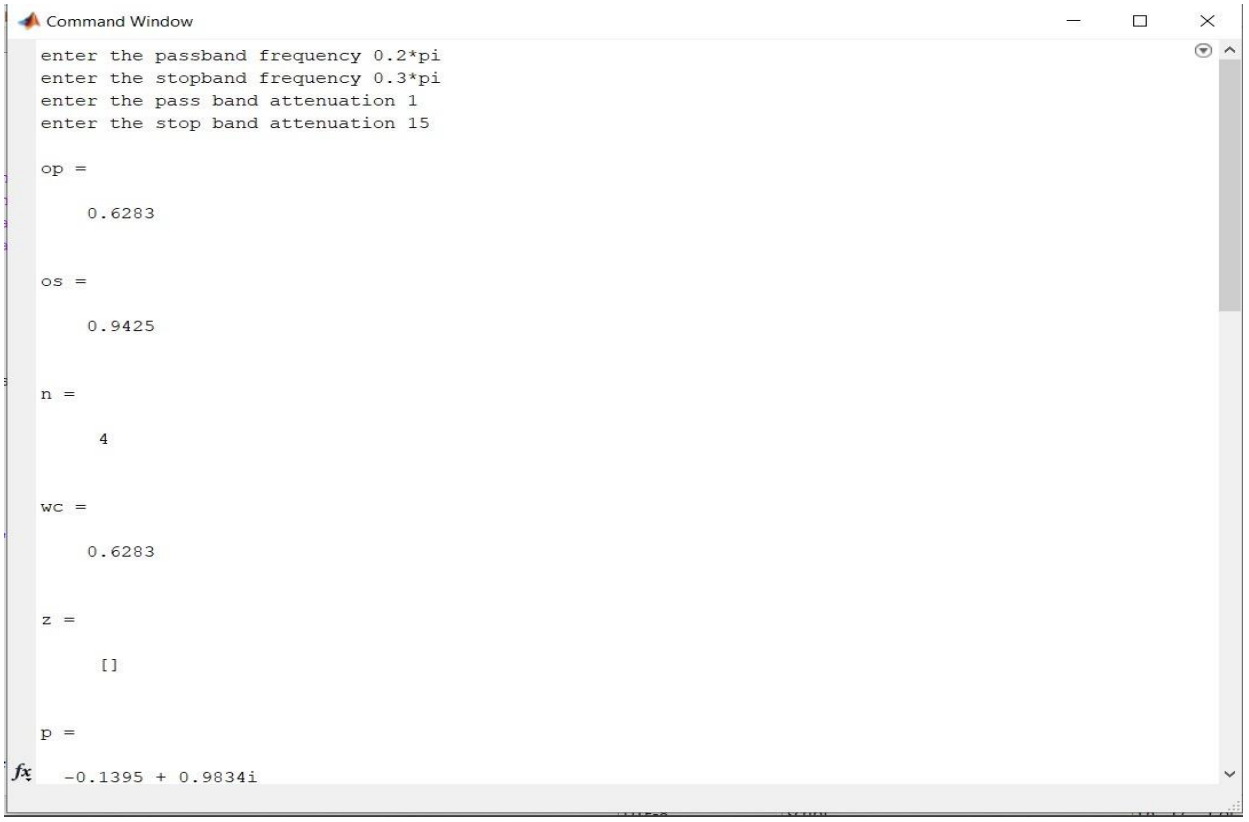


PROGRAM

```
clc;
clear all;
close all;
T=1;
fs=1/T;
wp = input('enter the passband frequency ');
ws = input('enter the stopband frequency ');
rp = input('enter the pass band attenuation ');
rs = input('enter the stop band attenuation ');
%calculation of op and os in iiv method
op=wp/T;
os=ws/T;
display(op);
display(os);
[n,wc] = cheb1ord(op,os,rp,rs,'s');
display(n);
display(wc);
[z,p,k] = cheb1ap(n,rp);
display(z);
display(p);
display(k);
[b,a] = cheby1(n,rp,1,'low','s');
display(b);
display(a);
[bt,at] = lp2lp(b,a,wc);
display(bt);
display(at);
s= tf (bt,at);
display(s);
w=logspace(-10,10);
```

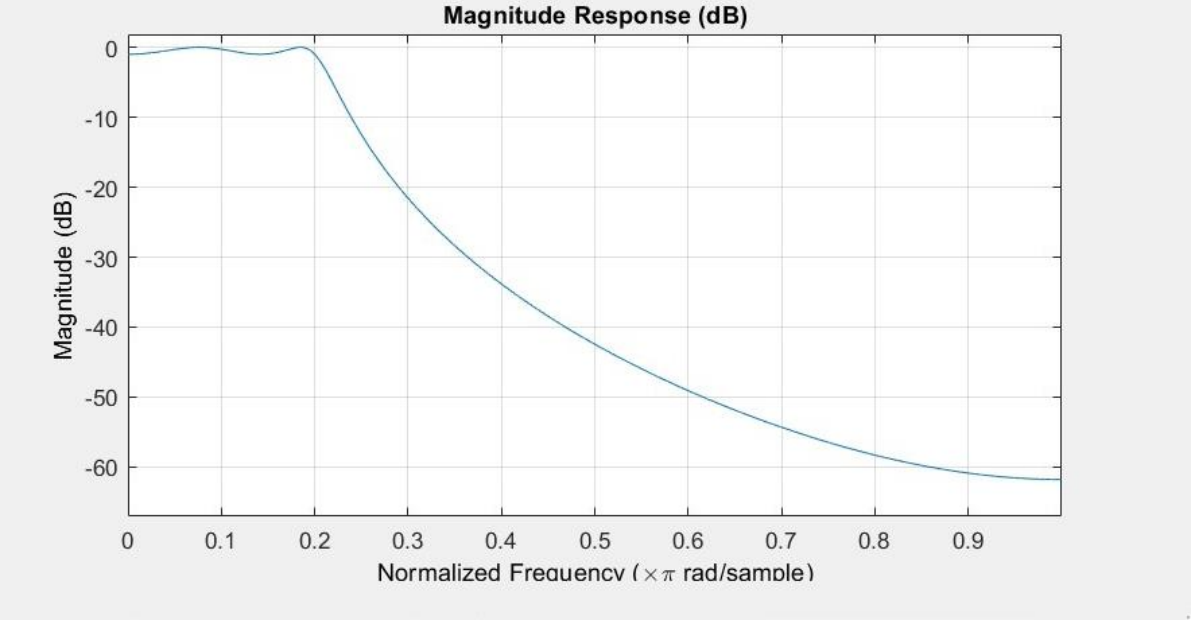
```
freqs(bt,at,w);
[bz,az] = impinvar(bt,at,fs);
display(bz);
display(az);
z=tf (bz,az,T,'variable','z^-1');
display(z);%required transfer function
w=0:pi/100:pi;
freqz(bz,az,w);
zplane(bz,az);%zero pole plot
fvtool(bz,az);%filter visualization technique
```

OUTPUT:



Command Window

```
    1.0000    0.5987    0.5740    0.1842    0.0430

s =

                      0.03829
  ------------------------------------------------
  s^4 + 0.5987 s^3 + 0.574 s^2 + 0.1842 s + 0.04296

Continuous-time transfer function.


bz =

    0.0000    0.0054    0.0181    0.0040


az =

    1.0000   -3.0591    3.8323   -2.2919    0.5495


z =

  1.388e-17 + 0.005373 z^-1 + 0.0181 z^-2 + 0.003985 z^-3
  ---------------------------------------------------------
  1 - 3.059 z^-1 + 3.832 z^-2 - 2.292 z^-3 + 0.5495 z^-4

Sample time: 1 seconds
Discrete-time transfer function.

fx >>
```



PRELAB:

1) What is chebyshev filter?
2) Give two difference between butterworth and chebyshey filter.
3) Differentiate between Chebyshev Type I and Type II filters in terms of their pole-zero placements and characteristics.
4) Explain the purpose and advantages of transforming analog filter designs into digital filters using methods like Bilinear Transformation and Impulse Invariance.
5) Describe the key differences between the Bilinear Transformation and the Impulse Invariance Method in the context of converting analog filters to digital filters.
6) How does the Bilinear Transformation map the s-plane in the analog domain to the z-plane in the digital domain? Discuss the mapping equation and its implications.
7) Compare and contrast the stability considerations when using the Bilinear Transformation versus the Impulse Invariance Method for analog-to-digital filter transformation.

POSTLAB:

1) What is pre-warping effect?
2) Explain how the order of the analog Chebyshev filter affects the digital filter obtained through the Bilinear Transformation.
3) Analyze the advantages and limitations of each transformation method (Bilinear Transformation and Impulse Invariance) in the context of Chebyshev filter design. When would you choose one method over the other?

RESULT:

EXPERIMENT :13a. INTERPOLATION IN TIME DOMAIN

Aim: To write code for interpolation of signal in time domain

Theory :

The idea of interpolation is a very familiar concept to most of us and has its origin in numerical analysis. Typically, interpolation is performed on a table of numbers representing a mathematical function. Such a table may be printed in a handbook or stored in a computer memory device. The interpolation, often simply linear (or straight line) approximation, creates an error called the interpolation error. The main difference between interpolation in digital signal processing and interpolation in numerical
analysis is that we will assume that the given data is bandlimited to some band of frequencies and develop schemes that are optimal on this basis, whereas a numerical analyst typically assumes that the data consists of samples of polynomials (or very nearly so) and develops schemes to minimize the resulting error. To motivate this concept of interpolation in signal processing, it is helpful to think of an underlying (or original) analog signal $x_a(t)$ that was sampled to produce the given discrete signal x(n). If the $x_a(t)$ was sampled at the minimum required rate, then, according to the sampling theorem, it can be recovered completely from the samples x(n). If we now sample this recovered analog signal, at say twice the old rate, we have succeeded in doubling the sampling rate or interpolating by a factor of 2 with zero interpolation error.

The process of sampling rate conversion in the digital domain can be viewed as a linear filtering operation, as illustrated in Figure. The input signal x(n) is characterized by the sampling rate Fx = 1/Tx, and the output signal y(m) is characterized by the sampling rate Fy =1/Ty, where Tx and Ty are the corresponding sampling intervals. In our treatment, the ratio Fy/Fx is constrained to be rational

$$\frac{F_y}{F_x} = \frac{I}{D}$$

Let v(m) denote the intermediate sequence with a rate Fy = IFx, which is obtained from x(n) by adding I − 1 zeros between successive values of x(n). Thus,

$$v(m) = \begin{cases} x(m/I), & m = 0, \pm I, \pm 2I, \dots \\ 0, & \text{otherwise} \end{cases}$$

and its sampling rate is identical to the rate of v(m). The block diagram of the upsampler is shown in Figure. Again, any system containing the upsampler is a time-varying system

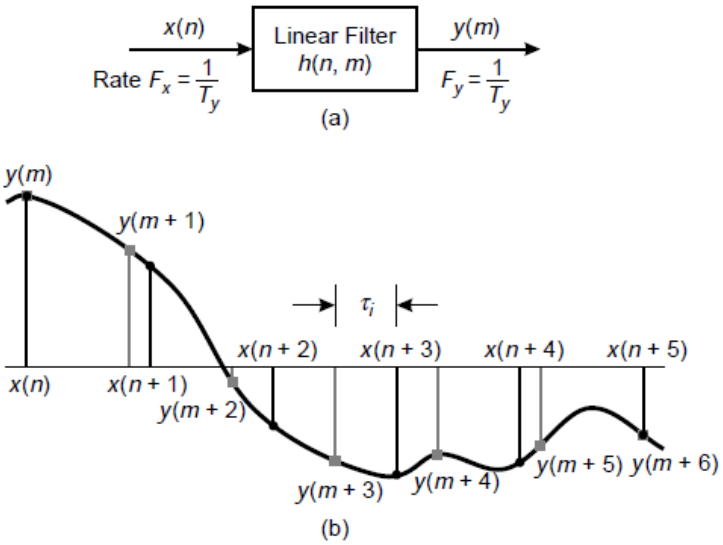


Figure1 : Sampling rate conversion views as a linear filtering process

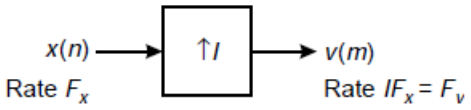


Figure 2: Interpolation by factor I

// PROGRAM FOR INTERPOLATION

// Program to do Interpolation of Signal

// clear work space variables

clf(); clc; clear; close;

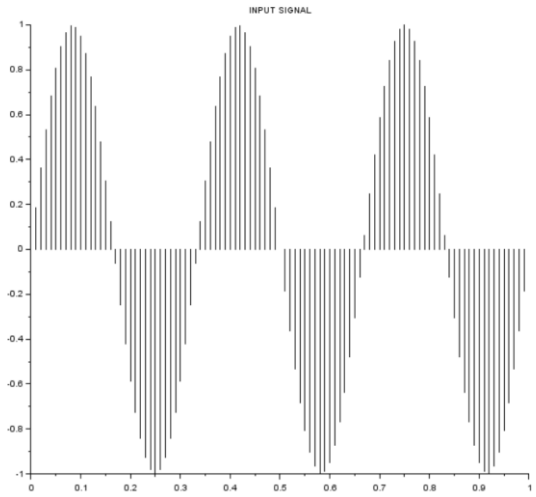
// Set Initialization Variables

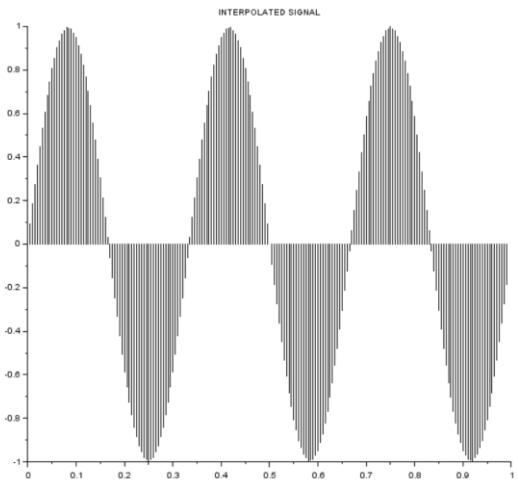
interp_fac = 2;

samp_freq = 100;

freq_cycles = 3;

```
time_index = 0:99;
// compute interpolation frequency with Sampling
inter_samp_freq = samp_freq*(interp_fac);
// Map time axis for before and after interpolation
time_axis = time_index/samp_freq;
new_time_index = 0:1/interp_fac:99;
new_time_axis = new_time_index / samp_freq;
// Define the input signal
inp_sig = sin(2*%pi*freq_cycles*time_axis);
// Do the interpolation using interp1 function on SCILAB
out_sig = interp1(time_axis,inp_sig,new_time_axis);
// Display the output
subplot(1,2,1)
plot2d3(time_axis,inp_sig);
title('INPUT SIGNAL');
subplot(1,2,2)
plot2d3(new_time_axis,out_sig);
title('INTERPOLATED SIGNAL')
```





Input Signal

Interpolated Signal

Pre lab

1. What is difference between Upsampling & Interpolation?
2. Compare Decimation & Interpolation?

Post lab

1. Modify the program to work with 4 Cycle Cos Signal and present the code & output?
2. Modify the above program for interpolation factor I = 3 and present the code & output?

RESULT:

EXPERIMENT 13b. INTERPOLATION IN FREQUENCY DOMAIN

Aim: To write code for interpolation of signal in frequency domain .

Theory:

Using fourier transform we will be able to do interpolation using zero padding in the frequency domain which will give exact bandlimited interpolation in the frequency domain. The DFT of the band limited signals for the entire non zero portions of x(n) extended by zeros yields exact interpolation of the complex spectrum.

Because fast fourier transform is so efficient, zero padding in FFT is highly practical method of interpolating spectra of finite duration signals and is used extensively in practice.

$$\omega_y = \frac{\omega_x}{I}$$

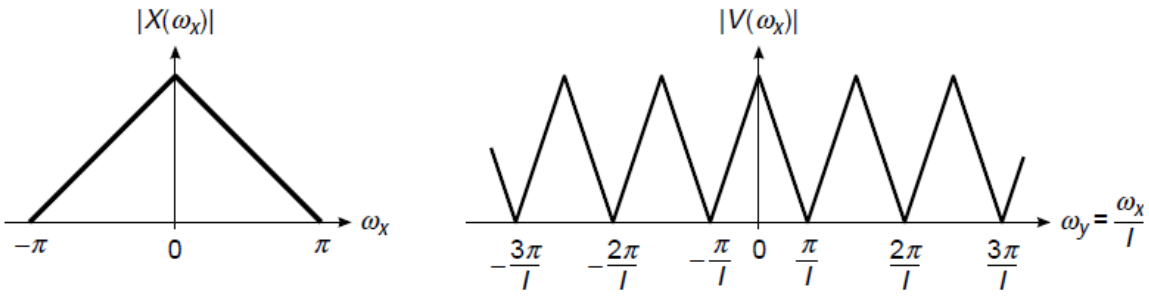


Figure 3: Frequency interpolation spectrum.

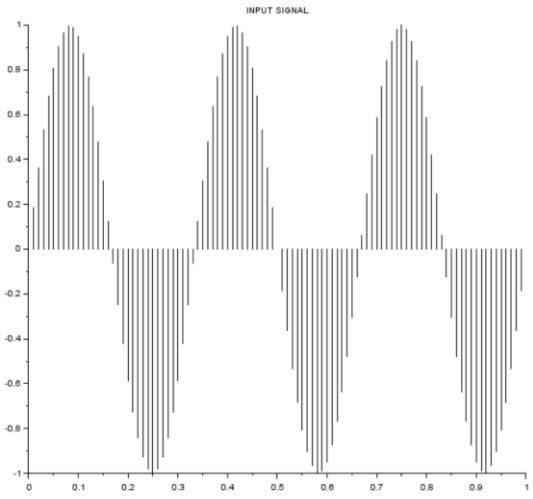
We observe that the sampling rate increase, obtained by the addition of $I - 1$ zero samples between successive values of $x(n)$, results in a signal whose spectrum is an I-fold periodic repetition of the input signal spectrum.

/ Program to do interpolation in the frequency domain

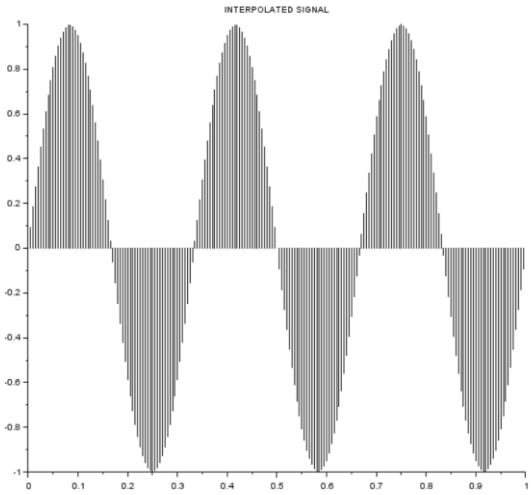
clf();clc;clear;close;

```
// Input sinusoidal signal
samp_freq = 100;
sig_freq = 3;
interp_fac = 2;
// Time axis of the Sinusoidal Signal
time_index = 0:99;
time_axis = time_index/samp_freq;
inp_sig = sin(2*%pi*sig_freq*time_axis);
subplot(1,2,1)
plot2d3(time_axis,inp_sig );
// Frequency domain interpolation using zero padding
// Transpose of the signal
inp_sig = inp_sig(:);
// Take fft of the signal
sig_fft = fft(inp_sig);
// Do zero padding in frequency domain for interpolation
sig_len = length(inp_sig);
// compute how many zeros needed using the interpolation formula (N*(I-1))
zeropad_len = round(sig_len*(interp_fac - 1));
// middle symmetry for splitting FFT in to two halves
mid_symmetry = ceil((sig_len+1)/2);
// Do zero padding here
frq_interp_sig = [sig_fft(1:mid_symmetry); zeros(zeropad_len, 1); sig_fft(mid_symmetry+1:$)];
```

```
// Take inverse fourier transform
time_interp_sig = interp_fac* real(ifft(frq_interp_sig));
interp_sig_len = length(time_interp_sig);
// compute new time axis
new_time_axis = (0:interp_sig_len-1)/(samp_freq*interp_fac);
subplot(1,2,2)
plot2d3(new_time_axis, time_interp_sig)
```



Input Signal



Interpolated Signal

Pre Lab:

1. Explain how the interpolation in frequency domain is advantageous over time domain interpolation?
2. Compare time domain & freq domain interpolation in coding logic?

Post Lab:

1. For the given code vary the length of the FFT to 256 and compute the output?
2. Change the amplitude of the output of the given code to [-2 2]?

RESULT:

EXPERIMENT- 14a. DECIMATION IN TIME DOMAIN

Aim: To write code for decimation of signal .

Theory:

In digital signal processing, down sampling, compression, and decimation are terms associated with the process of resampling in a multi-rate digital signal processing system. Decimation is a term that historically means the removal of every tenth one. But in signal processing, decimation by a factor of 10 actually means keeping only every tenth sample. This factor multiplies the sampling interval or, equivalently, divides the sampling rate. For example, if compact disc audio at 44,100 samples/second is decimated by a factor of 5/4, the resulting sample rate is 35,280. A system component that performs decimation is called a decimator. Decimation by an integer factor is also called compression.

Rate reduction by an integer factor M can be explained as a two-step process, with an equivalent implementation that is more efficient

1. Reduce high-frequency signal components with a digital lowpass filter.
2. Decimate the filtered signal by M; that is, keep only every M^{th} sample.

Step 2 alone allows high-frequency signal components to be misinterpreted by subsequent users of the data, which is a form of distortion called aliasing. Step 1, when necessary, suppresses aliasing to an acceptable level. In this application, the filter is called an anti-aliasing filter, and its design is discussed below.

When the anti-aliasing filter is an IIR design, it relies on feedback from output to input, prior to the second step. With FIR filtering, it is an easy matter to compute only every M^{th} output. The calculation performed by a decimating FIR filter for the n^{th} output sample is a dot product.

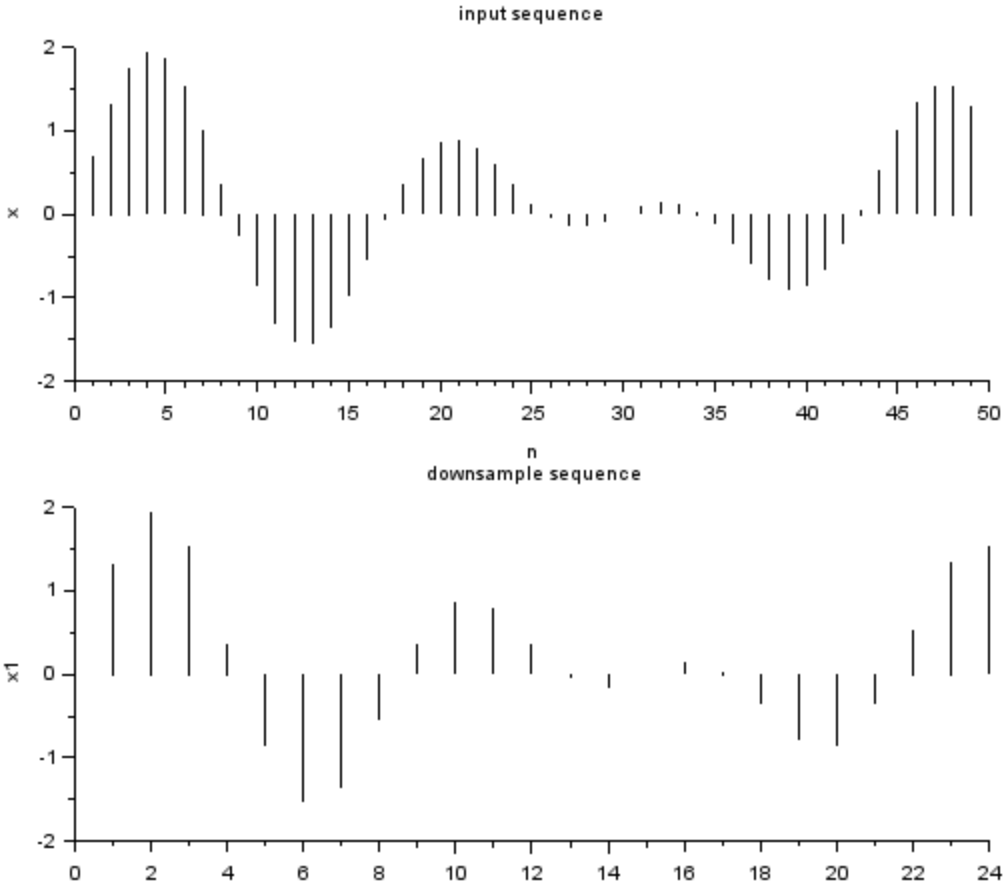
$$y[n] = \sum_{k=0}^{K-1} x[nM - k] \cdot h[k],$$

where the h[•] sequence is the impulse response, and K is its length. x[•] represents the input sequence being downsampled. In a general purpose processor, after computing y[n], the easiest

way to compute y[n+1] is to advance the starting index in the x[•] array by M, and recompute the dot product. In the case M=2, h[•] can be designed as a half-band filter, where almost half of the coefficients are zero and need not be included in the dot products.

Impulse response coefficients taken at intervals of M form a subsequence, and there are M such subsequences (phases) multiplexed together. The dot product is the sum of the dot products of each subsequence with the corresponding samples of the x[•] sequence. Furthermore, because of downsampling by M, the stream of x[•] samples involved in any one of the M dot products is never involved in the other dot products. Thus M low-order FIR filters are each filtering one of M multiplexed phases of the input stream, and the M outputs are being summed. This viewpoint offers a different implementation that might be advantageous in a multi-processor architecture. In other words, the input stream is demultiplexed and sent through a bank of M filters whose outputs are summed. When implemented that way, it is called a **polyphase** filter.

```
// Program to do Decimation of Signal
// clear work space variables

clear all;
N=50;
n=0:1:N-1;
x=sin(2*%pi*n/20)+sin(2*%pi*n/15)
M=2;
x1=x(1:M:N);
n1=1:1:N/M;
subplot(2,1,1),plot2d3(n,x)
xlabel('n'),ylabel('x')
title('input sequence')
subplot(2,1,2),plot2d3(n1-1,x1)
xlabel('n'),ylabel('x1')
title('downsample sequence')
```



Pre Lab

1. What is difference between down sampling& decimation?

2. What is the “decimation factor”?

Post lab

1. What happens if we violate the Nyquist criteria in downsampling or decimating?
2. Which signals can be downsampled?

RESULT:

EXPERIMEN-14b. DECIMATION IN FREQUENCY DOMAIN

Aim: To write code for decimation of signal in frequency domain using SCILAB

Let X(f) be the Fourier transform of any function, x(t), whose samples at some interval, T, equal the x[n] sequence. Then the discrete-time Fourier transform (DTFT) is a Fourier series representation of a periodic summation of X(f).

$$\underbrace{\sum_{n=-\infty}^{\infty} \overbrace{x(nT)}^{x[n]}\, \mathrm{e}^{-\mathrm{i}2\pi fnT}}_{\mathrm{DTFT}} = \frac{1}{T}\sum_{k=-\infty}^{\infty} X\left(f - \frac{k}{T}\right)$$

When T has units of seconds, f has units of hertz. Replacing T with MT in the formulas above gives the DTFT of the decimated sequence, x[nM]:

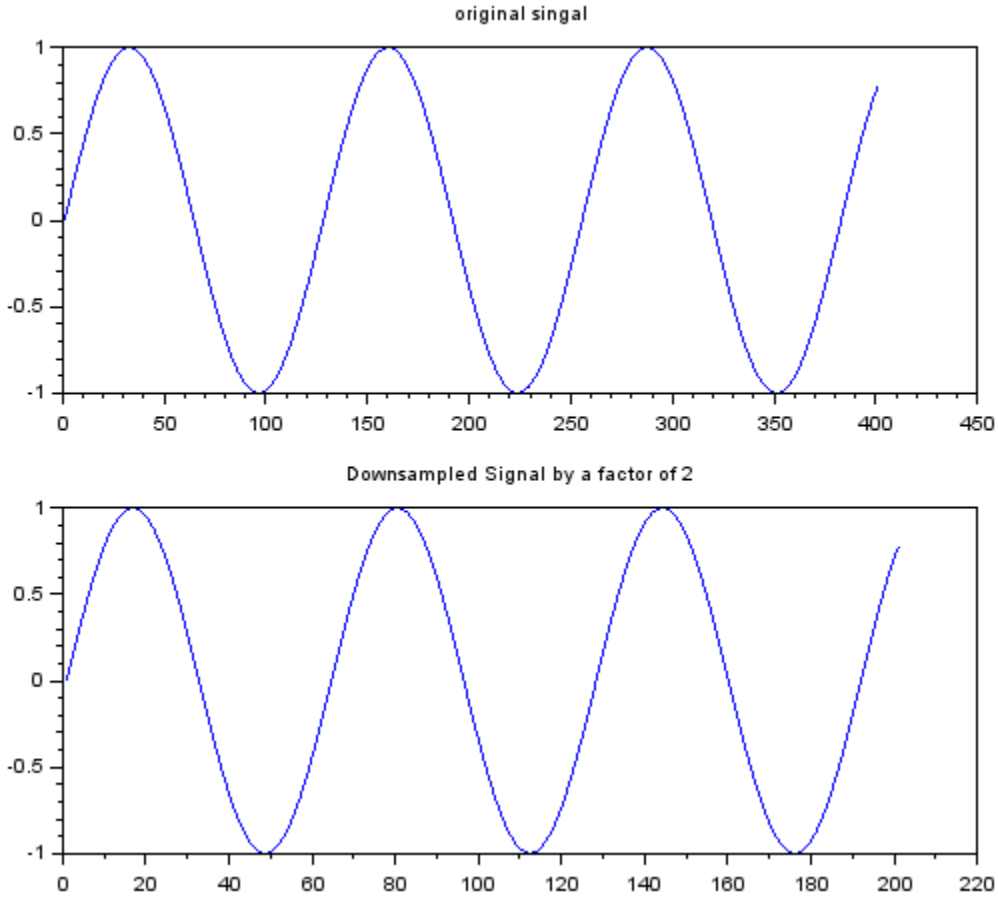
$$\sum_{n=-\infty}^{\infty} x(n \cdot MT)\, \mathrm{e}^{-\mathrm{i}2\pi fn(MT)} = \frac{1}{MT}\sum_{k=-\infty}^{\infty} X\left(f - \tfrac{k}{MT}\right)$$

The periodic summation has been reduced in amplitude and periodicity by a factor of *M*. An example of both these distributions is depicted in the two traces. Aliasing occurs when adjacent copies of *X*(*f*) overlap. The purpose of the anti-aliasing filter is to ensure that the reduced periodicity does not create overlap.

// Program to do decimation in the frequency domain

```
clear;
clc;
n=0:%pi/200:2*%pi;
x=sin(%pi*n);//original signal
downsampling_x=x(1:2:length(x));//downsampled by a factor of 2
subplot(2,1,1)
plot(1:length(x),x);
```

```
xtitle('original singal')
subplot(2,1,2)
plot(1:length(downsampling_x),downsampling_x);
xtitle('Downsampled Signal by a factor of 2');
```



PRE LAB:

1. Explain how the decimation in frequency domain is advantageous over time domain decimation?
2. Compare time domain & frequency domain decimation in coding logic?

POST LAB:

1. What is the need for anti-aliasing filter prior to downsampling?
2. Define sampling rate conversion.

RESULT:

Laboratory Report Cover Sheet

SRM Institute of Science and Technology
College of Engineering and Technology
Department of Electronics and Communication Engineering

18ECC204J DIGITAL SIGNAL PROCESSING

Fifth Semester, 2023-24 (Odd semester)

Name :

Register No. :

Day / Session :

Venue :

Title of Experiment :

Date of Conduction :

Date of Submission :

Particulars	Max. Marks	Marks Obtained
Pre lab	10	
Lab Performance	15	
Post lab	10	
Viva	5	
Total	40	

REPORT VERIFICATION

Staff Name :

Signature :

EXPERIMENT 15a: DESIGN OF ANTI -ALIASING FILTER

Aim: To study the characteristics of anti-aliasing filter

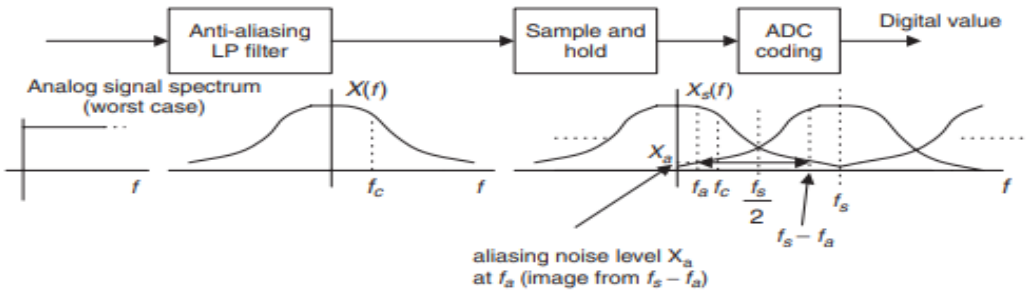
Theory: An **anti-aliasing filter** (**AAF**) is a filter used before a signal sampler to restrict the bandwidth of a signal to satisfy the Nyquist–Shannon sampling theorem over the band of interest. Since the theorem states that unambiguous reconstruction of the signal from its samples is possible when the power of frequencies above the Nyquist frequency is zero, a brick wall filter is an idealized but impractical AAF. A practical AAF trades off between bandwidth and aliasing. A practical anti-aliasing filter will typically permit some aliasing to occur or attenuate or otherwise distort some in-band frequencies close to the Nyquist limit. For this reason, many practical systems sample higher than would be theoretically required by a perfect AAF in order to ensure that all frequencies of interest can be reconstructed, a practice called oversampling.

As we have seen, when sampling a signal that contains frequencies that are above half of the sampling frequency, the sampling maps these to some other frequencies within the Nyquist frequency. These so-called *image frequencies* or *alias frequencies* are often unwanted, since they do not represent the original signal. Instead, one uses an anti-aliasing filter (AAF) to filter the input signal before sampling.

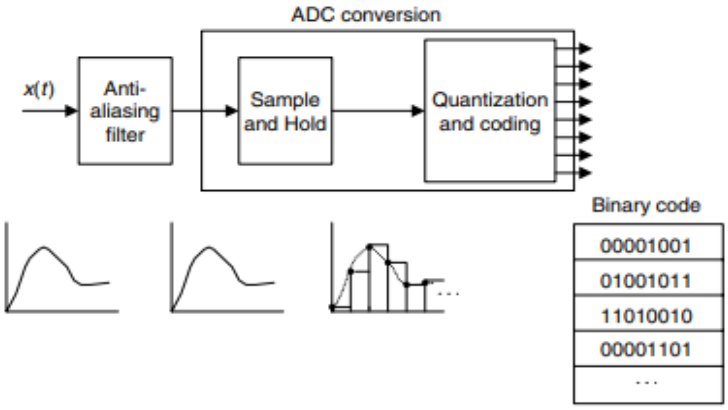
The anti-aliasing filter is basically a low-pass filter with (ideal) cutoff frequency of Fs/2. Hence, it blocks all frequencies that would create images in the sampled signal, before sampling the signal. Accordingly, there is a loss in the information about high frequencies when applying the anti-aliasing filter. However, the same loss would again be incurred when sampling the signal with frequency Fs/2, since the output frequencies cannot be unambiguously mapped to the input frequencies due to the aliasing effect.

In practice, the analog signal to be digitized may contain other frequency components in addition to the folding frequency, such as high-frequency noise. To satisfy the sampling theorem condition, we apply an anti-aliasing filter to limit the input analog signal, so that all the frequency components are less than the folding frequency (half of the sampling rate). Considering the worst case, where

the analog signal to be sampled has a flat frequency spectrum, the band-limited spectrum X(f) and sampled spectrum Xs(f) are depicted in Figure given below, where the shape of each replica in the sampled signal spectrum is the same as that of the anti-aliasing filter magnitude frequency response.



Spectrum of the sampled analog signal with a practical anti-aliasing filter.




```
clc ;
clf ;
 clear all;
 b=input('enter no of bits');
 n=input('enter band width in KHZ');
 As=20*log10(2^b*sqrt(6));
 Vs=(10^(0.1*As)-1)^(1/(2*n));
 fp=4;
 fs=Vs*fp;
```

```
S=2*fs;
fa=S-fp;
Va=fa/fp;
Aa =10* log10 (1+ Va ^(2* n ) )
```

Simulation Output:

No of bits	Frequency in (KHz)	OUTPUT
4	50	
8	100	
12	150	

Simulation Output:

- Output for b = 4 & n = 50 Hz

Variable Browser

Name	Value	Type	Visibility	Memory
Aa	61.5	Double	local	216 B
As	31.9	Double	local	216 B
S	8.61	Double	local	216 B
Va	1.15	Double	local	216 B
Vs	1.08	Double	local	216 B
a	4.61	Double	local	216 B
b	4	Double	local	216 B
fa	4.61	Double	local	216 B
fp	4	Double	local	216 B
fs	4.3	Double	local	216 B
n	50	Double	local	216 B

- Output for b = 8 & n = 100 Hz

Variable Browser

Name	Value	Type	Visibility	Memory
Aa	109	Double	local	216 B
As	55.9	Double	local	216 B
S	8.53	Double	local	216 B
Va	1.13	Double	local	216 B
Vs	1.07	Double	local	216 B
a	4.53	Double	local	216 B
b	8	Double	local	216 B
fa	4.53	Double	local	216 B
fp	4	Double	local	216 B
fs	4.27	Double	local	216 B
n	100	Double	local	216 B

- Output for b = 12 & n = 150 Hz

Variable Browser

Name	Value	Type	Visibility	Memory
Aa	155	Double	local	216 B
As	80	Double	local	216 B
S	8.51	Double	local	216 B
Va	1.13	Double	local	216 B
Vs	1.06	Double	local	216 B
a	4.51	Double	local	216 B
b	12	Double	local	216 B
fa	4.51	Double	local	216 B
fp	4	Double	local	216 B
fs	4.25	Double	local	216 B
n	150	Double	local	216 B

Pre-lab questions:

1. What is meant by anti-aliasing filter ?
2. Which type of filter used for anti-aliasing?

Post Lab

1. list the advantages of anti-aliasing filter

2.Mention the difference between anti-aliasing and anti-imaging filter.

EXPERIMENT 156 DESIGN OF ANTI-IMAGING FILTER

Aim: To study the characteristics of anti-imaging filter

Theory :

In a mixed-signal system (analog and digital), a **reconstruction filter**, sometimes called an **anti-imaging filter**, is used to construct a smooth analog signal from a digital input, as in the case of a digital to analog converter (DAC) or other sampled data output device.

While in theory a DAC outputs a series of discrete Dirac impulses, in practice, a real DAC outputs pulses with finite bandwidth and width. Both idealized Dirac pulses, zero-order held steps and other output pulses, if unfiltered, would contain spurious high-frequency replicas, "*or images*" of the original bandlimited signal. Thus, the reconstruction filter smooths the waveform to remove image frequencies (copies) above the Nyquist limit. In doing so, it reconstructs the continuous time signal (whether originally sampled, or modelled by digital logic) corresponding to the digital time sequence.

Practical filters have non-flat frequency or phase response in the pass band and incomplete suppression of the signal elsewhere. The ideal sinc waveform has an infinite response to a signal, in both the positive and negative time directions, which is impossible to perform in real time – as it would require infinite delay. Consequently, real reconstruction filters typically either allow some energy above the Nyquist rate, attenuate some in-band frequencies, or both. For this reason, oversampling may be used to ensure that frequencies of interest are accurately reproduced without excess energy being emitted out of band.

In systems that have both, the anti-aliasing filter and a reconstruction filter may be of identical design. For example, both the input and the output for audio equipment may be sampled at 44.1 kHz. In this case, both audio filters block as much as possible above 22 kHz and pass as much as possible below 20 kHz.

Alternatively, a system may have no reconstruction filter and simply tolerate some energy being wasted reproducing higher frequency images of the primary signal spectrum.

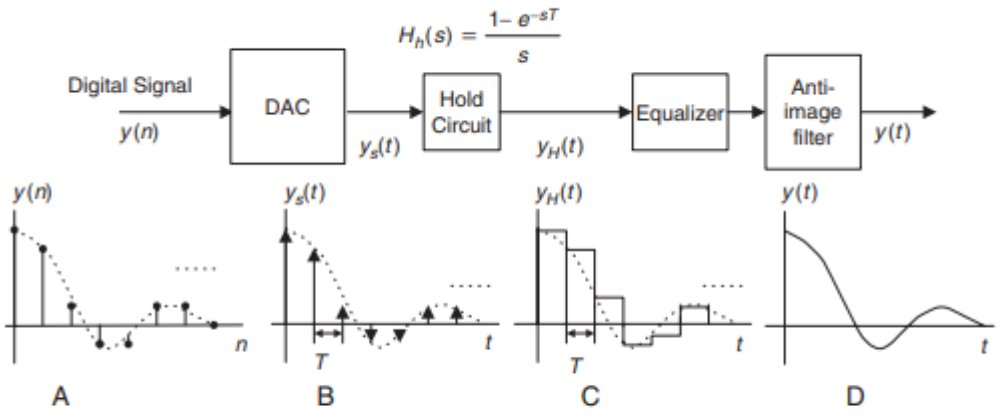


FIGURE 2.19 **Signal notations at the practical reconstruction stage. (a) Processed digital signal. (b) Recovered ideal sampled signal. (c) Recovered sample-and-hold voltage. (d) Recovered analog signal.**

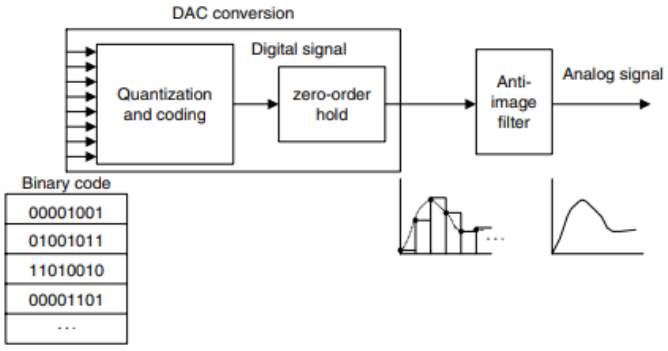
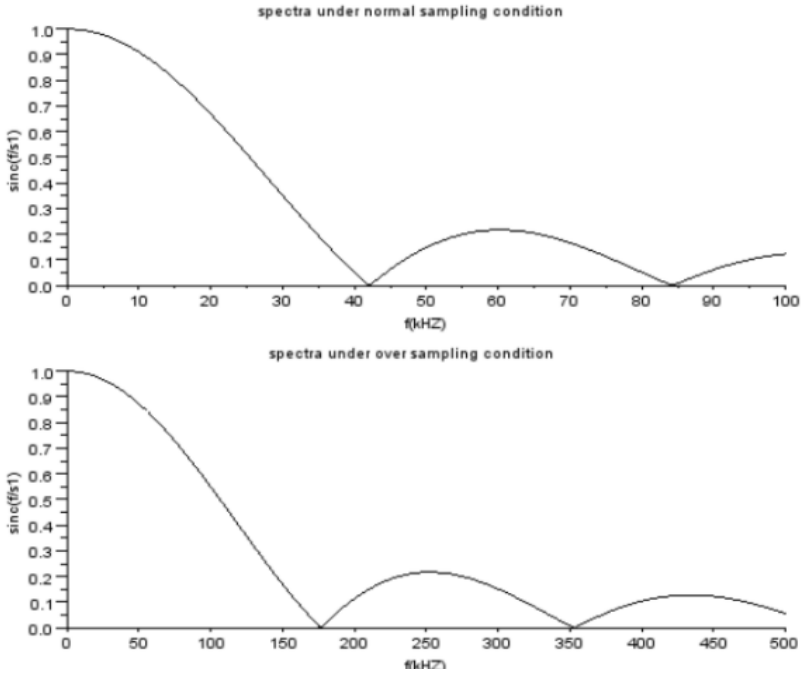


FIGURE 2.32 **Typical DAC process.**

```
clc ;
clf ;
clear all;
// Anti Imaging Filter considerations
 Ap =0.5; // pass band attenuation
 fp =20; // pass band edge frequency
 As =60; // stop band attenuation
```

```
S =42.1;
 fs =S - fp ; // stop band edge frequency
 e = sqrt (10^(0.1* Ap ) -1) ;
 e1 = sqrt (10^(0.1* As ) -1) ;
n =( log10 ( e1 / e ) ) /( log10 ( fs / fp ) ) ;
 n = ceil ( n ) // design of nth order but worth filter
 // ( b ) Assuming Zero−order hold sampling
S1 =176.4;
 fs1 = S1 - fp;
 Ap =0.316;
 e2 = sqrt (10^(0.1* Ap ) -1);
 n1 =( log10 ( e1 / e2 ) ) /( log ( fs1 / fp ) ) ; //new o r d e r of but worth filter
 n1 = ceil ( n1 )
 f =0:100;
 x = abs( sinc ( f * %pi / S ) ) ;
 f1 =0:500;
 x1 =abs( sinc ( f1 * %pi / S1 ) ) ;
 a = gca () ;
 subplot (211) ;
 plot2d (f , x ) ;
 xtitle (" spectra under normal sampling condition " ," f (kHZ ) " ," s i n c ( f / s1 ) ") ;
 subplot (212);
 plot2d ( f1,x1 );
 xtitle (" spectra under over sampling condition " ," f (kHZ ) " ," s i n c ( f / s1 ) ");
```

Simulation Output:



Pre-lab

1. What is meant by anti-imaging filter ?
2. Write another name of anti-imaging filter.

Post-Lab

1. List the applications of anti-imaging filter.
2. Mention the advantages of the anti-imaging filter.

Result: