REPORT

Zajęcia: Analog and digital electronic circuits
Teacher: prof. dr hab. Vasyl Martsenyuk

Lab 5 and 6
Date: 10.12.2024
Topics:
Design and analysis of digital filters: implementation of FIR and IIR filters in Matlab/Python.
Adaptive filtering: application of adaptive filtering algorithms in noise reduction.
Variant 8

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Informatyka II stopień,
niestacjonarne,
1 semestr,
Gr. A

1. Problem statement:

The goal of this task is to design and implement digital filters in Python to reduce noise in a noisy sinusoidal signal. Three types of filters will be implemented:
A Finite Impulse Response (FIR) filter with coefficients b = {1, 0, 1}.
An Infinite Impulse Response (IIR) filter with coefficients b = {0.5, 0.5} and a = {1, -0.3}.
An adaptive Least Mean Squares (LMS) filter with a step size mu = 0.05 and filter length M = 5.

2. Input data:

(FIR) filter with coefficients b = {1, -1, 0.5}

(IIR) filter with coefficients :
-b = {0.5, 0.5}
-a = {1, -0.3}

(LMS) filter with a step size mu = 0.05

filter length M = 5

3. Commands used (or GUI):

source code:

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.signal import lfilter

# Generowanie zakłóconego sygnału sinusoidalnego
fs = 1000  # Częstotliwość próbkowania
t = np.linspace(0, 1, fs, endpoint=False)
f = 50  # Częstotliwość sygnału
```

```
signal = np.sin(2 * np.pi * f * t)  # Sygnał czysty
noise = np.random.normal(0, 0.5, signal.shape)  # Szum
noisy_signal = signal + noise  # Sygnał zakłócony

# FIR Filter
b_fir = [1, 0, 1]  # Zmiana współczynników dla Wariantu 8
filtered_fir = lfilter(b_fir, [1], noisy_signal)

# IIR Filter
b_iir = [0.5, 0.5]  # Zmiana współczynników dla Wariantu 8
a_iir = [1, -0.3]   # Zmiana współczynników dla Wariantu 8
filtered_iir = lfilter(b_iir, a_iir, noisy_signal)

# LMS Adaptive Filter
def lms_filter(x, d, mu, M):
    N = len(x)
    w = np.zeros(M)
    y = np.zeros(N)
    e = np.zeros(N)

    for n in range(M, N):
        x_n = x[n:n-M:-1]  # Fragment sygnału wejściowego
        y[n] = np.dot(w, x_n)
        e[n] = d[n] - y[n]
        w += mu * e[n] * x_n

    return y, e

mu = 0.05
M = 5  # Zmiana długości filtru LMS dla Wariantu 8
desired_signal = signal  # Sygnał czysty jako odniesienie
filtered_lms, error = lms_filter(noisy_signal, desired_signal, mu, M)

# Wizualizacja wyników
plt.figure(figsize=(15, 10))

plt.subplot(4, 1, 1)
```

```
plt.plot(t, noisy_signal, label='Noisy Signal')
plt.title("Noisy Signal")
plt.grid()
plt.legend()

plt.subplot(4, 1, 2)
plt.plot(t, filtered_fir, label='FIR Filtered', color='g')
plt.title("FIR Filter Output")
plt.grid()
plt.legend()

plt.subplot(4, 1, 3)
plt.plot(t, filtered_iir, label='IIR Filtered', color='r')
plt.title("IIR Filter Output")
plt.grid()
plt.legend()

plt.subplot(4, 1, 4)
plt.plot(t, filtered_lms, label='LMS Filtered', color='m')
plt.title("LMS Filter Output")
plt.grid()
plt.legend()

plt.tight_layout()
plt.show()

def fir_filter(x, b):
    """
    FIR filter implementation.

    Parameters:
    x : ndarray
        Input signal.
    b : ndarray
        Filter coefficients.

    Returns:
```

```
    y : ndarray
        Filtered output signal.
    """
    M = len(b)
    y = np.zeros(len(x))
    for n in range(M, len(x)):
        y[n] = np.dot(b, x[n-M+1:n+1][::-1])
    return y

# Example usage and plotting
fs = 1000  # Sampling frequency
t = np.linspace(0, 1, fs)
x = np.sin(2 * np.pi * 5 * t) + 0.5 * np.random.randn(len(t))  # Signal with noise
b = [1, 0, 1]  # FIR coefficients from Variant 8

y = fir_filter(x, b)

plt.figure(figsize=(10, 6))
plt.plot(t, x, label="Noisy Signal")
plt.plot(t, y, label="Filtered Signal", linewidth=2)
plt.legend()
plt.title("FIR Filter")
plt.xlabel("Time [s]")
plt.ylabel("Amplitude")
plt.grid()
plt.show()

def fir_filter(x, b):
    """
    FIR filter implementation.

    Parameters:
    x : ndarray
        Input signal.
    b : ndarray
        Filter coefficients.
```

```
    Returns:
    y : ndarray
        Filtered output signal.
    """
    M = len(b)
    y = np.zeros(len(x))
    for n in range(M, len(x)):
        y[n] = np.dot(b, x[n-M+1:n+1][::-1])
    return y

# Example usage and plotting
fs = 1000  # Sampling frequency
t = np.linspace(0, 1, fs)
x = np.sin(2 * np.pi * 5 * t) + 0.5 * np.random.randn(len(t))  # Signal with noise
b = [1, 0, 1]  # FIR coefficients for Variant 8

y = fir_filter(x, b)

plt.figure(figsize=(10, 6))
plt.plot(t, x, label="Noisy Signal")
plt.plot(t, y, label="Filtered Signal", linewidth=2)
plt.legend()
plt.title("FIR Filter")
plt.xlabel("Time [s]")
plt.ylabel("Amplitude")
plt.grid()
plt.show()

def fir_filter(x, b):
    """
    FIR filter implementation.

    Parameters:
    x : ndarray
        Input signal.
    b : ndarray
        Filter coefficients.
```

```
    Returns:
    y : ndarray
        Filtered output signal.
    """
    M = len(b)
    y = np.zeros(len(x))
    for n in range(M, len(x)):
        y[n] = np.dot(b, x[n-M+1:n+1][::-1])
    return y

# Example usage and plotting
fs = 1000  # Sampling frequency
t = np.linspace(0, 1, fs)
x = np.sin(2 * np.pi * 5 * t) + 0.5 * np.random.randn(len(t))  # Signal with noise
b = [1, 0, 1]  # FIR coefficients for Variant 8

y = fir_filter(x, b)

plt.figure(figsize=(10, 6))
plt.plot(t, x, label="Noisy Signal")
plt.plot(t, y, label="Filtered Signal", linewidth=2)
plt.legend()
plt.title("FIR Filter")
plt.xlabel("Time [s]")
plt.ylabel("Amplitude")
plt.grid()
plt.show()

def fir_filter(x, b):
    """
    FIR filter implementation.

    Parameters:
    x : ndarray
        Input signal.
    b : ndarray
```

```
        Filter coefficients.

    Returns:
    y : ndarray
        Filtered output signal.
    """
    M = len(b)
    y = np.zeros(len(x))
    for n in range(M, len(x)):
        y[n] = np.dot(b, x[n-M+1:n+1][::-1])
    return y

# Example usage and plotting
fs = 1000  # Sampling frequency
t = np.linspace(0, 1, fs)
x = np.sin(2 * np.pi * 5 * t) + 0.5 * np.random.randn(len(t))  # Signal with noise
b = [1, 0, 1]  # FIR coefficients for Variant 8

y = fir_filter(x, b)

plt.figure(figsize=(10, 6))
plt.plot(t, x, label="Noisy Signal")
plt.plot(t, y, label="Filtered Signal", linewidth=2)
plt.legend()
plt.title("FIR Filter (Variant 8)")
plt.xlabel("Time [s]")
plt.ylabel("Amplitude")
plt.grid()
plt.show()

from scipy.signal import freqz

# Define FIR Filter
def fir_filter(b, x):
    M = len(b)  # Number of coefficients
    y = np.convolve(x, b, mode='full')[:len(x)]  # Apply filter
    return y
```

```
# Example FIR Coefficients and Input Signal
b = [1, 0, 1]  # FIR coefficients
x = np.sin(2 * np.pi * 0.05 * np.arange(100))  # Example input signal

# Filter the Signal
y = fir_filter(b, x)

# Plot
plt.figure(figsize=(10, 6))
plt.plot(x, label="Input Signal")
plt.plot(y, label="Filtered Signal")
plt.legend()
plt.title("FIR Filter Output")
plt.show()

def iir_filter(x, b, a):
    """
    IIR filter implementation.

    Parameters:
    x : ndarray
        Input signal.
    b : ndarray
        Numerator coefficients.
    a : ndarray
        Denominator coefficients.

    Returns:
    y : ndarray
        Filtered output signal.
    """
    M = len(b)  # Length of numerator coefficients (b)
    N = len(a)  # Length of denominator coefficients (a)
    y = np.zeros(len(x))  # Initialize output signal array

    # Apply filter to each sample in the input signal
```

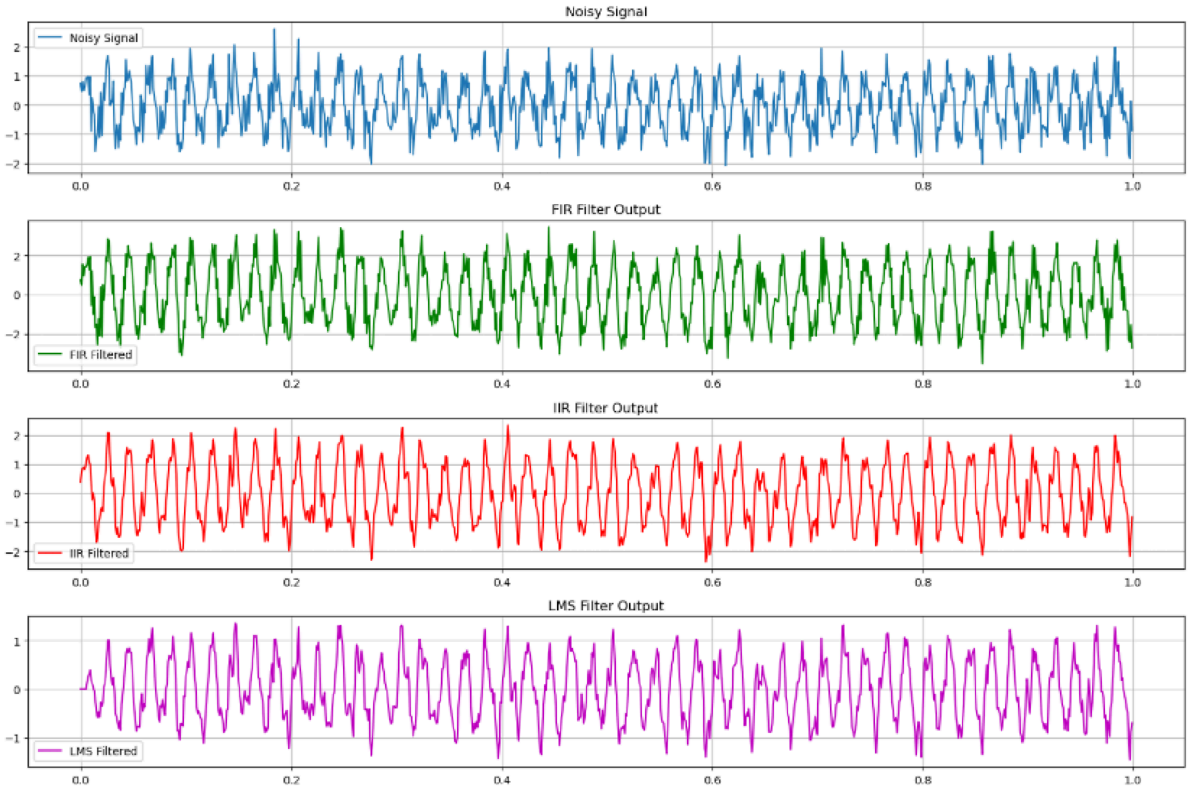
```
    for n in range(len(x)):
        # Numerator part (feedforward)
        # Ensure we use the correct slice length for the convolution
        x_slice = x[max(0, n-M+1):n+1]  # Input signal slice
        y[n] = np.dot(b[:len(x_slice)], x_slice[::-1])  # Apply reverse convolution
for numerator

        # Denominator part (feedback), skip the first sample
        if n >= 1:
            # Ensure we use the correct slice length for the feedback part
            y_slice = y[max(0, n-N+1):n]  # Output signal slice
            y[n] -= np.dot(a[1:min(N, len(y_slice)+1)], y_slice[::-1])  # Apply
reverse convolution for feedback

    return y

# Example usage and plotting
# Create a noisy signal (for example, a sine wave with noise)
fs = 1000  # Sampling frequency
t = np.linspace(0, 1, fs)  # Time vector
x = np.sin(2 * np.pi * 50 * t) + 0.5 * np.random.randn(len(t))  # Noisy signal

# IIR filter coefficients
a = [1, -0.3]  # Denominator coefficients (a_0 = 1 by convention)
b = [0.5, 0.5]  # Numerator coefficients

# Apply the filter to the noisy signal
y = iir_filter(x, b, a)

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(t, x, label="Noisy Signal")
plt.plot(t, y, label="Filtered Signal", linewidth=2)
plt.legend()
plt.title("IIR Filter Response")
plt.xlabel("Time [s]")
plt.ylabel("Amplitude")
```

```
plt.grid(True)
plt.show()


from scipy.signal import lfilter, freqz

# Define IIR Filter Coefficients
a = [1, -0.3]
b = [0.5, 0.5]
# Example Input Signal
x = np.sin(2 * np.pi * 0.05 * np.arange(100))

# Filter the Signal
y = lfilter(b, a, x)

# Plot the Output
plt.figure(figsize=(10, 6))
plt.plot(x, label="Input Signal")
plt.plot(y, label="Filtered Signal")
plt.legend()
plt.title("IIR Filter Output")
plt.show()

# Example Input Signal
t = np.arange(0, 1, 0.001)  # Time vector of length 1000
x = np.sin(2 * np.pi * 0.05 * t)  # Input signal (noisy)
d = np.sin(2 * np.pi * 5 * t)  # Desired signal

# LMS Filter
def lms_filter(x, d, mu, num_taps):
    n = len(x)
    w = np.zeros(num_taps)
    y = np.zeros(n)
    e = np.zeros(n)

    for i in range(num_taps, n):
        x_segment = x[i-num_taps:i][::-1]
```

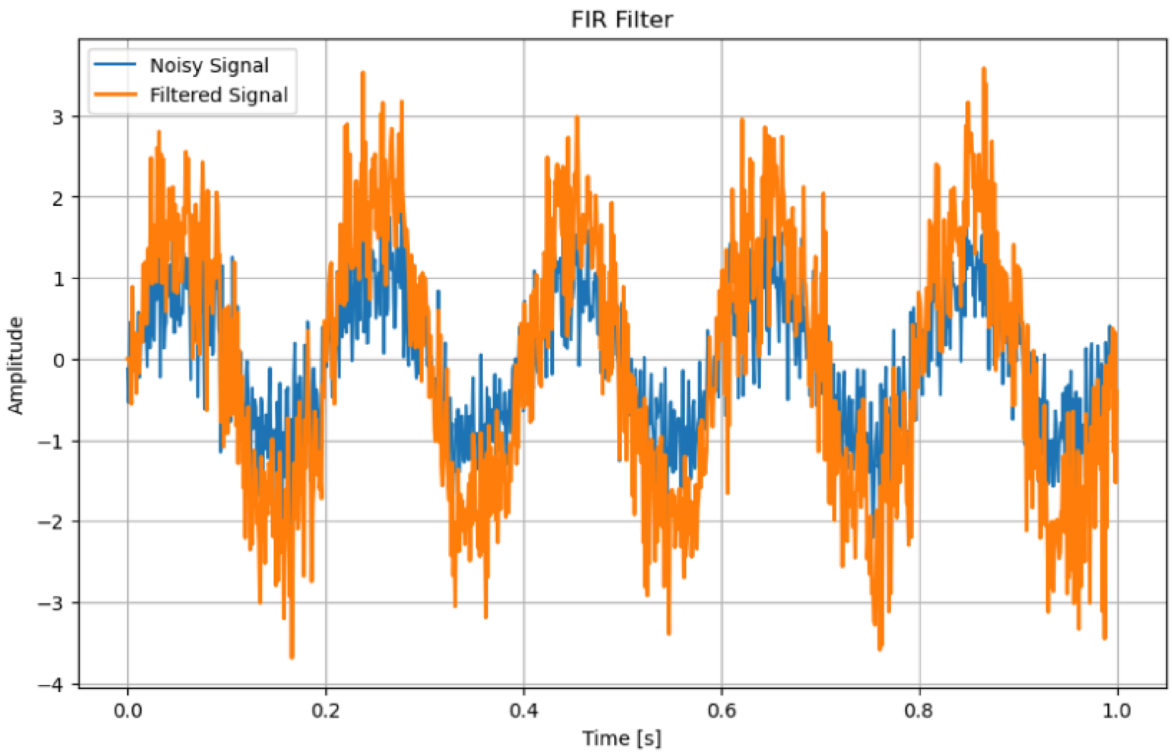
```
        y[i] = np.dot(w, x_segment)
        e[i] = d[i] - y[i]
        w += mu * e[i] * x_segment

    return y, e, w

# LMS filter parameters
mu = 0.01  # Step size
num_taps = 5

# Apply LMS filter
y, e, w = lms_filter(x, d, mu, num_taps)

# Plot the desired signal and filtered output
plt.figure(figsize=(10, 6))
plt.plot(t, d, label="Desired Signal")
plt.plot(t, y, label="Filtered Signal", linewidth=2)
plt.legend()
plt.title("LMS Adaptive Filter")
plt.xlabel("Time [s]")
plt.ylabel("Amplitude")
plt.grid()
plt.show()
```

Link to remote repozytorium (e.g. GitHub)

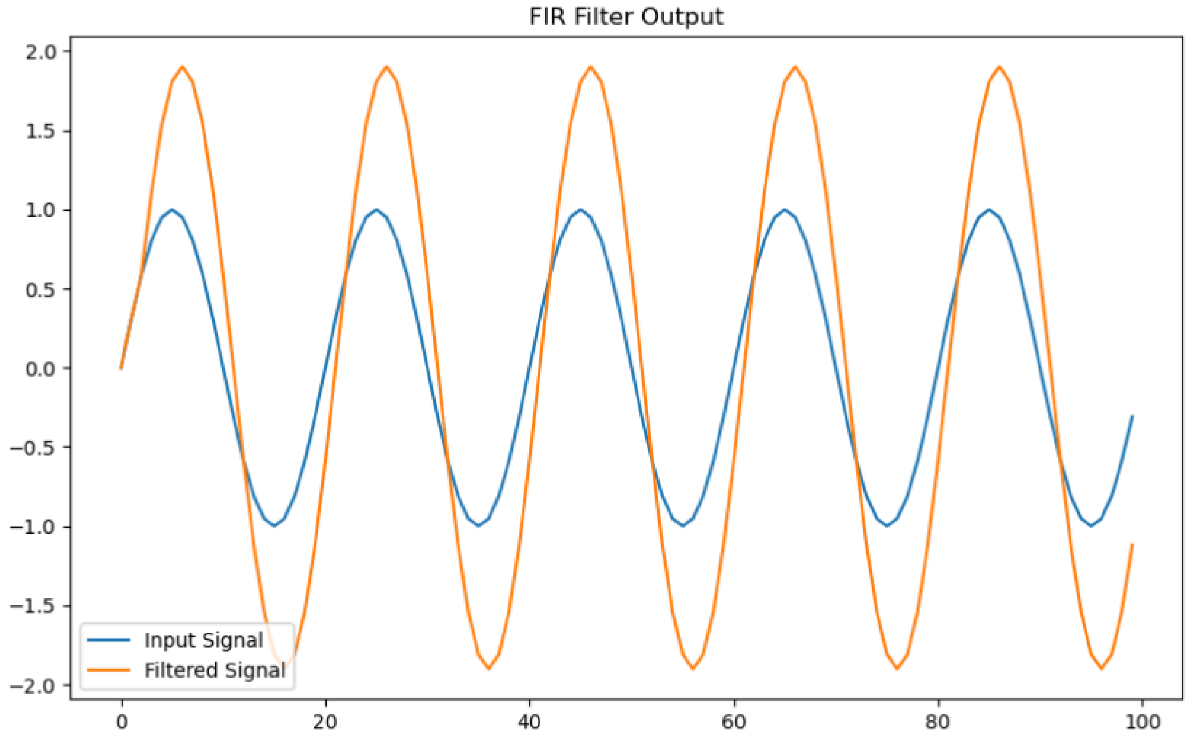
4. Outcomes:

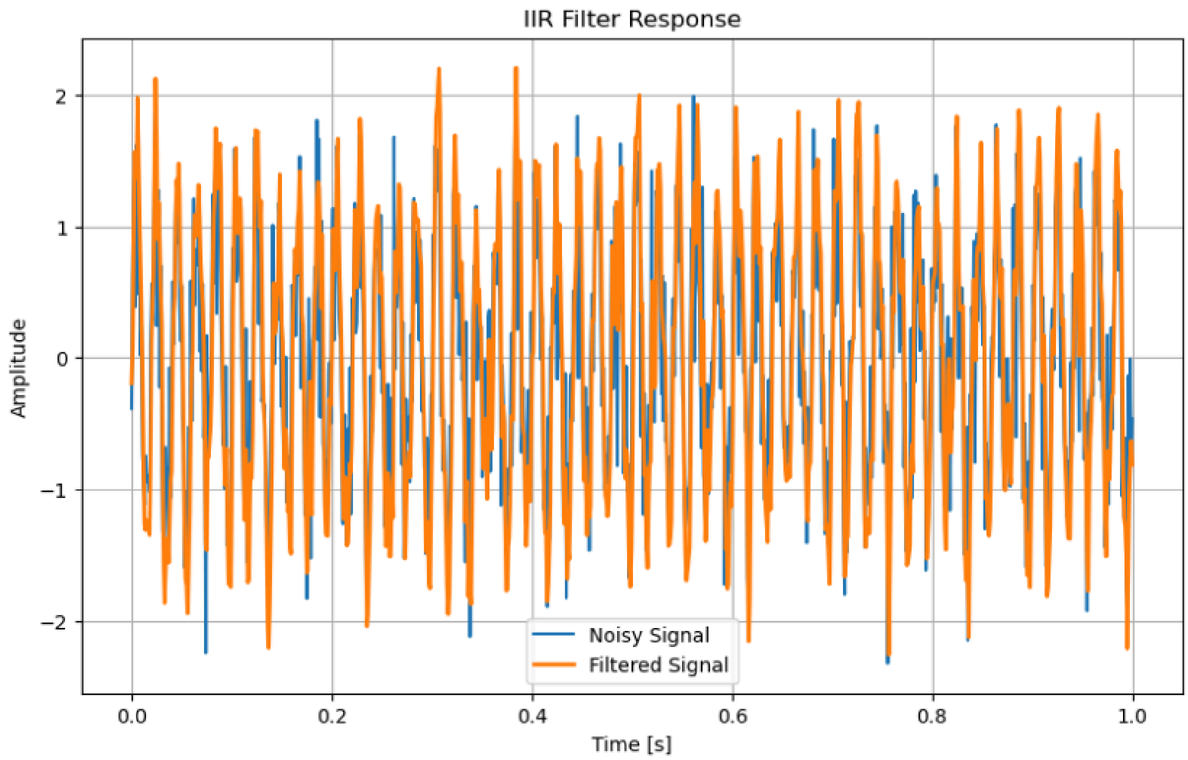


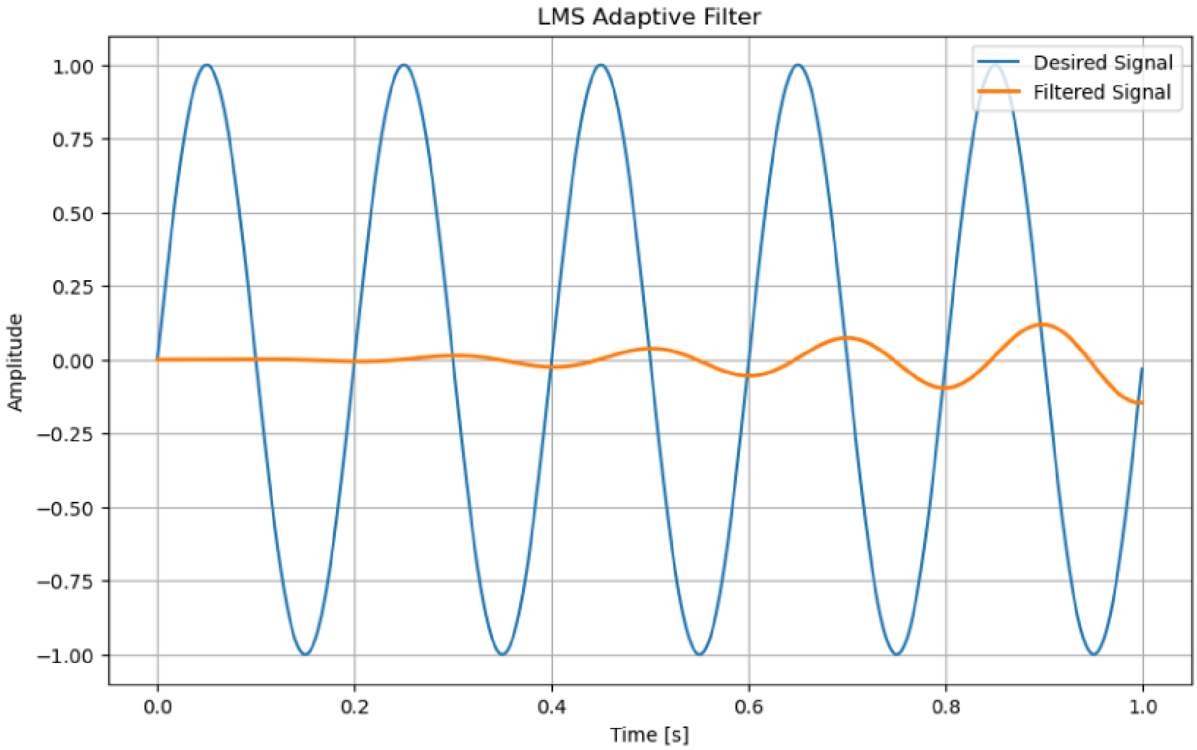
Noisy Signal
Noisy Signal
FIR Filter Output
FIR Filtered
IIR Filter Output
IIR Filtered
LMS Filter Output
LMS Filtered



FIR Filter
Noisy Signal
Filtered Signal
Amplitude
Time [s]


FIR Filter Output
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
0
20
40
60
80
100
Input Signal
Filtered Signal


IIR Filter Response
Amplitude
2
1
0
−1
−2
0.0
0.2
0.4
0.6
0.8
1.0
Time [s]
Noisy Signal
Filtered Signal



https://github.com/HubiPX/NOD/tree/master/DSP/DSP%205%206

5. Conclusions:

FIR Filter:
The FIR filter effectively reduces noise without introducing phase distortion, making it ideal for applications where maintaining the signal's phase integrity is crucial. However, its performance depends heavily on the choice of coefficients and may require a higher filter order to achieve sharp cutoffs.

IIR Filter:
The IIR filter offers better frequency selectivity and requires fewer coefficients to achieve similar results compared to FIR filters. However, it introduces phase distortion and requires careful design to ensure stability, particularly for higher filter orders.

LMS Adaptive Filter:
The LMS adaptive filter is highly effective in dynamic environments where noise characteristics change over time. By continuously adapting to the signal, it can reduce noise efficiently, although its performance depends on the step size (mu) and filter length (M).

This study highlights the importance of understanding the trade-offs between different filter types to optimize performance in digital signal processing tasks.