CHALMERS

Chalmers University of Technology

Applied Signal Processing

Project Part-2 Report- Adaptive Noise Cancellation

Group No: 19

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1 Project description

The project is to design an adaptive noise-cancellation feature for data transmission system over an acoustic channel. This part of the project is divided into two parts:
1. Implementation and testing of LMS algorithm.
2. Investigate the properties of the LMS filter by applying it to an active noise cancellation problem.

2 Empirical section:

2.1 Question-1

[Figure 1, 2, 3, 4, 5, 6]

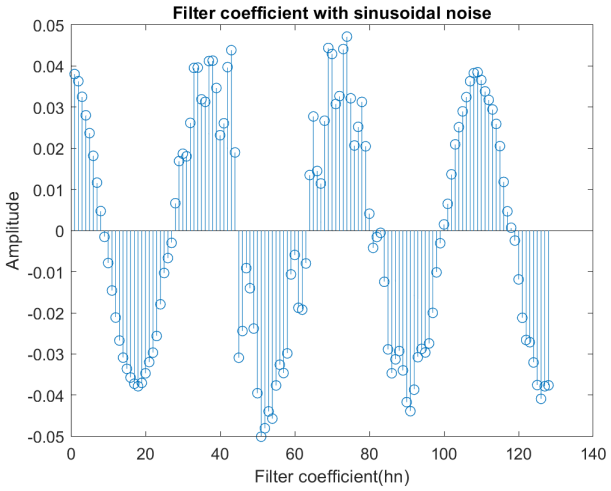


Figure 1: Frequency coefficients of Hsin

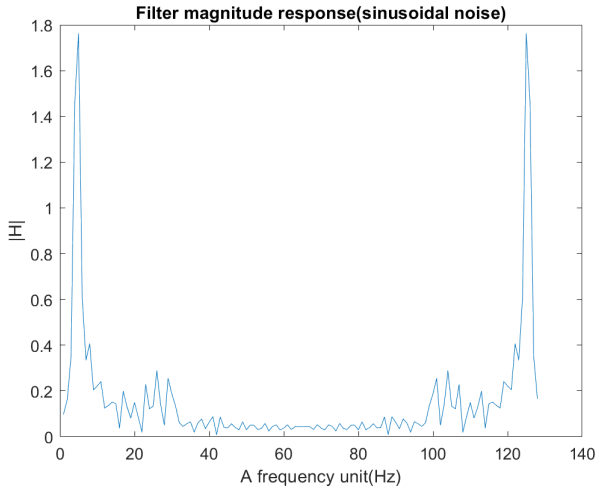


Figure 2: Magnitude response of Hsin

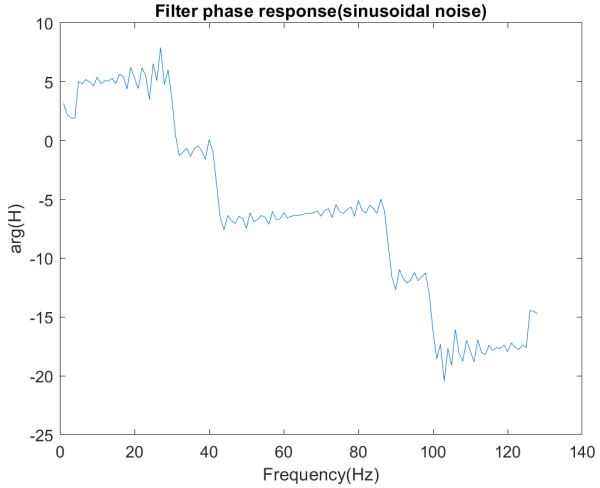


Figure 3: Phase response of Hsin

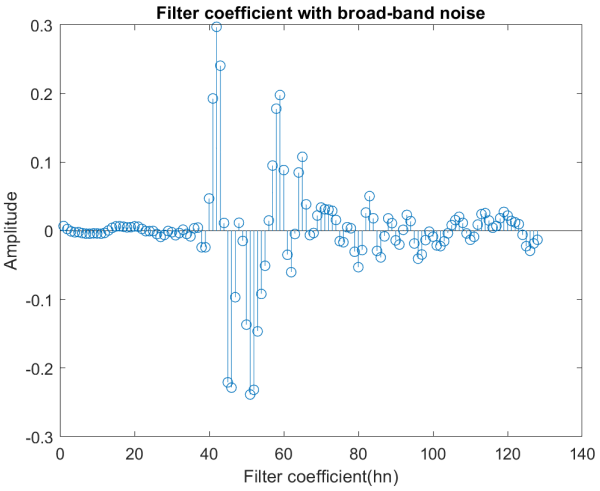


Figure 4: Frequency coefficients of Hbb

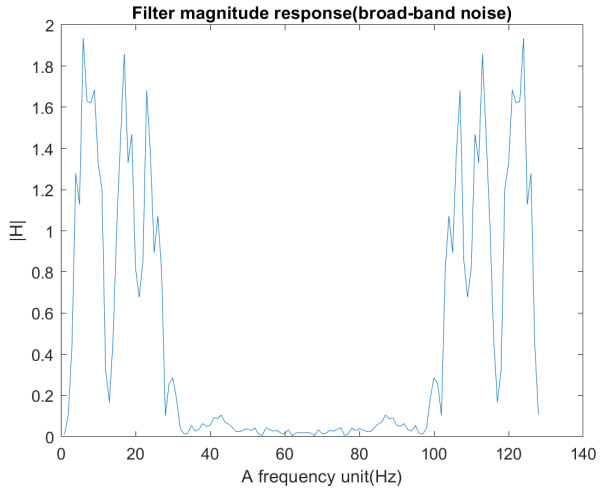


Figure 5: Magnitude response of Hbb

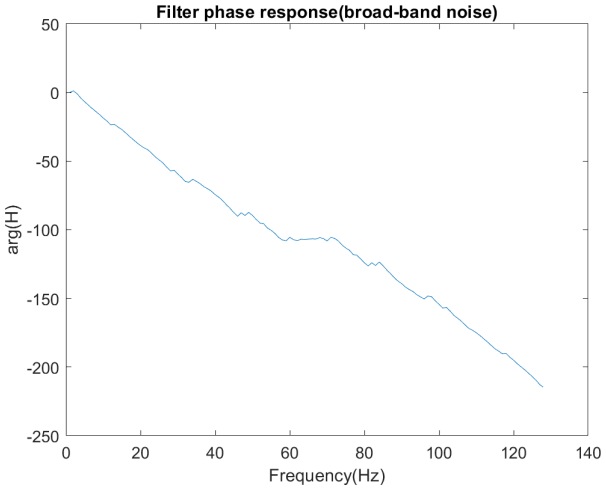


Figure 6: Phase response of Hbb

2.2 Question-2

2.2.1 Question-2a

When we changed the characteristic of the input signal or channel without updating the filter coefficient, the error was increasing but the adaptive noise cancellation was working to an extent. When we introduced a large book between the speaker and the DSP kit, the adaptive noise cancellation becomes inefficient since the channels h and $\hat{h}$ are different.

$$\text{e} = \text{x} - \hat{x}$$

$$\text{e} = \text{s(n)} + \sum_{k=0}^{\infty} h(k).y(n-k) - \sum_{k=0}^{M-1} \hat{h(k)}.y(n-k)$$

where,

$\sum_{k=0}^{\infty} h(k).y(n-k)$ - noise through actual channel

$\sum_{k=0}^{M-1} \hat{h(k)}.y(n-k)$ - noise through estimated channel

2.2.2 Question-2b

When we raise or lower the volume of the output speaker, it increases or decreases the amplitude of the disturbance signal respectively. When we kept at a high volume, the error was large and when we reduced the volume, the error also got reduced. In (2a) when the channel was changed, the efficiency of adaptive noise-cancellation decreased.

2.2.3 Question-2c

When we used cell phones as signal sources, the LMS filter was able to remove the disturbance signal. From this it can be concluded that the LMS filter filters out the disturbance signal independently of the type of signal source. But in (2a), the LMS filter is dependent on the change of channel. i.e, it loses its efficiency when h and $\hat{h}$ difference increases. It can be observed that if we increase the volume on the cellphone, it causes clipping of the signal due to high amplitude.

2.3 Question-3

For different LMS taps 100, 50 and 25, it was observed that the number filter coefficient and its corresponding amplitudes are getting reduced. This means that when we reduce the LMS taps, the performance of the filter decreases. We can observe that up to n=40, the coefficients are nearly zero. Therefore we cannot decrease less than 40. [Figure 7 8 9]

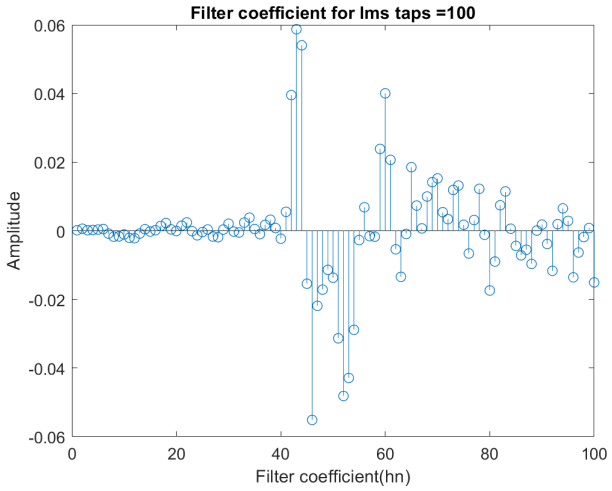


Figure 7: Stem plot of Hbb at n=100

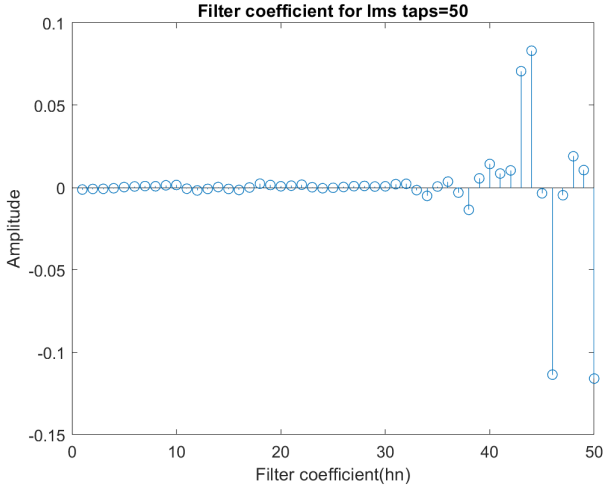


Figure 8: Stem plot of Hbb at n=50

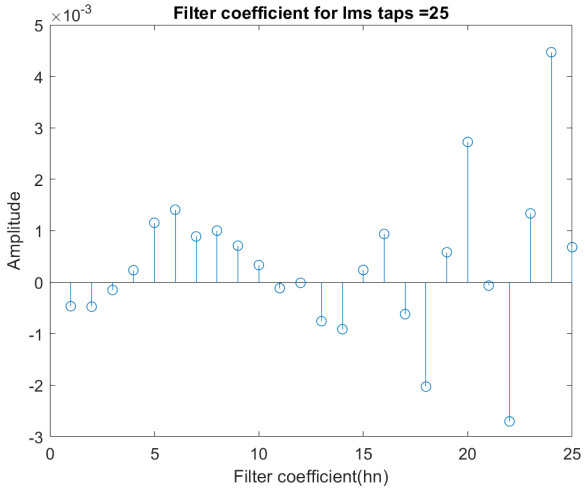


Figure 9: Stem plot of Hbb at n=25

2.4 Question-4

When LMS taps were moved from 100 to 10, the filter coefficients from 10 to 100 get removed and when we change back LMS taps from 10 to 100, the filter coefficients length got increased from 10 to 100 by adding zeros. It was observed that the error increased when we moved back LMS taps from 10 to 100.
Yes, if we reset lms taps or not, the results remain the same. If we start with lms taps at 10 and increase to 100 and returns back to 10, we wont loose any components of filter coefficients. But if we start with lms taps at 100 and move to 10 and returns back to 100, we will loose coefficients from 10 to 100 range. [Figure 10 11 12 13]

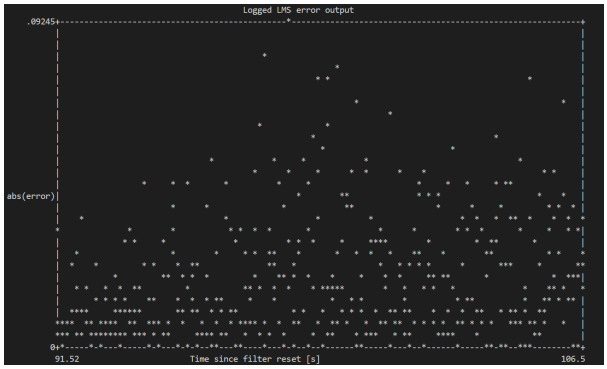


Figure 10: Error plot when LMS taps changed from 100 to 10(for Hsin)

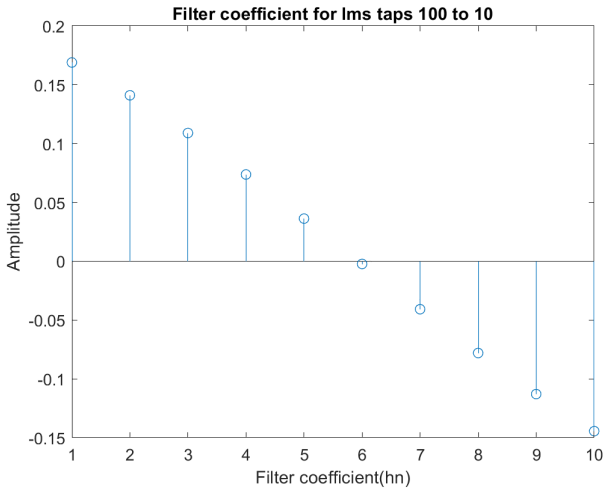


Figure 11: Filter coefficient when lms taps changed from 100 to 10(for Hsin)

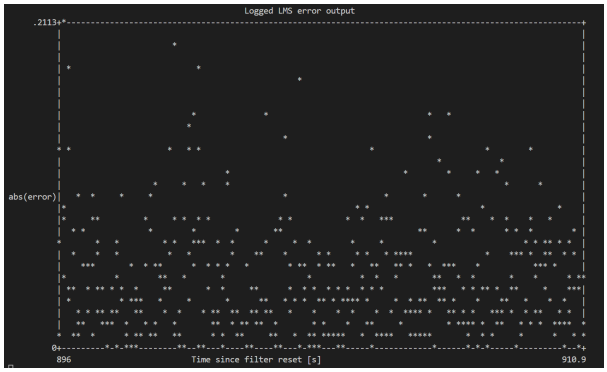


Figure 12: Error plot when lms taps changed back from 10 to 100(for Hsin)

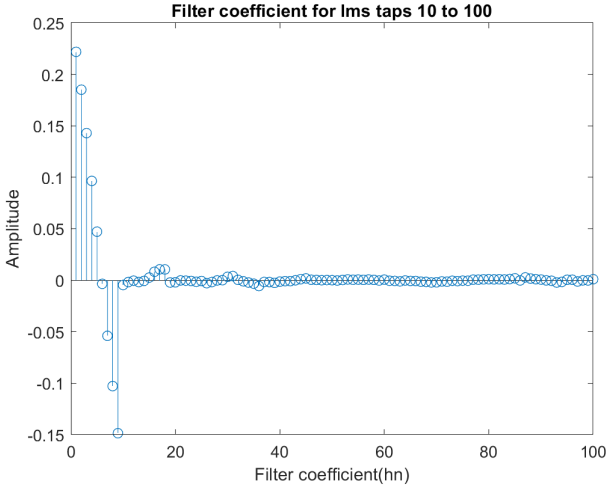


Figure 13: Filter coefficient when lms taps changed back from 10 to 100(for Hsin)

2.5 Question-5

For cases when the filter coefficient were kept fixed at $\mu = 0$ and noise is switched from sinusoidal to broadband noise, the broadband noise effectively attenuates the sinusoidal noise but in cases when we switch from broadband noise to sinusoidal noise keeping $\mu = 0$, sinusoidal noise is not able to effectively attenuate the broadband signal. Therefore, broadband noise is more effective in training compared to sinusoidal noise. [Figure **??** 14 **??** 15]

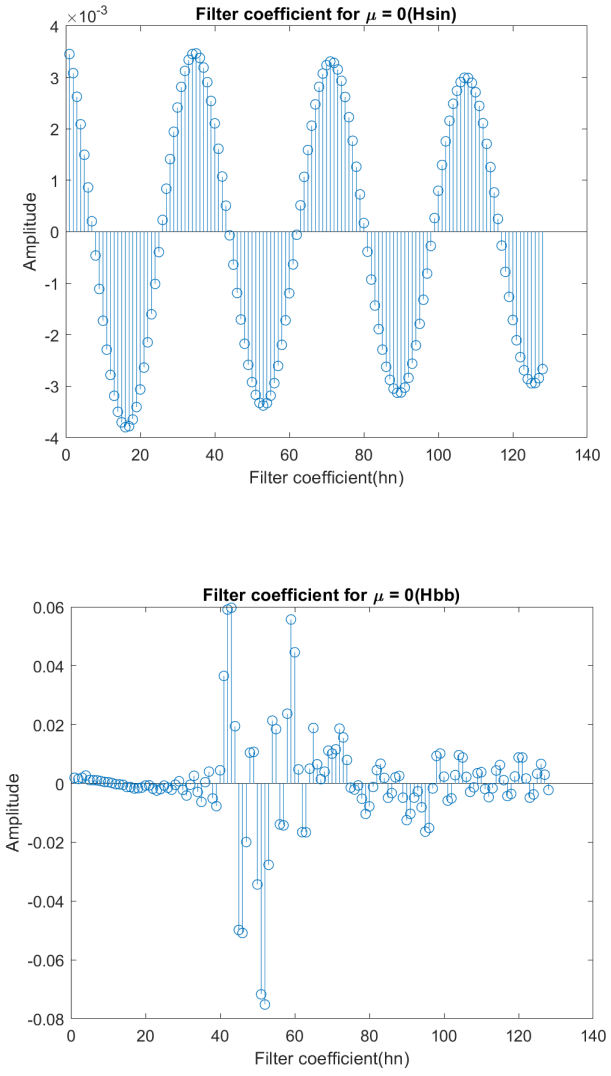
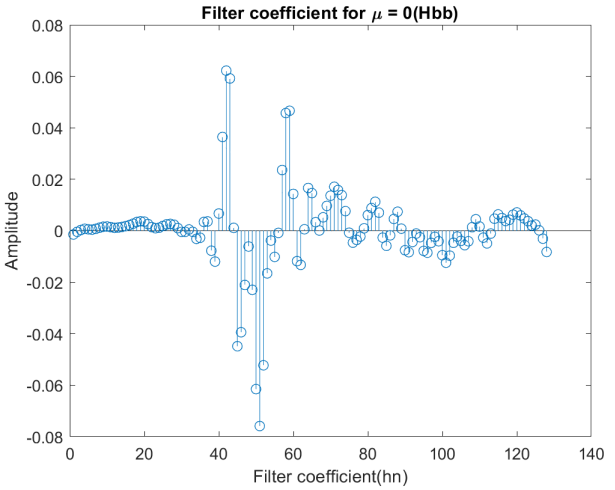


Figure 14: Filter coefficient when $\mu = 0$ (Hsin to Hbb)



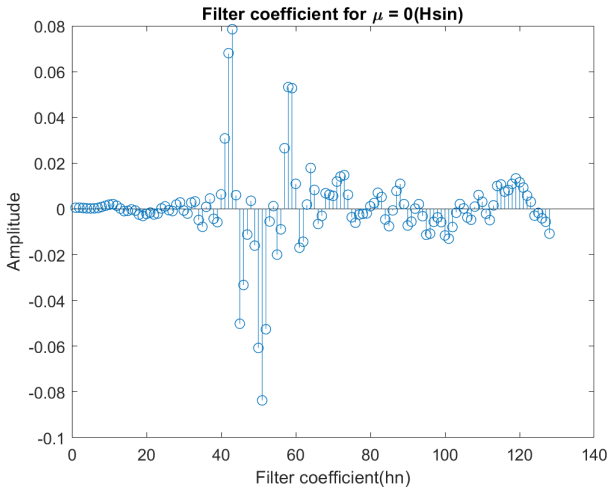


Figure 15: Filter coefficient when $\mu = 0$ (Hbb to Hsin)

2.6 Question-6

For the case when we used the cellphone as our signal source instead of speakers with broadband disturbance and kept $\mu = 0.01$, the filter coefficient saturates due to the clipping of the high amplitude signal produced by the cellphone. Since convolution in LMS algorithm are linear operations, it wont give accurate results for non-linear functions such as amplitude clipping. [Figure 16]

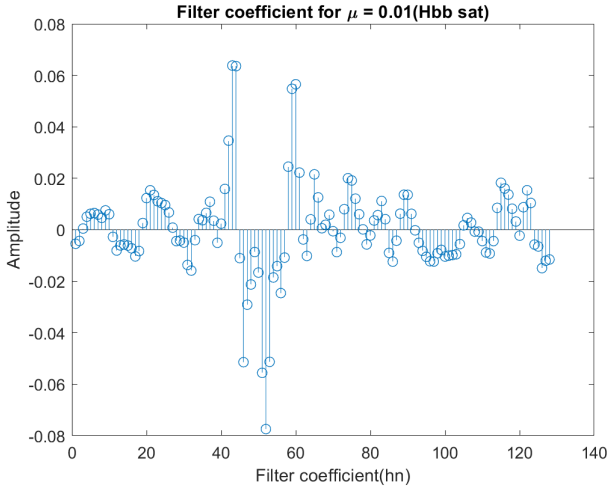


Figure 16: Filter coefficient when $\mu = 0$ and cellphone as signal source (Hsat)

3 Analytical section:

3.1 Question-1

3.1.1 Question-1a

Step size is an important parameter that determines adaptability. When step size increases the filter quickly converges towards the global minimum and vice-versa when step size decreases, as mentioned in the below table. [Table 1]

μ	Adaptability	σ^2_{LMS}
small	slow	small
large	fast	large

Table 1: The relationship between μ and adaptability

3.1.2 Question-1b

The maximum possible value at which filter converges is when $0 < \mu < \frac{1}{\sigma_y^2}$ (where σ_y^2 is the variance of white noise signal) and above which the filter starts diverging away such that it misses the global minimum when $\mu > \frac{1}{\sigma_y^2}$

3.1.3 Question-1c

The step size still has an effect on the filter after it converges because when step size is increased, the level of residual error increases and vice versa, so the value of step size should be dynamic so that the filter keeps adapting to the global minimum by reducing the residual error.

3.2 Question-2

In both cases, h_{opt} is the same but the noise sources are different (sinusoidal and broadband). To derive the same h_{opt}, the H should be different. For channels with broadband disturbance, when the channel is reset and the filter length is changed, it does not change the channel estimation behaviour. Since broadband disturbance consists of multiple frequencies, it gives a unique solution since the channel has an infinite impulse response. Whereas for sinusoidal disturbance, when the channel is reset and the length of the filter is increased, it does not give a unique solution since the channel has a finite impulse response.

3.3 Question-3

In this case, we kept filter coefficients fixed at $\mu = 0.001$, when we switch from sinusoidal noise to broadband noise, the broadband noise attenuates the sinusoidal noise but when we switch back from broadband to sinusoidal noise, sinusoidal was not able to effectively attenuate the broadband noise. This makes broadband disturbance comparatively more efficient. For broadband noise, the signal power is located in range [0, 2000] Hz whereas for sinusoidal noise, the signal power lies at fo = 440 Hz which is already covered by the broadband disturbance.

$$\hat{h_{opt}} = arg\ min_h\ E[|Y\ (H - \hat{H})^2|]$$

[Figure 17 and 18]

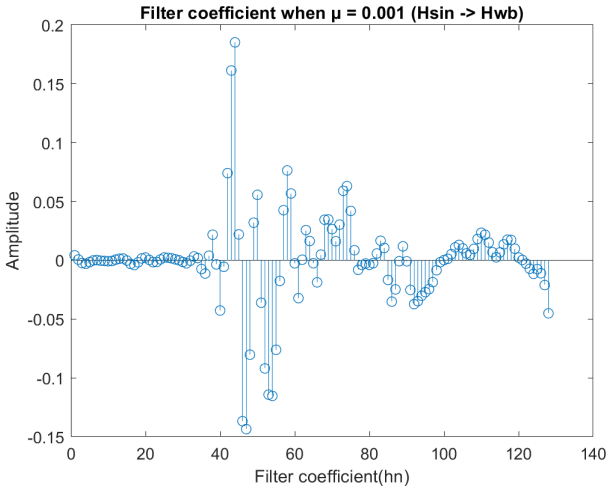


Figure 17: Filter coefficient when $\mu = 0.001$ (Hsin to Hwb)

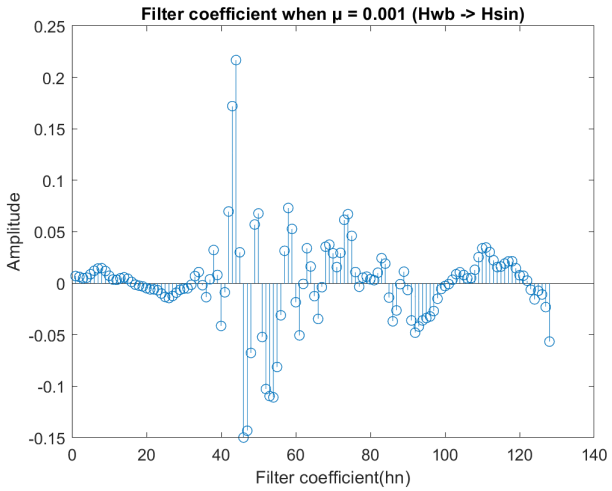


Figure 18: Filter coefficient when $\mu = 0.001$ (Hwb to Hsin)

3.4 Question-4

LMS filter at fo = 440 Hz, the magnitude and phase of Hsin(fo) and Hbb(fo) are similar. Since broadband disturbance has a large frequency range, for other frequencies it will have corresponding magnitude and phase values whereas for sinusoidal disturbance, the magnitude and phase are nearly zero. [Figure 19 20, 21 22]

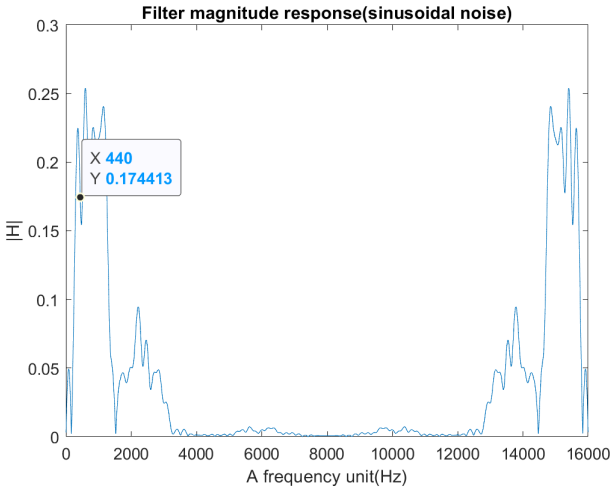


Figure 19: Magnitude response of Hsin(fo=440Hz)

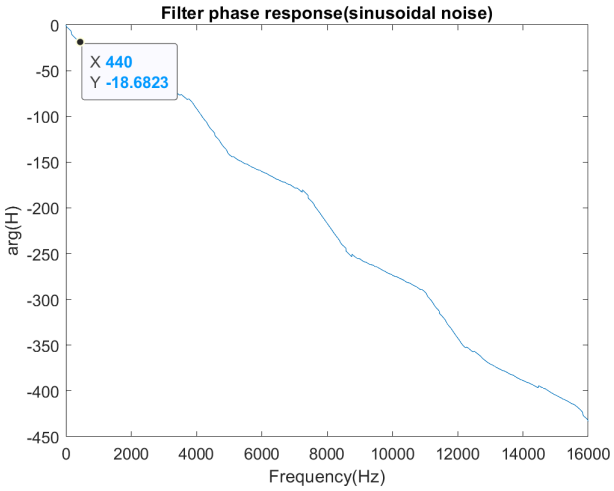


Figure 20: Phase response of Hsin(fo=440Hz)

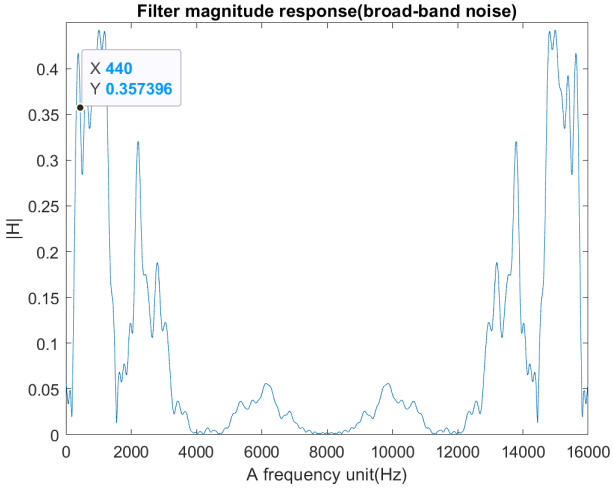


Figure 21: Magnitude response of Hwb(fo=440Hz)

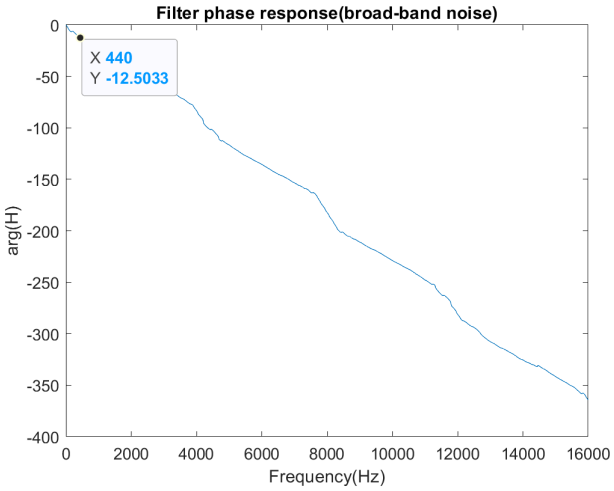


Figure 22: Phase response of Hwb(fo=440Hz)

3.5 Question-5

In order to remove the disturbance, the filter should have the same magnitude and phase component as the disturbance.

$$H(k) = \sum_{n=0}^{N-1} h(n) * e^{-j2*\pi*k*(n/N)}$$

$$\hat{h(n)} = [\hat{h(0)}\ \hat{h(1)}\ .....\ \hat{h(N-1)}]$$

Sinusoidal disturbance has the same component at frequencies +fo and -fo which makes it symmetric. At n=0, $\hat{h(0)}$ is real valued and at n=1, $\hat{h(1)}$ is a complex value. Therefore, the minimum theoretical length required to filter the sinusoidal disturbance is 2.

3.6 Question-6

For sinusoidal disturbance, the filter updating using LMS algorithm is given by,

$$\hat{h(n)} = \hat{h(n-1)} + (2^* \mu * y(n) * e(n))$$

Here, $\hat{h(n)}$ will be getting updated by its past value i.e, $\hat{h(n-1)}$ each time. Since (2* μ * e(n)) is a scalar, $\hat{h(n-1)}$ is a decaying exponential and y(n) is sinusoidal, thus the resultant filter $\hat{h(n)}$ will be also sinusoidal.

4 LMS algorithm using C-code

[Figure 23]

```
    int n;
    int i;
    for(n=0;n<block_size;n++){
        float * y_book = &lms_state[n];
        arm_dot_prod_f32(lms_coeffs, y_book, lms_taps, xhat+n);
        e[n] = x[n] - xhat[n];
        for(i=0;i<lms_taps;i++){
            lms_coeffs[i] += 2 * lms_mu * y_book[i] * e[n];
        }
    }
#endif

    /* Update lms state, ensure the lms_taps-1 first values correspond to the
    * lms_taps-1 last values of y, i.e.
    * [ y[end - lms_taps - 1], ..., y[end], ... <don't care values, will be filled with new y on next call> ...]
    * As y is defined as a pointer to const data we need to typecast
    */
    arm_copy_f32( &((float *) y)[block_size - (lms_taps-1)], lms_state, lms_taps-1);
};
```

Figure 23: LMS algorithm using C-code