W2008 EECS 452 Project

Active Noise Cancellation Headsets

Kuang-Hung liu, Liang-Chieh Chen, Timothy Ma, Gowtham Bellala, Kifung Chu

4 / 15 / 2008

Outline

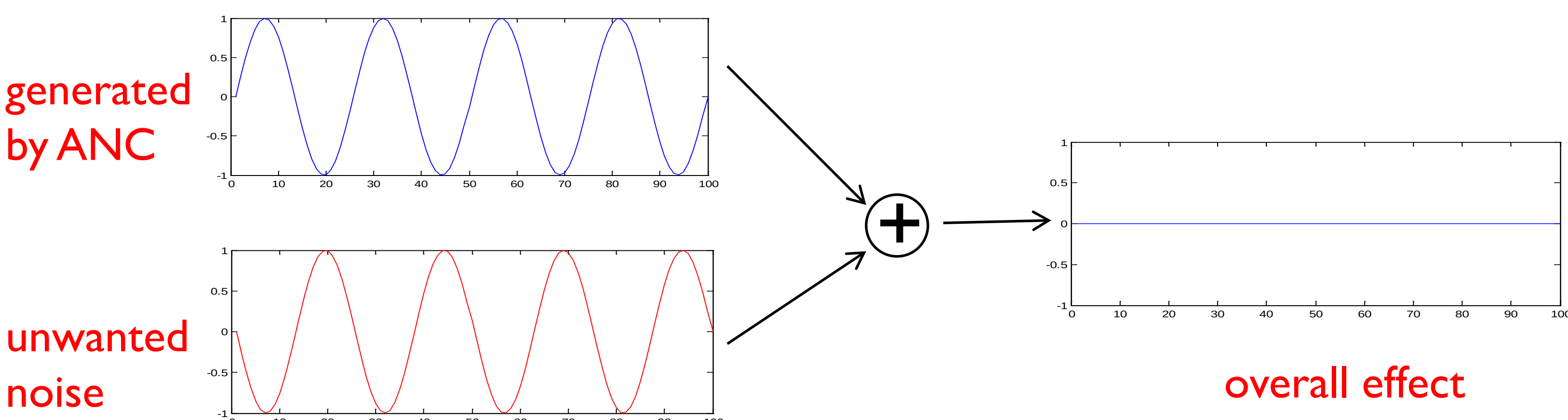
- Motivation & Introduction
- Challenges
- Approach 1
- Approach 2
- Demonstration
- Conclusion & future work

Motivation

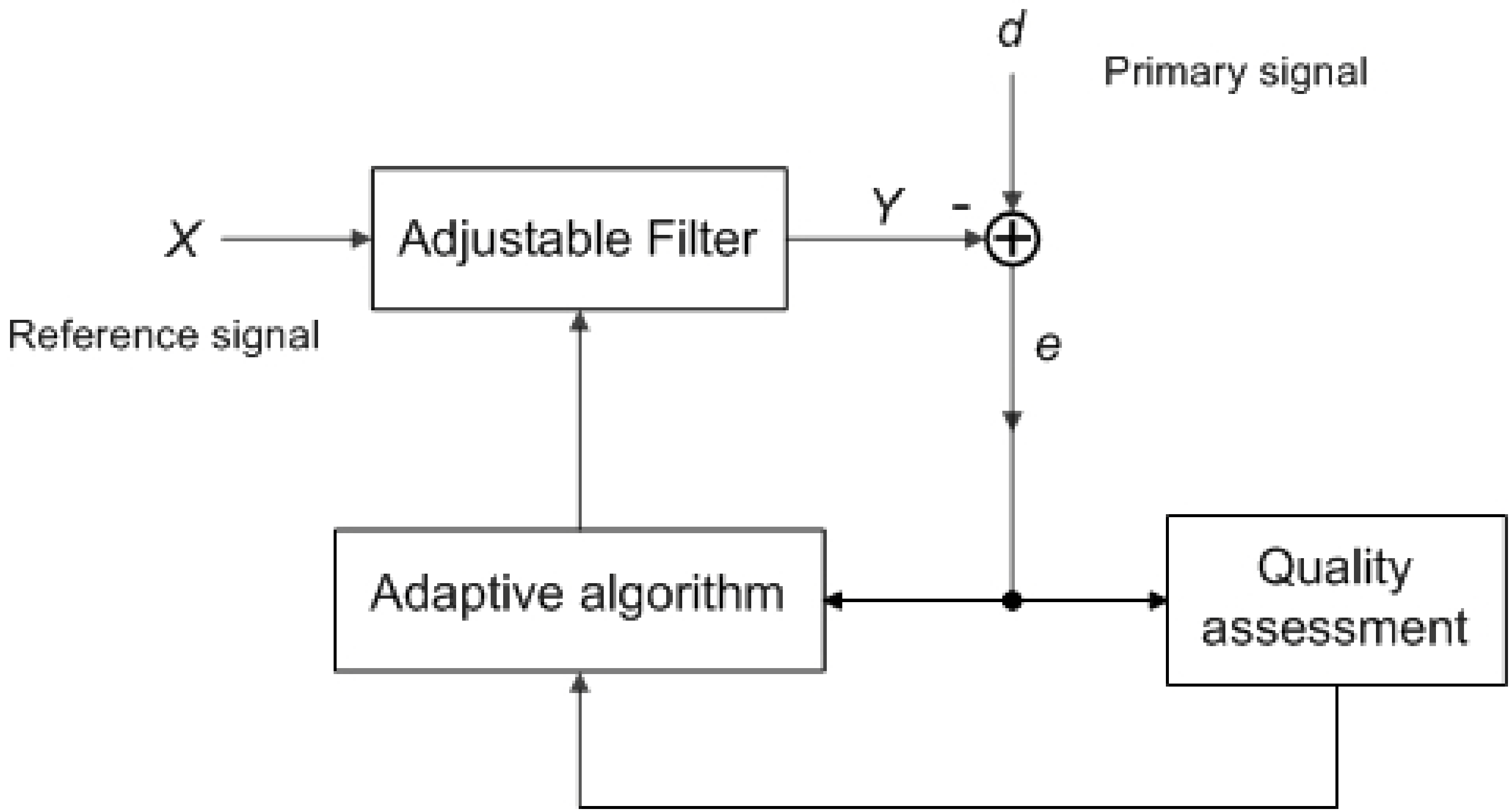
- Noise levels in human settings have come under scrutiny for reasons including health concerns and improvement of the quality of life.
- For low-frequency noises, passive methods are either ineffective or tend to be very expensive or bulky.
- Active Noise Cancellation(ANC) systems have become an effective technique for designing ANC headphones.

Introduction

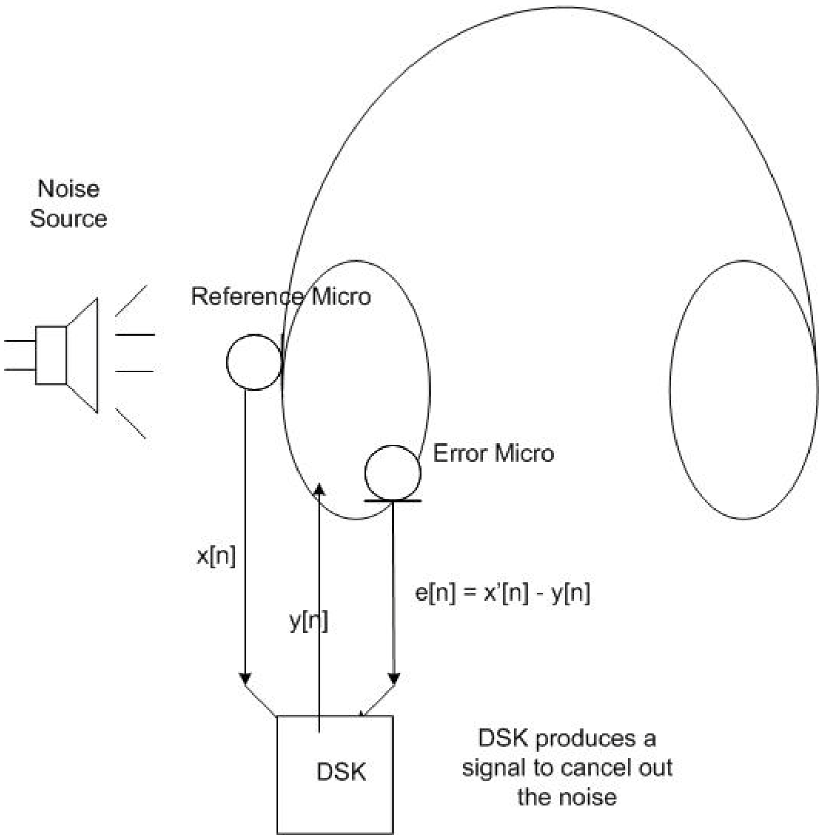
- Application of adaptive signal processing.
- Use destructive interference to cancel out unwanted noise.
- ANC headsets works best for cancelling lower frequency sounds that are continuous and periodic.
- Higher frequency and impulse are hard to control.

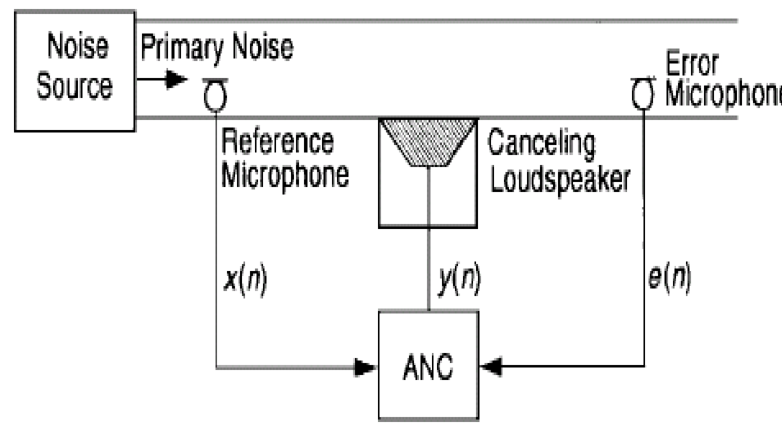


Adaptive Filter Framework



Equivalent Model





Challenge

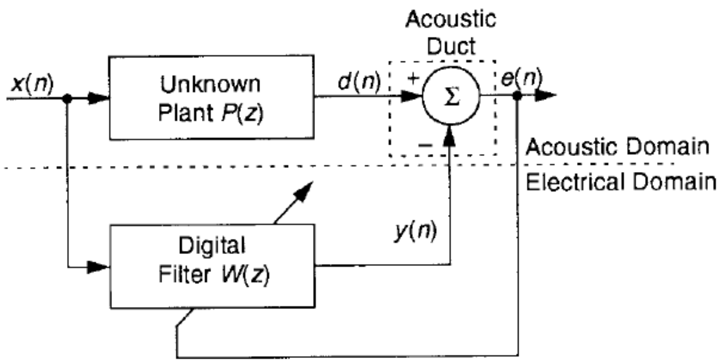
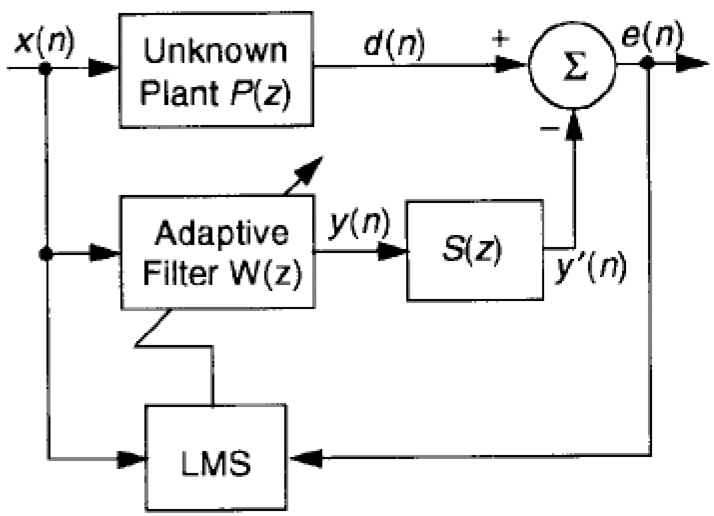
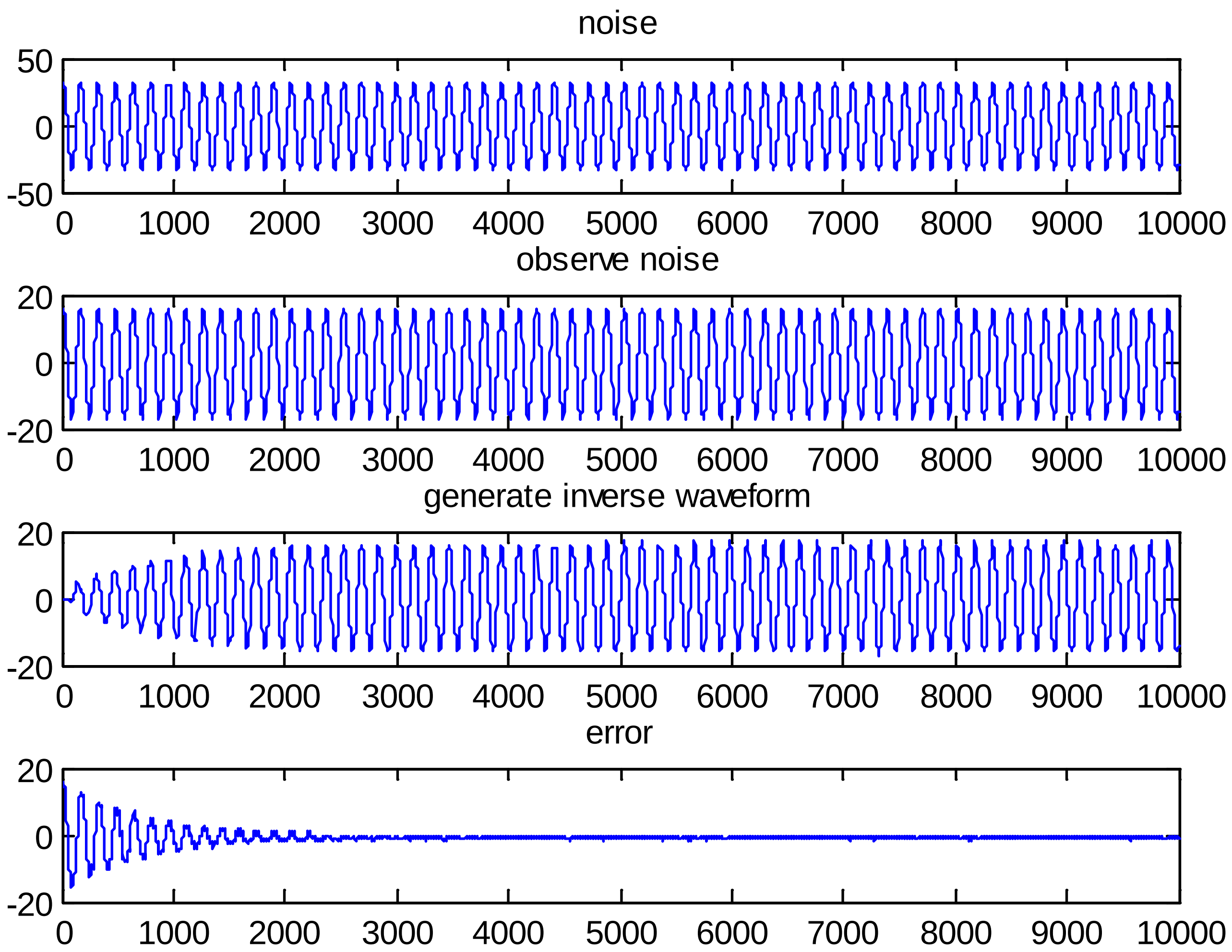


Fig. 2. System identification viewpoint of ANC.

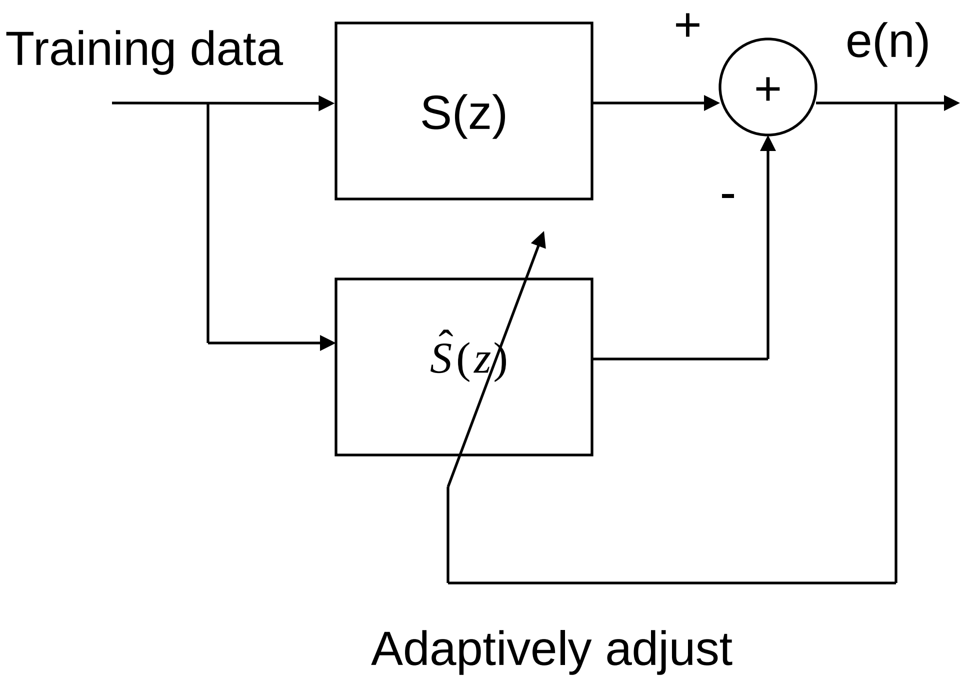


- Difficulty:
  (1) The acoustic superposition in the space (from the canceling loudspeaker to the error microphone) is sensitive to phase mismatch.
  (2) ANC system is sensitive to uncorrelated noise.
- Solution:
  (1) Compensate for the secondary-path transfer function S(z), which includes the D/A converter, reconstruction filter, anti-aliasing filter, A/D converter.
  (2) Use FPGA to reduce system delay.
  (3) Add protection to the algorithm.

Matlab Example



Approach 1 : off-line estimation of S(z)



- Off-line estimation:

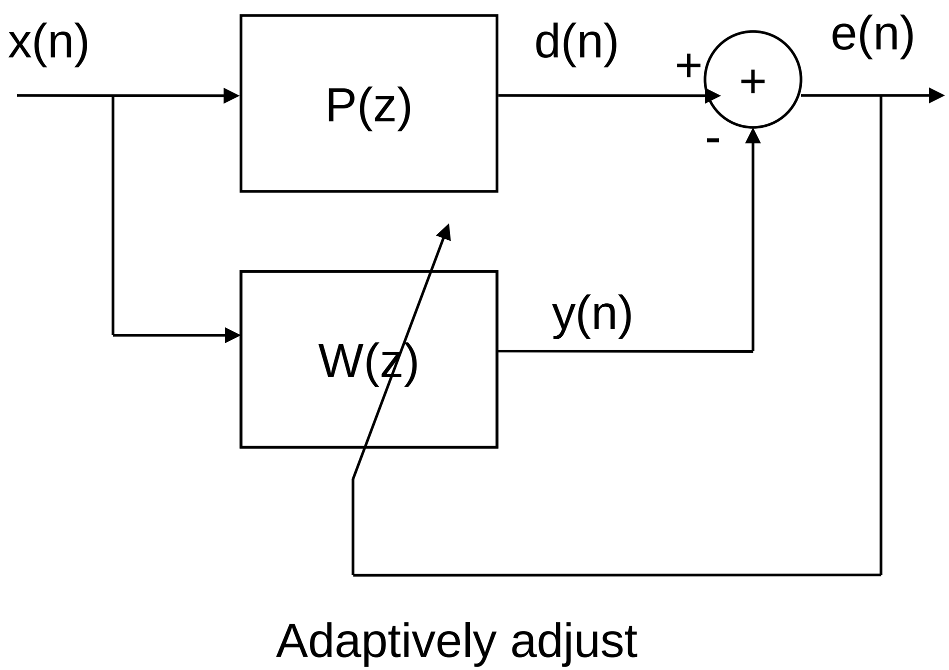
  Send a sequence of training data to estimate S(z) before Noise Cancellation.

- Challenge:

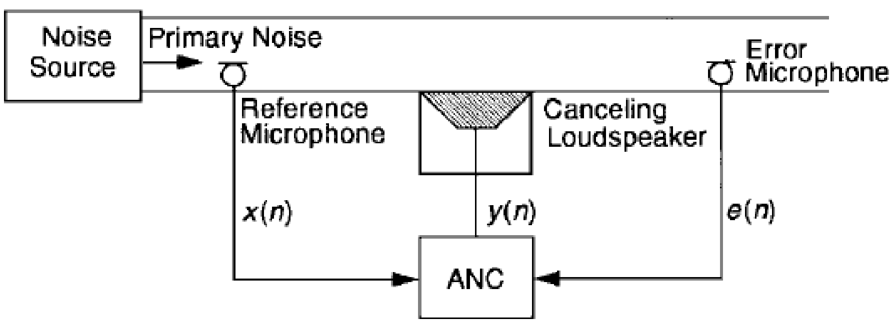
  It's better to train the filter with white noise. But because of the limited number of coefficients of the filter, we just train the filter with 200Hz sine waveform.

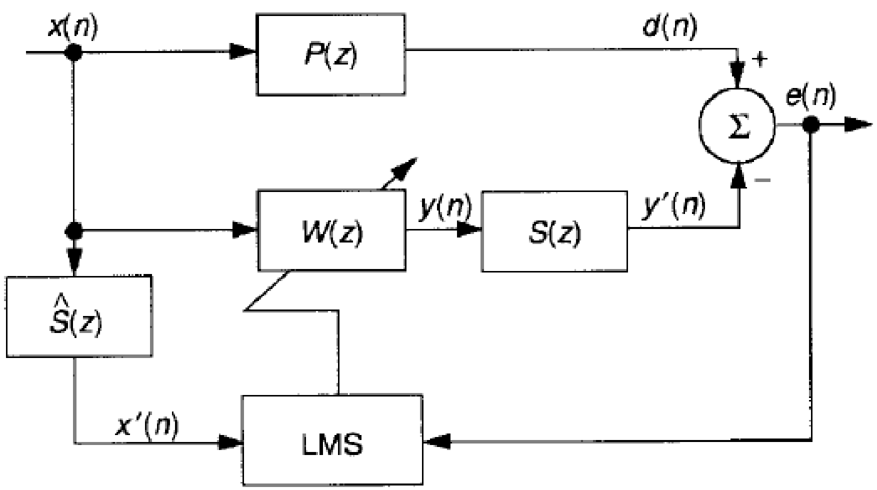
Adaptive Algorithms

- FxLMS
- FULMS
- Feedback
- Hybrid



FxLMS algorithm





Advantages:

- *Simple and neat*
- *Incorporates secondary path effect*
- *Tolerant to errors made in estimation of S(z)*
  ➔ *offline estimation sufficient*

Disadvantages:

- *Higher order filters* ➔ *slow*
- *Acoustic feedback*
- *Convergence rate depends on accuracy of the estimation of S(z)*

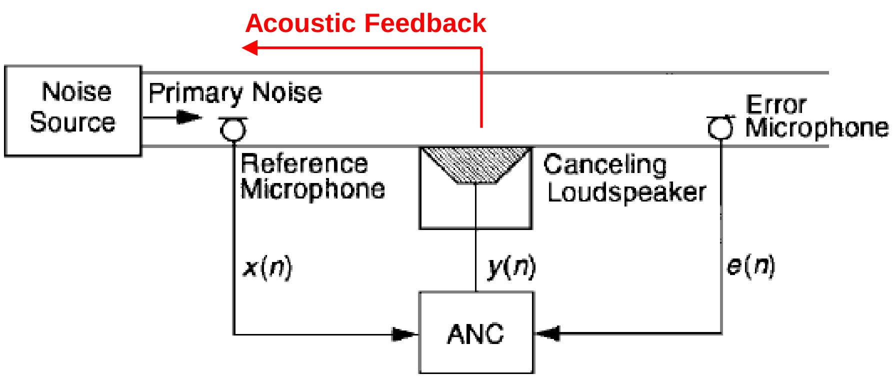
Equations:

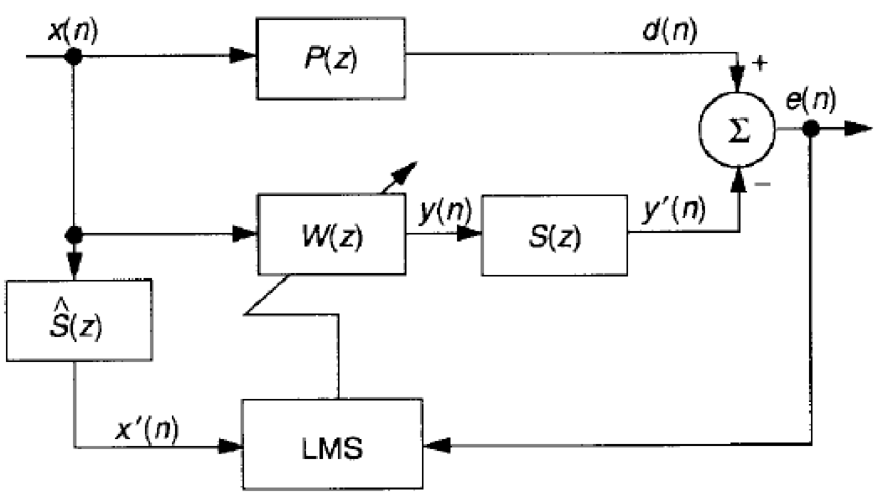
$$y(n) = w^T(n)x(n)$$

$$Update\ weights: w(n+1) = w(n) + \mu\, x'(n)e(n)$$

$$where \quad x'(n) = \hat{s}(n) \otimes x(n)$$

FxLMS algorithm





Advantages:

- *Simple and neat*
- *Incorporates secondary path effect*
- *Tolerant to errors made in estimation of S(z)* ➔ *offline estimation sufficient*

Disadvantages:

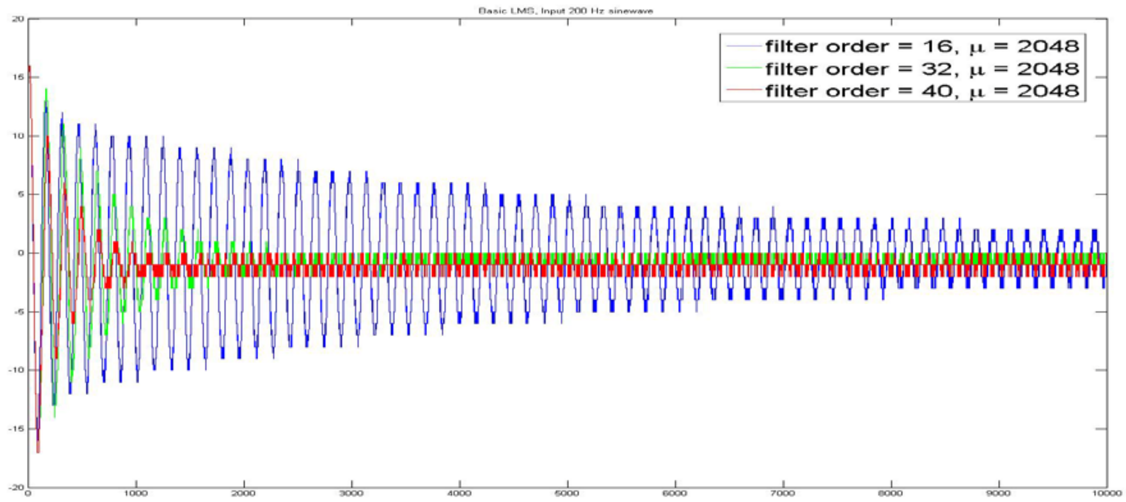
- *Higher order filters* ➔ *slow*
- *Acoustic feedback*
- *Convergence rate depends on accuracy of the estimation of S(z)*

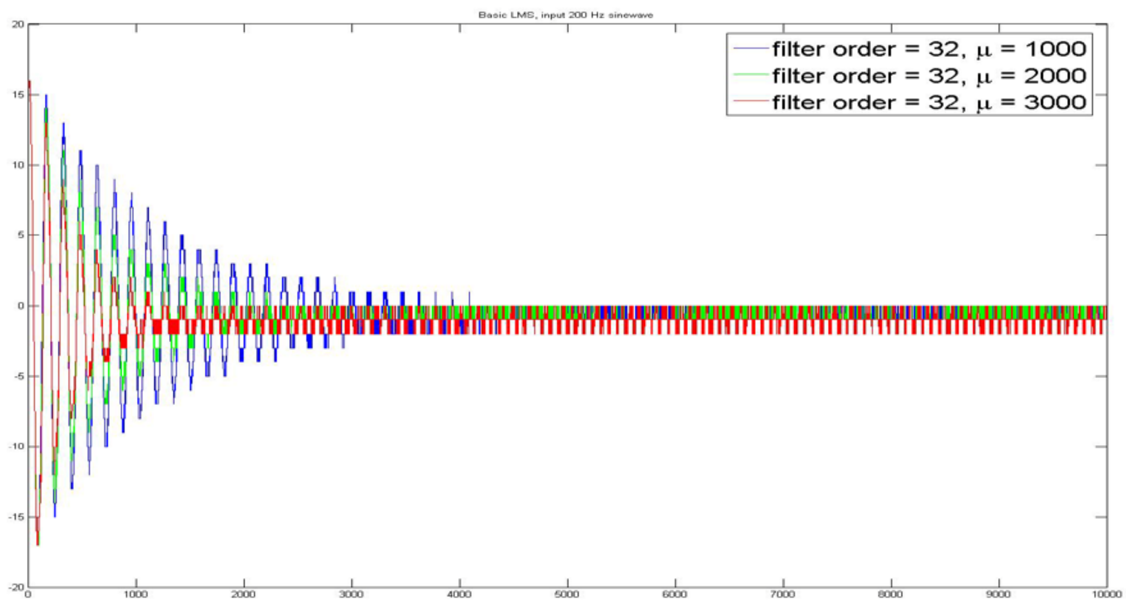
Equations:

$$y(n) = w^T(n)x(n)$$

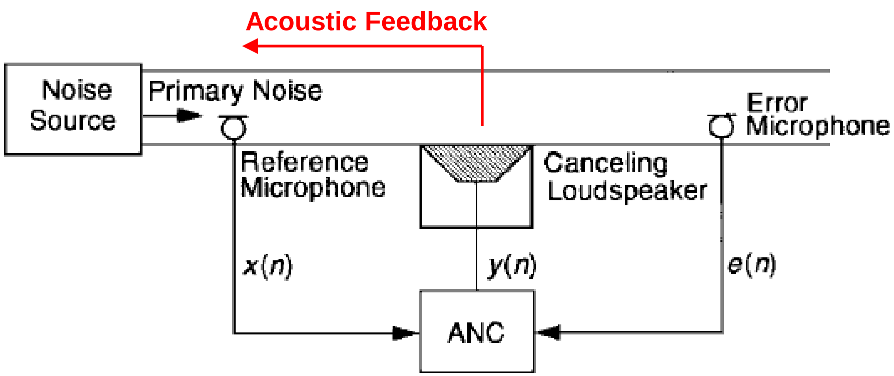
$$Update\ weights: w(n+1) = w(n) + \mu\, x'(n)e(n)$$

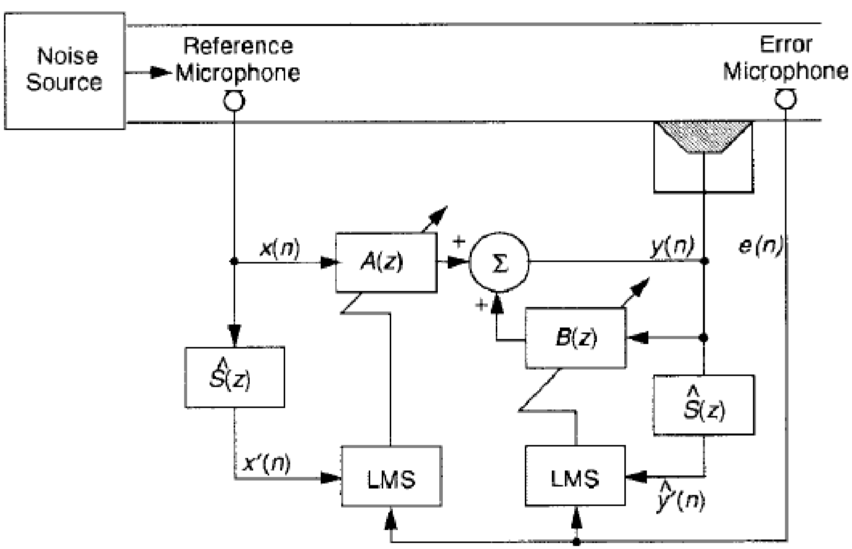
$$where \quad x'(n) = \hat{s}(n) \otimes x(n)$$


Basic LMS, Input 200 Hz sinewave
filter order = 16, μ = 2048
filter order = 32, μ = 2048
filter order = 40, μ = 2048
20
15
10
5
0
-5
-10
-15
-20
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000


Basic LMS, input 200 Hz sinewave
filter order = 32, μ = 1000
filter order = 32, μ = 2000
filter order = 32, μ = 3000
20
15
10
5
0
-5
-10
-15
-20
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000

FuLMS Algorithm





Advantages:

- *Feedback Neutralization*
- *Feedback path designed using IIR filter*
- *IIR filter – lower order sufficient*

Disadvantages:

- *IIR filter – can become unstable*
- *Global convergence not guaranteed*

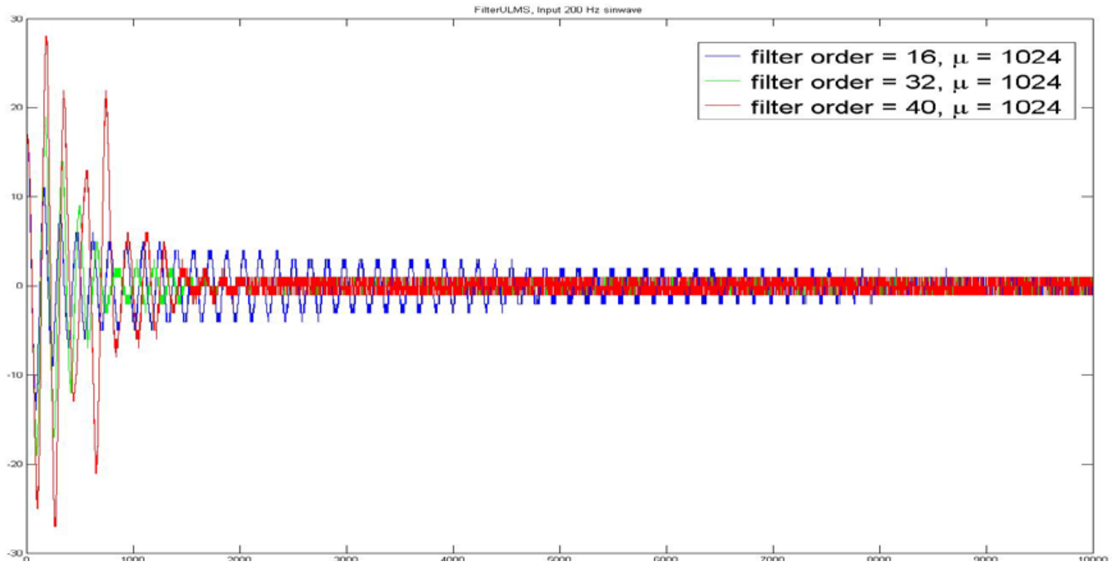
Equations:

$$y(n) = a^T(n)x(n) + b^T(n)y(n-1)$$

$$\text{Update weights}: a(n+1) = a(n) + \mu\, x'(n)e(n)$$

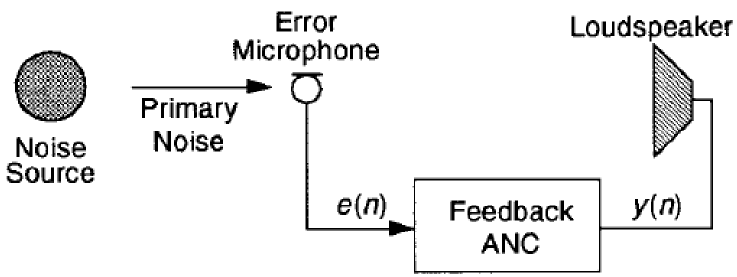
$$b(n+1) = b(n) + \mu\, \hat{y}'(n-1)e(n)$$

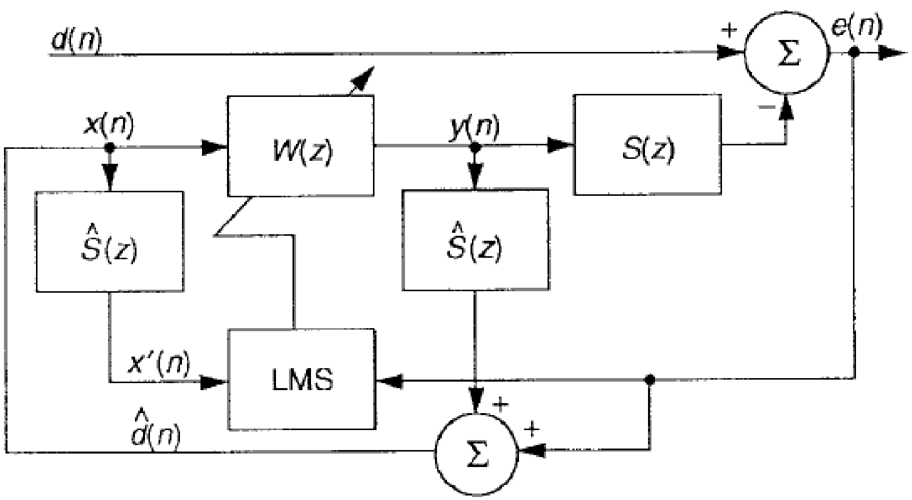
$$\text{where } \hat{y}'(n-1) = \hat{s}(n) \otimes y(n-1)$$


FilterULMS, Input 200 Hz sinwave
filter order = 16, μ = 1024
filter order = 32, μ = 1024
filter order = 40, μ = 1024
30
20
10
0
-10
-20
-30
0


Filter U LMS, input 200Hz sinewave
filter order = 32, μ = 1000
filter order = 32, μ = 2000
filter order = 32, μ = 3000
30
20
10
0
-10
-20
-30
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000

Feedback ANC





Advantages:
- *Requires only one microphone*
- *Additional filter not required for acoustic feedback neutralization*
- *Computationally less complex*

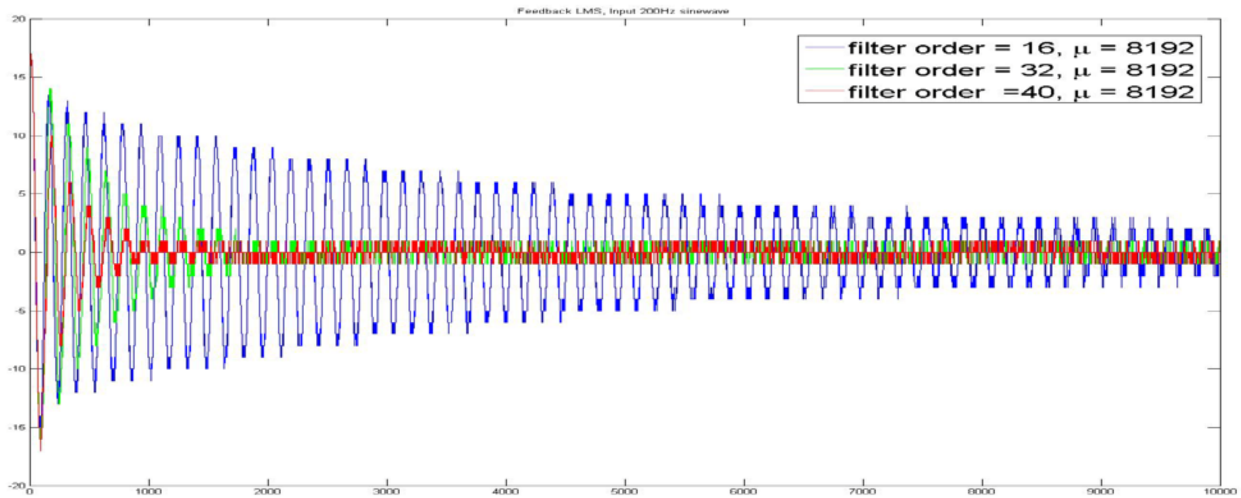
Disadvantages:
- *Same issues with IIR filter*

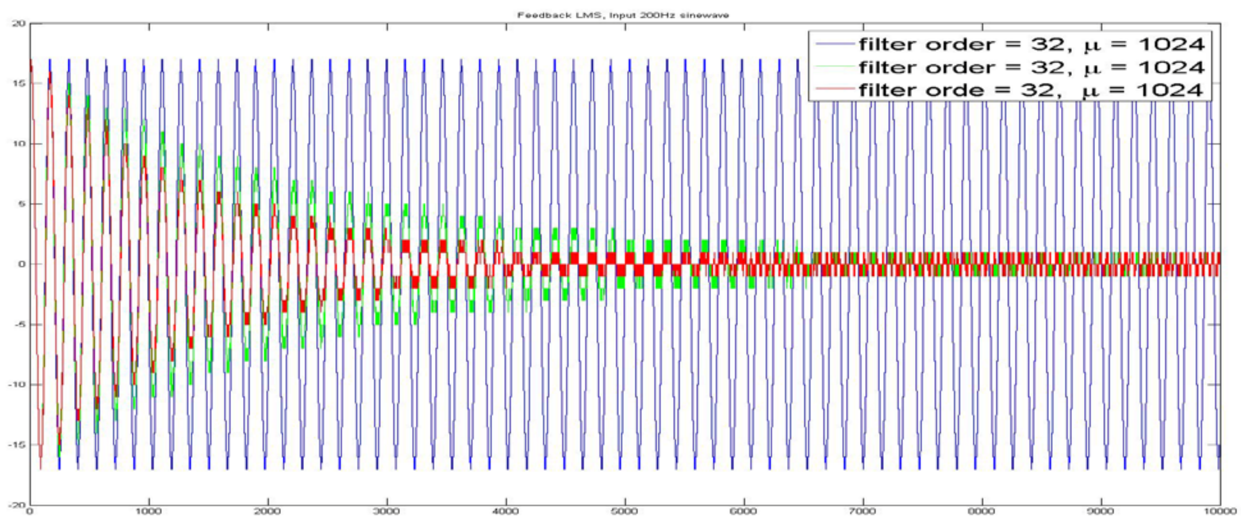
Equations:

$$y(n) = w^T(n)x(n)$$

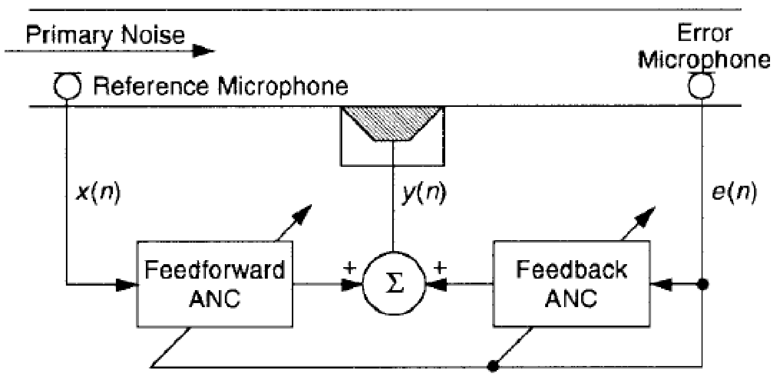
$$x(n) = e(n) + \sum_{m=0}^{M-1} \hat{s}_m y(n-m)$$

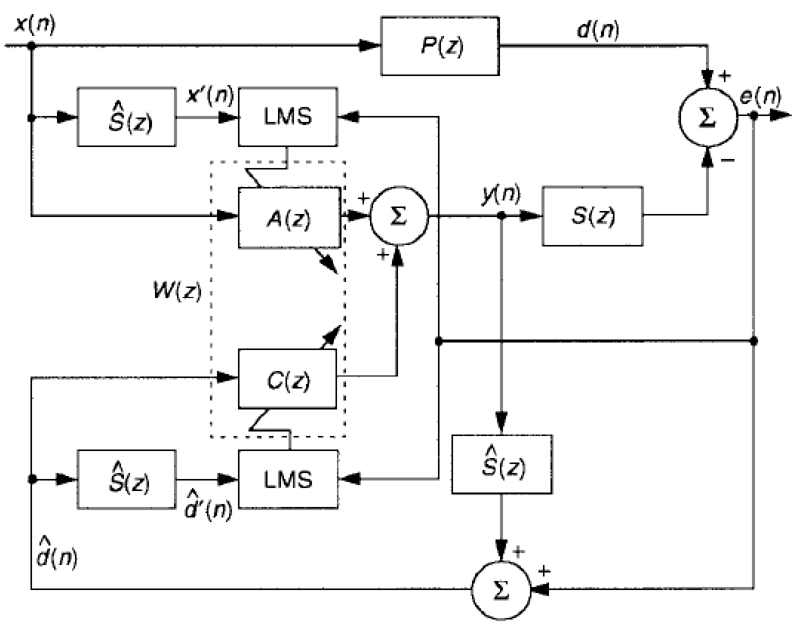
$$\text{Update weights}: w(n+1) = w(n) - \mu\, x'(n)e(n)$$


Feedback LMS, Input 200Hz sinewave
filter order = 16, μ = 8192
filter order = 32, μ = 8192
filter order =40, μ = 8192


Feedback LMS, Input 200Hz sinewave
filter order = 32, μ = 1024
filter order = 32, μ = 1024
filter orde = 32, μ = 1024

Hybrid ANC





<u>*Advantages:*</u>

- *Combines advantages of feedforward and feedback systems*
- *lower order filters*
- *relatively more stable than feedback ANC*

<u>*Disadvantages:*</u>

- *High computational complexity*

<u>*Equations:*</u>

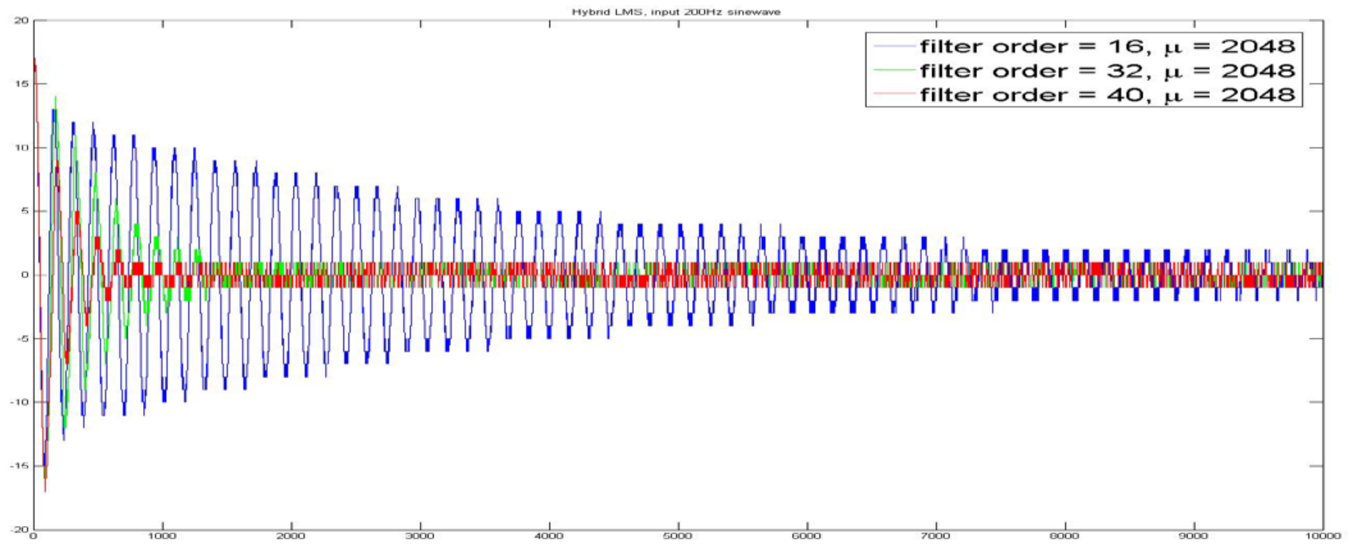
$$y(n) = a^T(n)x(n) + c^T(n)\hat{d}(n)$$

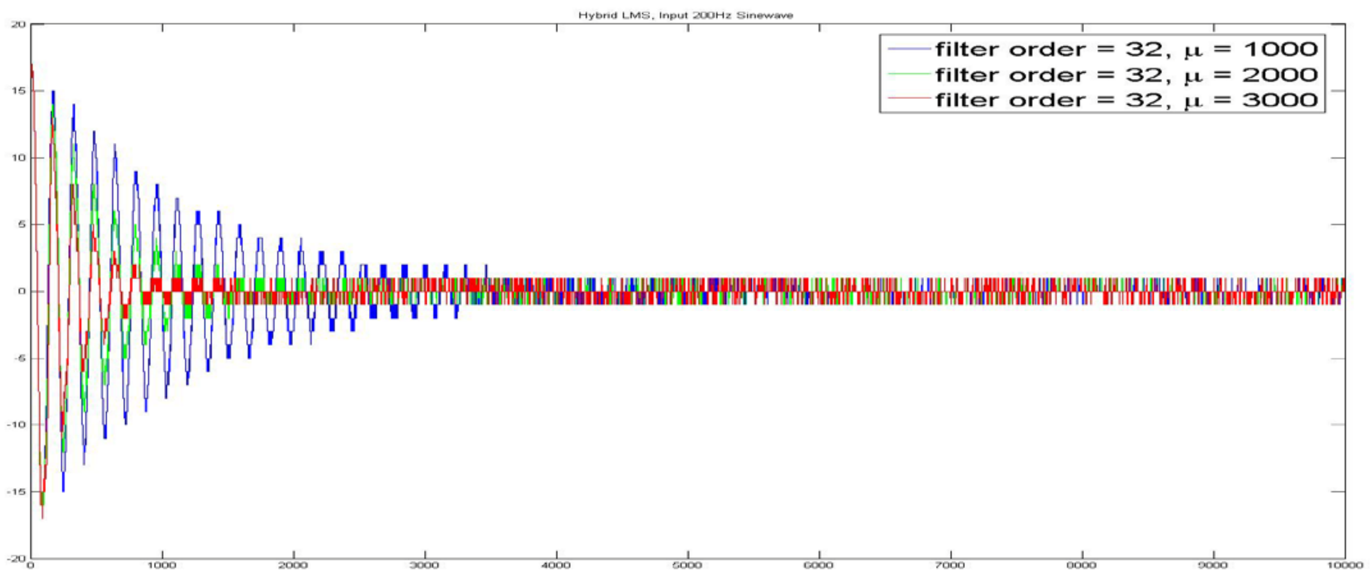
$$\text{Update weights}: a(n+1) = a(n) + \mu\, x'(n)e(n)$$

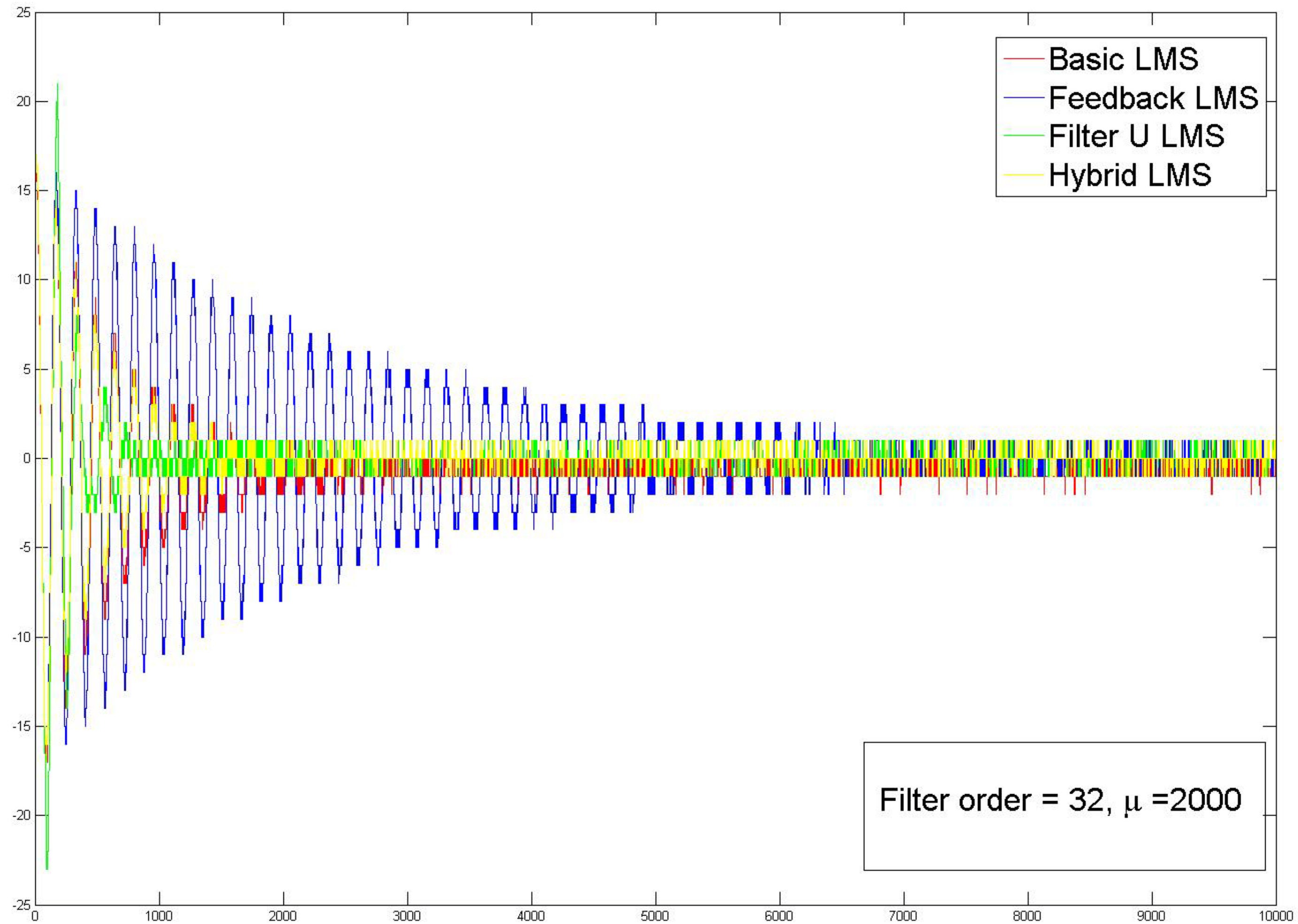
$$c(n+1) = c(n) + \mu\, \hat{d}'(n)e(n)$$

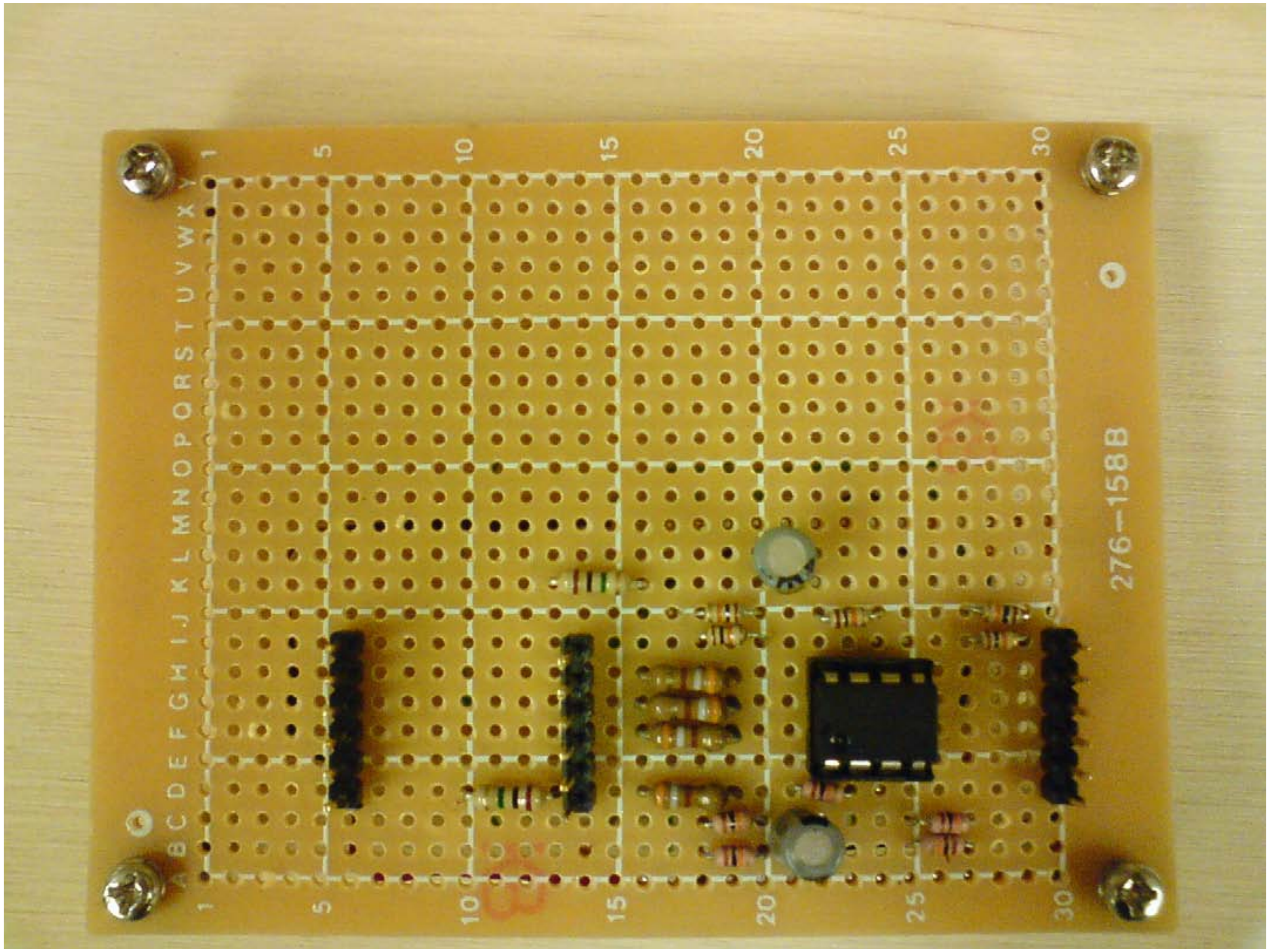
$$\text{where}\;\; \hat{d}'(n) = \hat{s}(n) \otimes \hat{d}(n)$$

$$\hat{d}(n) = e(n) + \hat{s}(n) \otimes y(n-1)$$


Hybrid LMS, input 200Hz sinewave
filter order = 16, μ = 2048
filter order = 32, μ = 2048
filter order = 40, μ = 2048
20
15
10
5
0
-5
-10
-15
-20
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000


Hybrid LMS, Input 200Hz Sinewave
filter order = 32, μ = 1000
filter order = 32, μ = 2000
filter order = 32, μ = 3000
20
15
10
5
0
-5
-10
-15
-20
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000


Basic LMS
Feedback LMS
Filter U LMS
Hybrid LMS
Filter order = 32, μ =2000
25
20
15
10
5
0
-5
-10
-15
-20
-25
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000


276-158B

How to adaptively adjust the filter coefficients?

- Considering the computation time, we use LMS:

  W(n+1) = W(n) + u * e(n) * W(n)

  u: step size

  e(n): error

  W(n): filter coefficients

- To make our system more stable, we use variations of LMS:

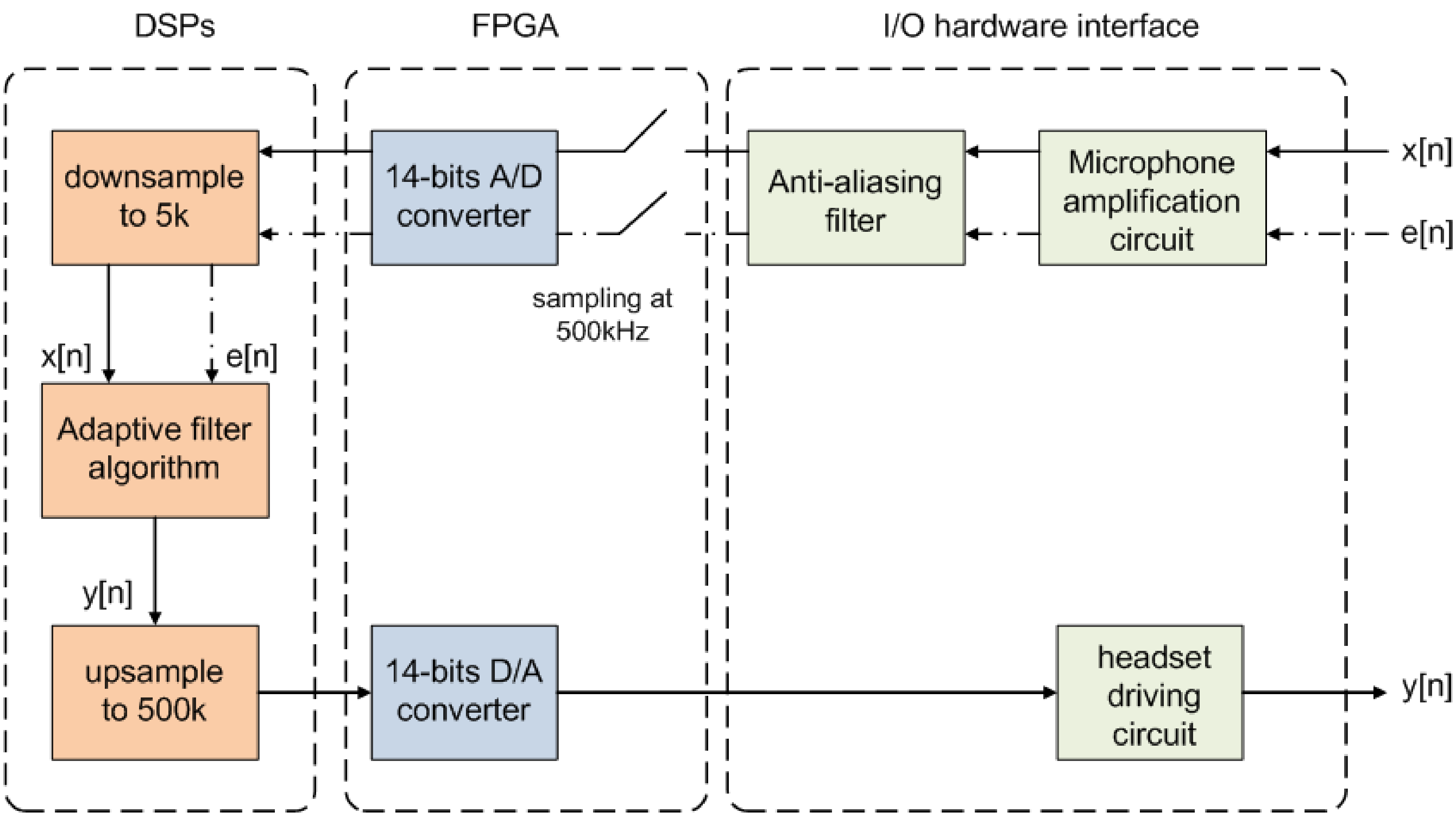
  (a) Leaky LMS: Introducing ‘a’ makes W(n) not change too rapidly

  W(n+1) = a * W(n) + u * e(n) * W(n), where a < 1

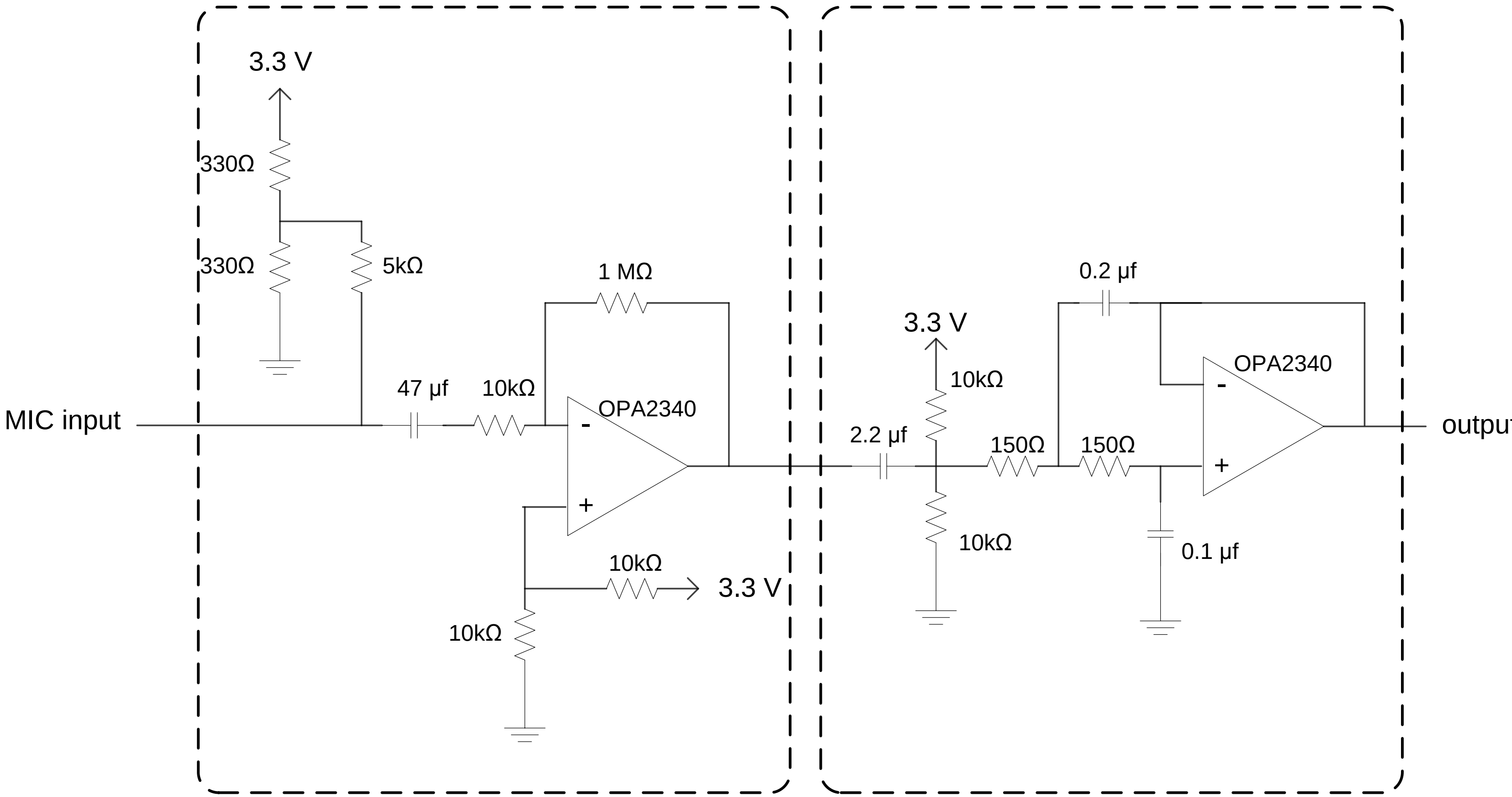
  (b) Normalize the coefficients W(n) to stabilize the output

  W(n+1) = W(n+1) / sqrt(sum(W(n+1)))

Approach 2:System architecture



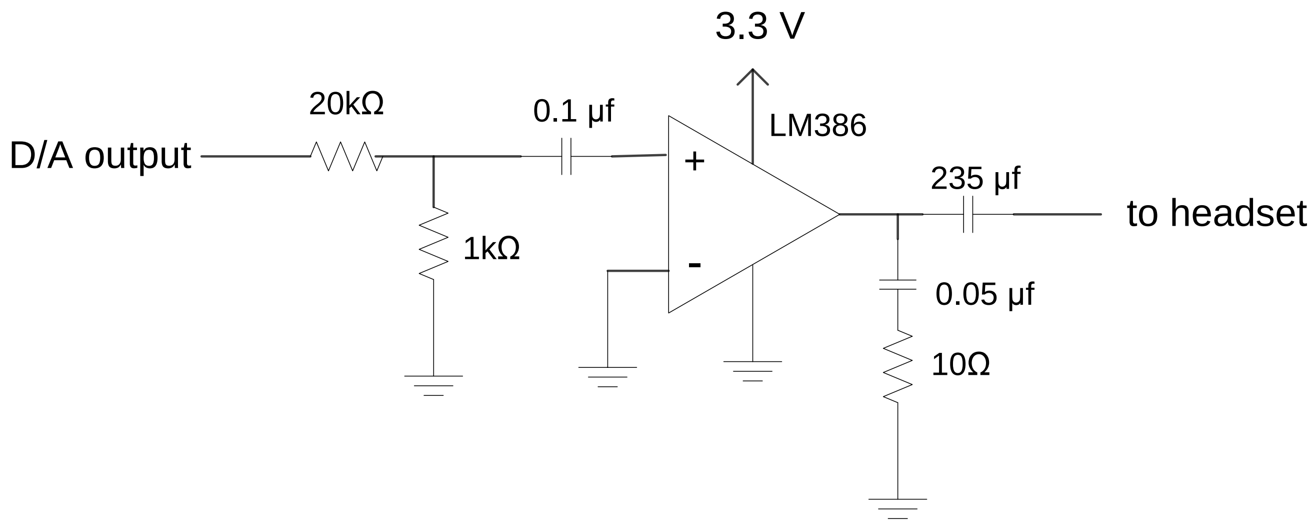
Input analog/digital interface



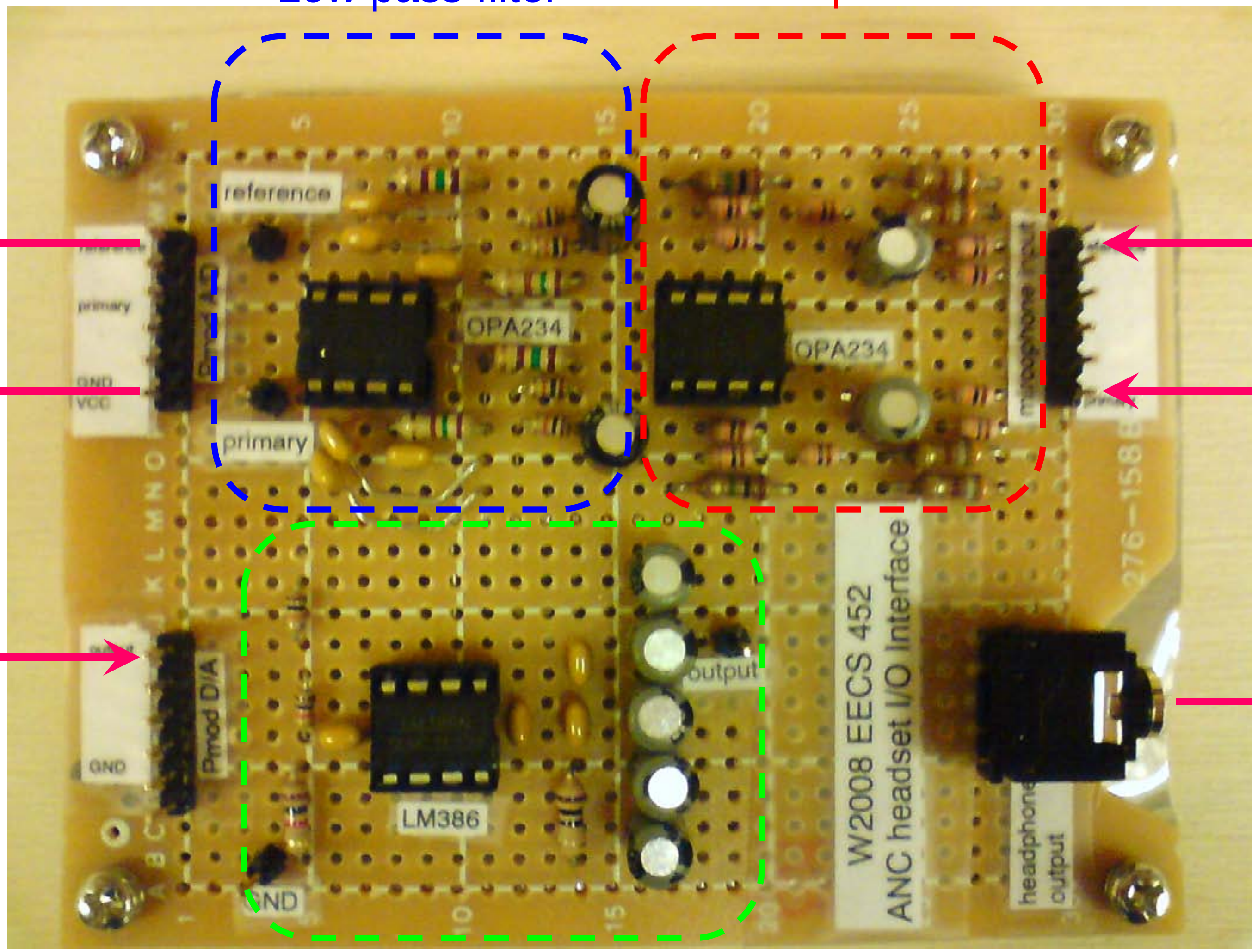
MIC amplification circuit

Single-Supply Sallen Key Low Pass
Butterworth Filter with cut-off freq 7.5k

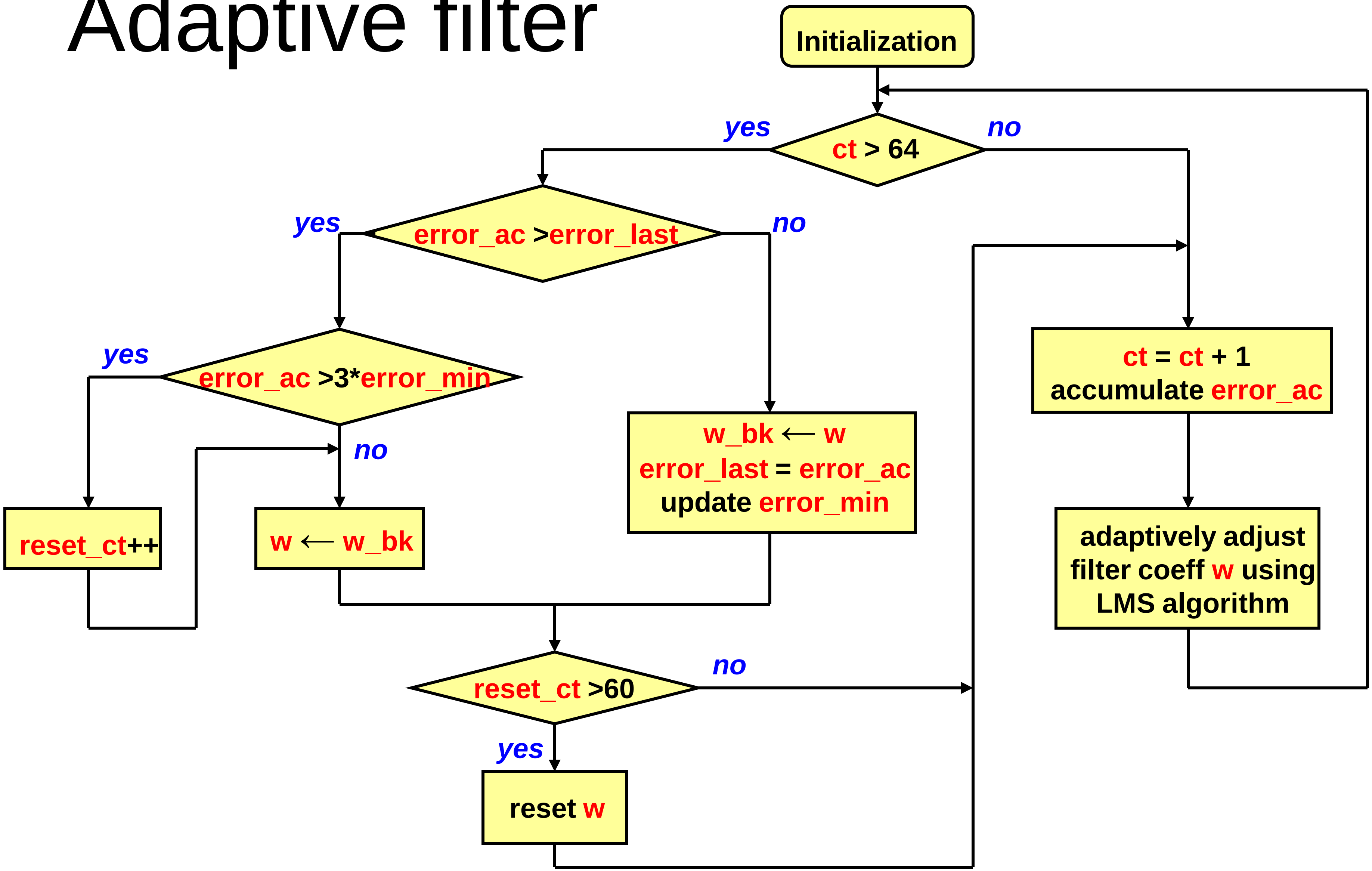
Output digital/analog interface



Amplification with gain 20

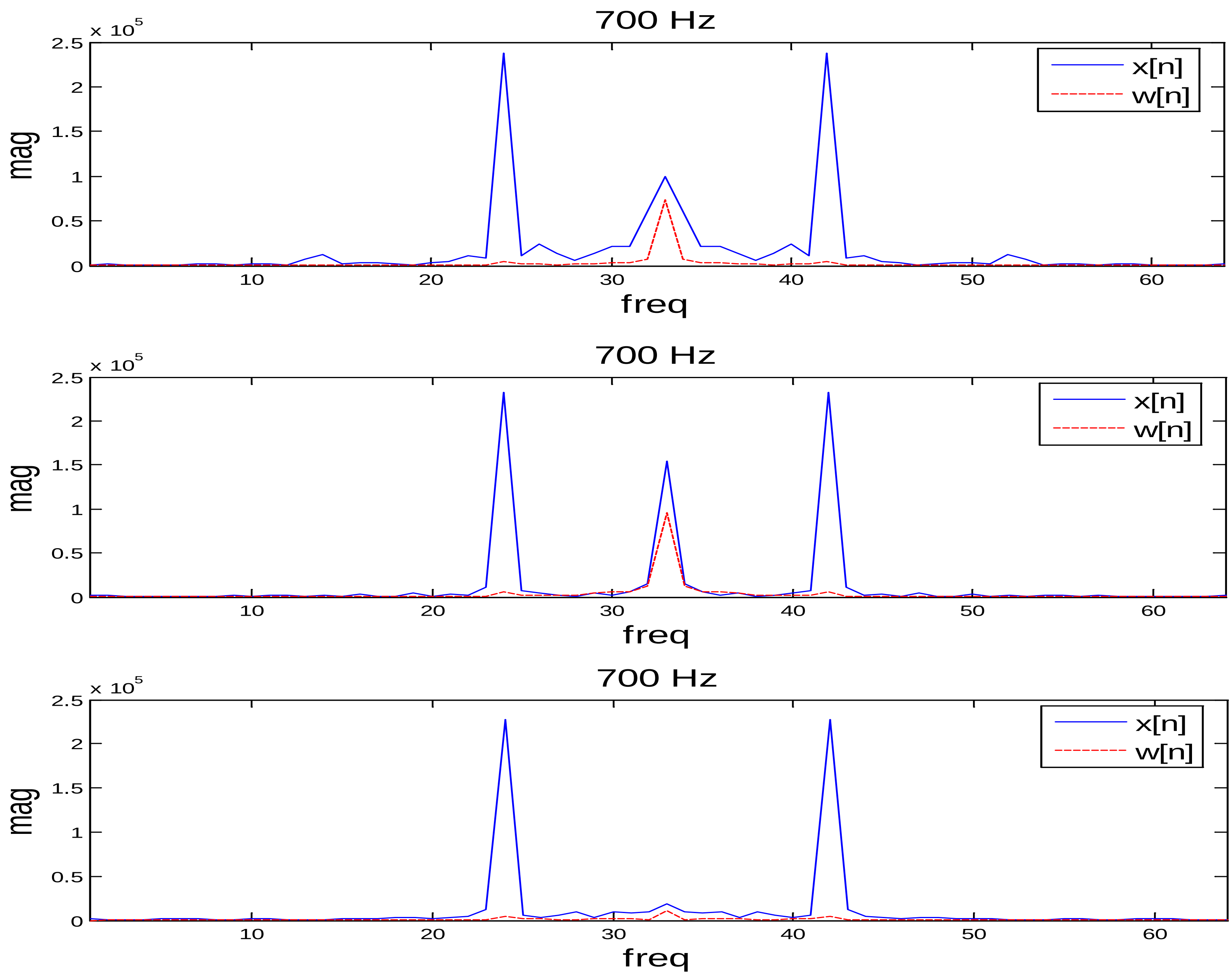

Low pass filter
MIC amplification circuit
to FPGA
x[n]
e[n]
from FPGA
y[n]
x[n]
e[n]
to
headset
Headphone driving circuit
reference
primary
OPA234
OPA234
LM386
output
GND
Pmod D/A
W2008 EECS 452
ANC headset I/O Interface
headphone
output

Adaptive filter

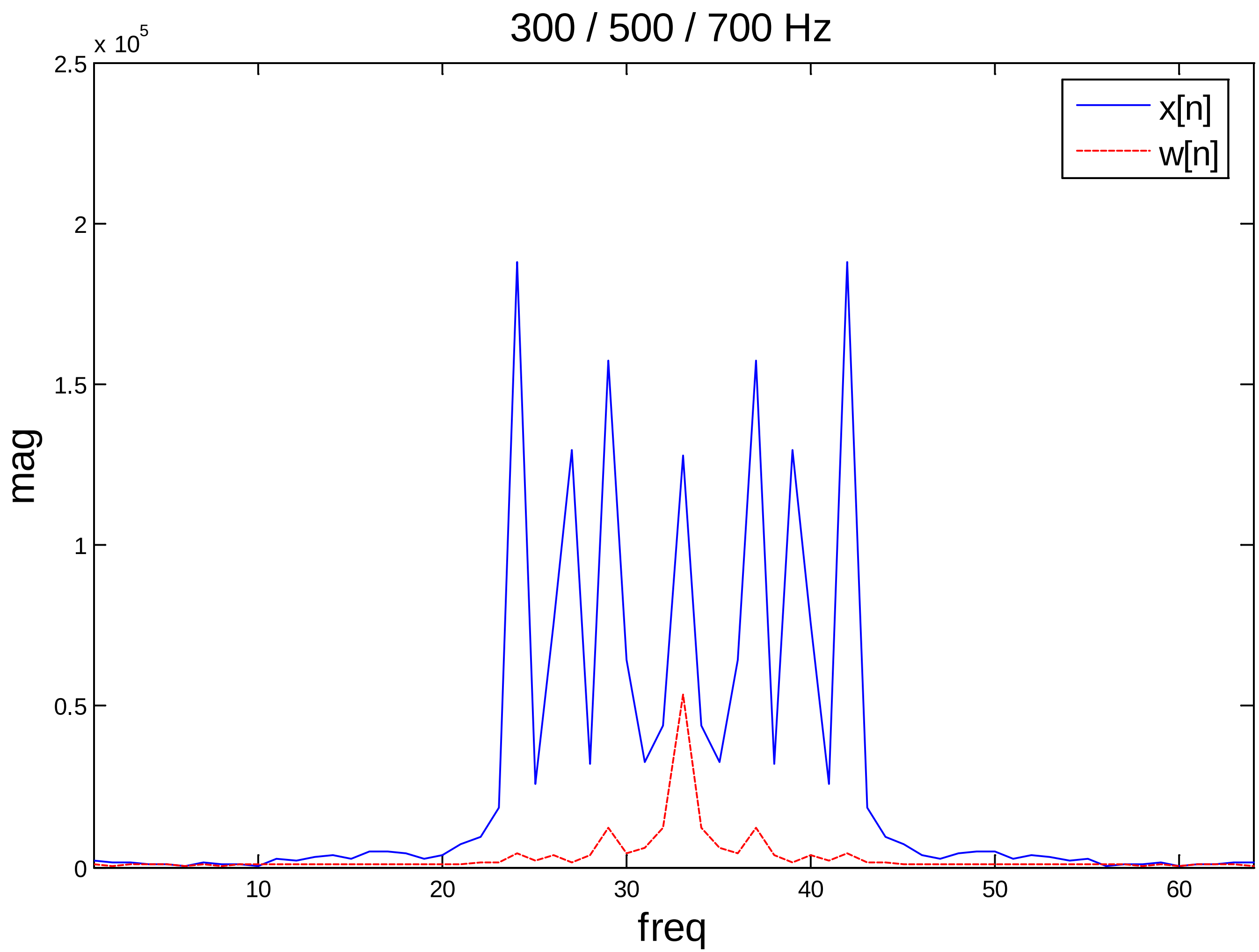


Sampling rate & filter size design consideration

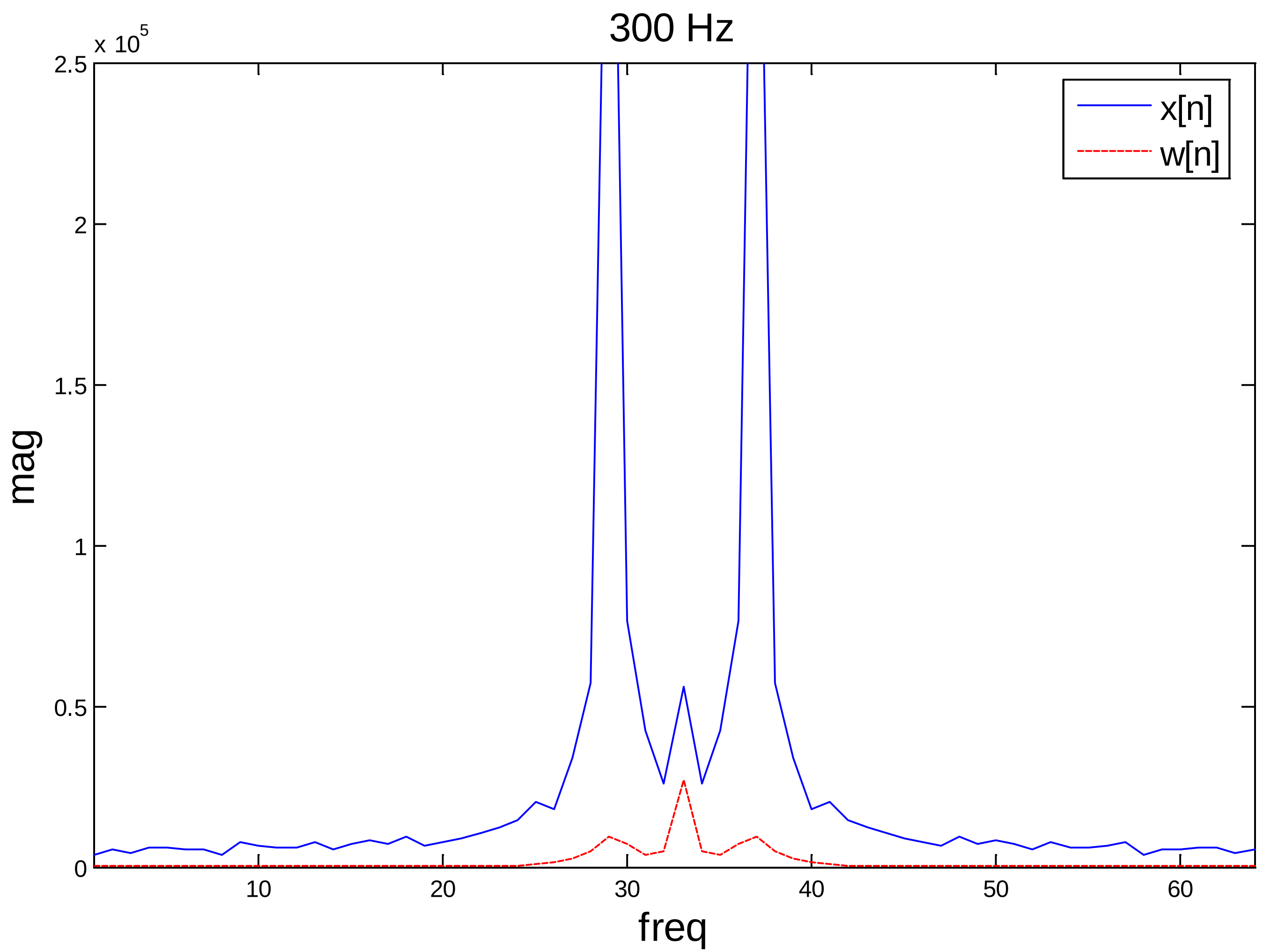
- Sampling rate determines processing speed constraint.
- Fix sampling rate
  - <u>Large filter size</u>: fine freq resolution, slow processing, slow response.
  - <u>Small filter size</u>: low freq resolution, fast processing, fast response.
- Fix filter size
  - <u>High sampling rate</u>: low freq resolution, less artifact in the D/A output.
  - <u>Low sampling rate</u>: high freq resolution, more artifact in the D/A output.


700 Hz
x 10^5
2.5
2
1.5
1
0.5
0
mag
10
20
30
40
50
60
freq
x[n]
w[n]
700 Hz
x 10^5
2.5
2
1.5
1
0.5
0
mag
10
20
30
40
50
60
freq
x[n]
w[n]
700 Hz
x 10^5
2.5
2
1.5
1
0.5
0
mag
10
20
30
40
50
60
freq
x[n]
w[n]

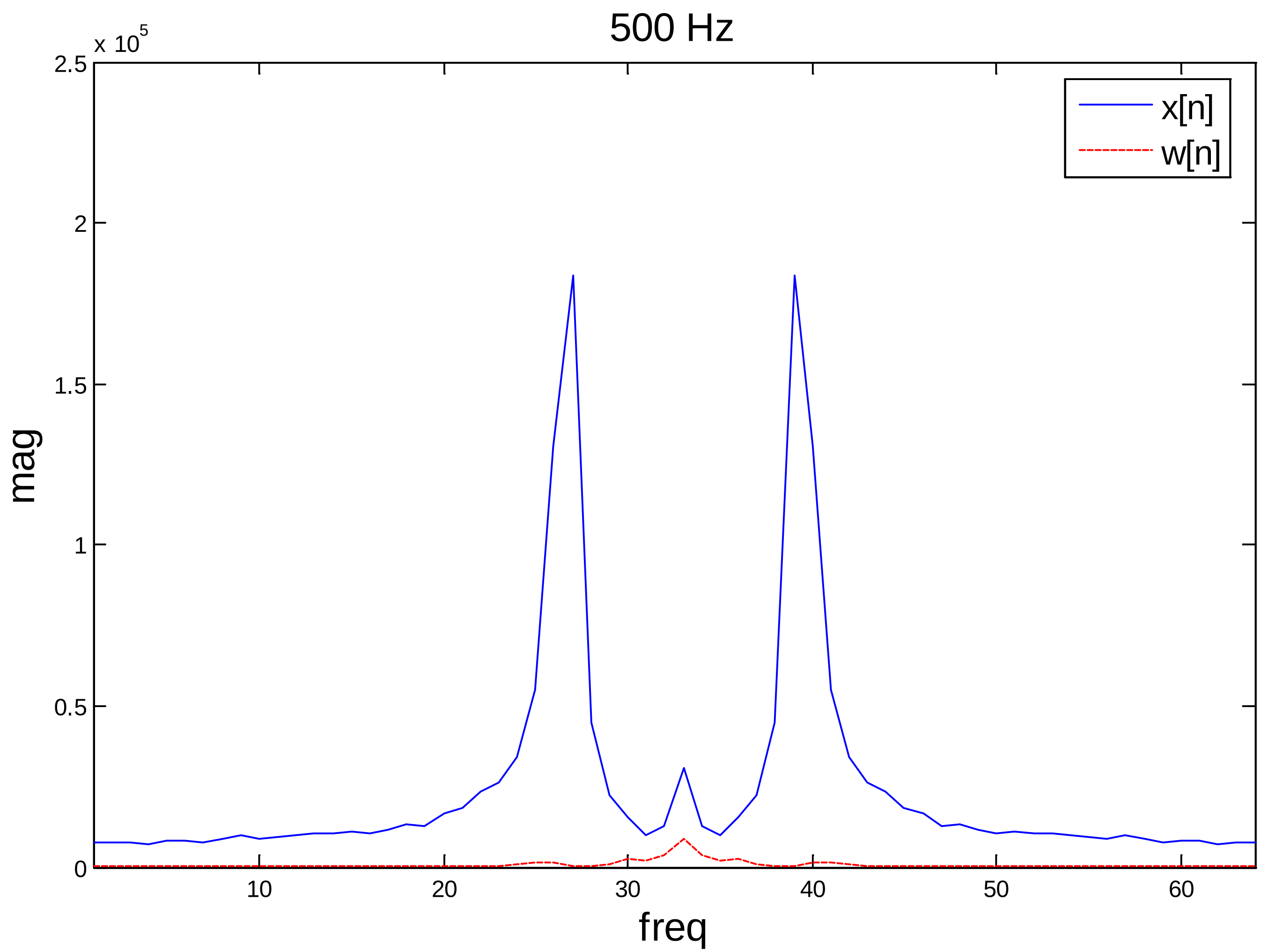
Experiment result (1)



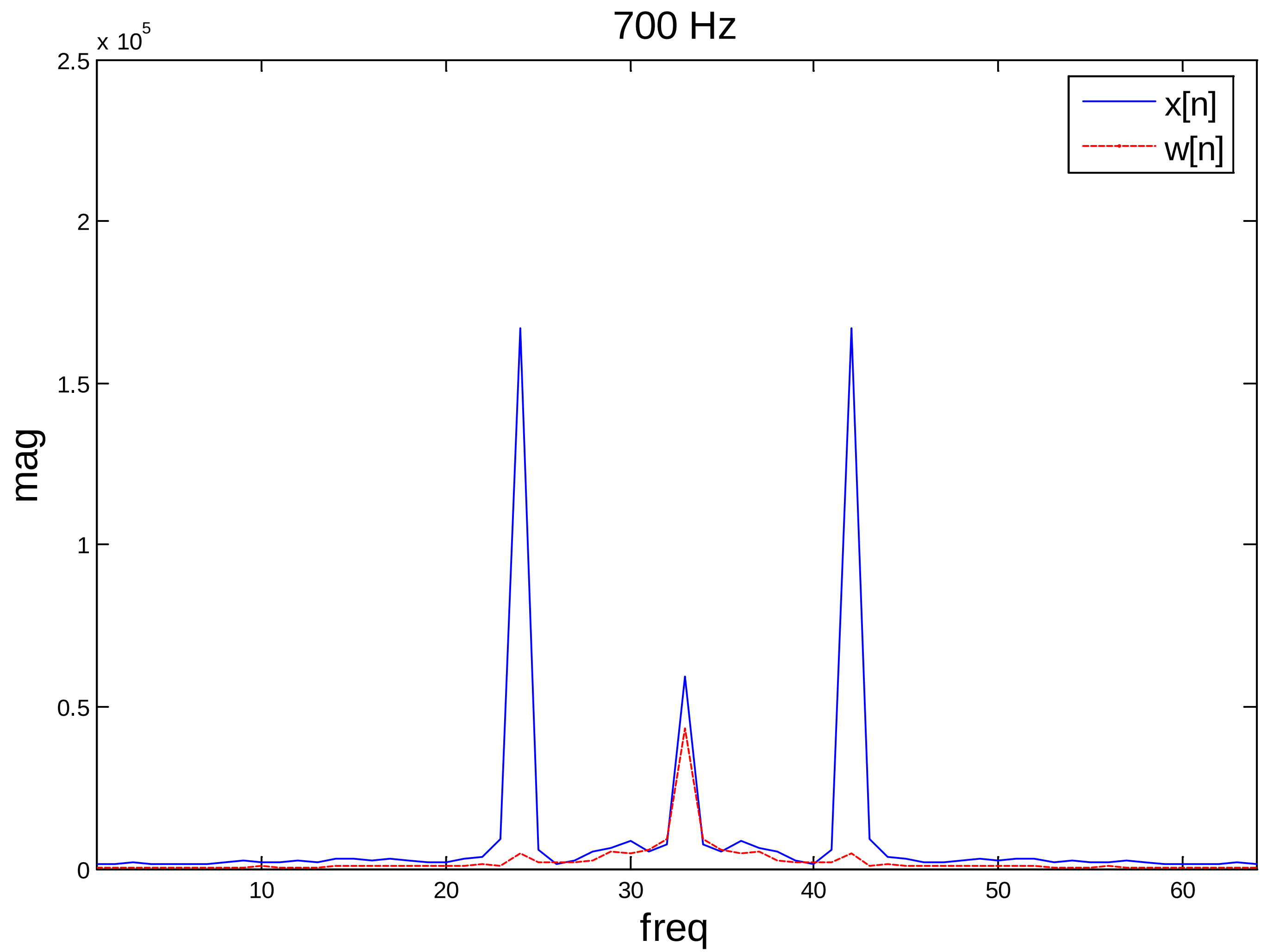
Experiment result (2)



Experiment result (3)



Experiment result (4)



Incorporate music source

- Assume music source is uncorrelated with the noise, and noise is a zero mean w.s.s random sequences.
- Adaptive algorithm will adjust filter coefficient so as to minimize MSE.

$$\begin{aligned} E[e^2] &= E[(d - Y)^2] \\ &= E[(m + y - Y)^2] \\ &= E[m^2] + E[(y - Y)^2] + \underbrace{2E[(y - Y)m]}_{= 0 \;\; Y,X \text{ uncorrelated with } m} \end{aligned}$$

- Since $E[m^2]$ does not depend on filter coeff, adaptive algorithm will select coeff to minimize $E[(y - Y)^2]$.

ANC system demonstration part 1:

Single tone and multiple tone artificial noise

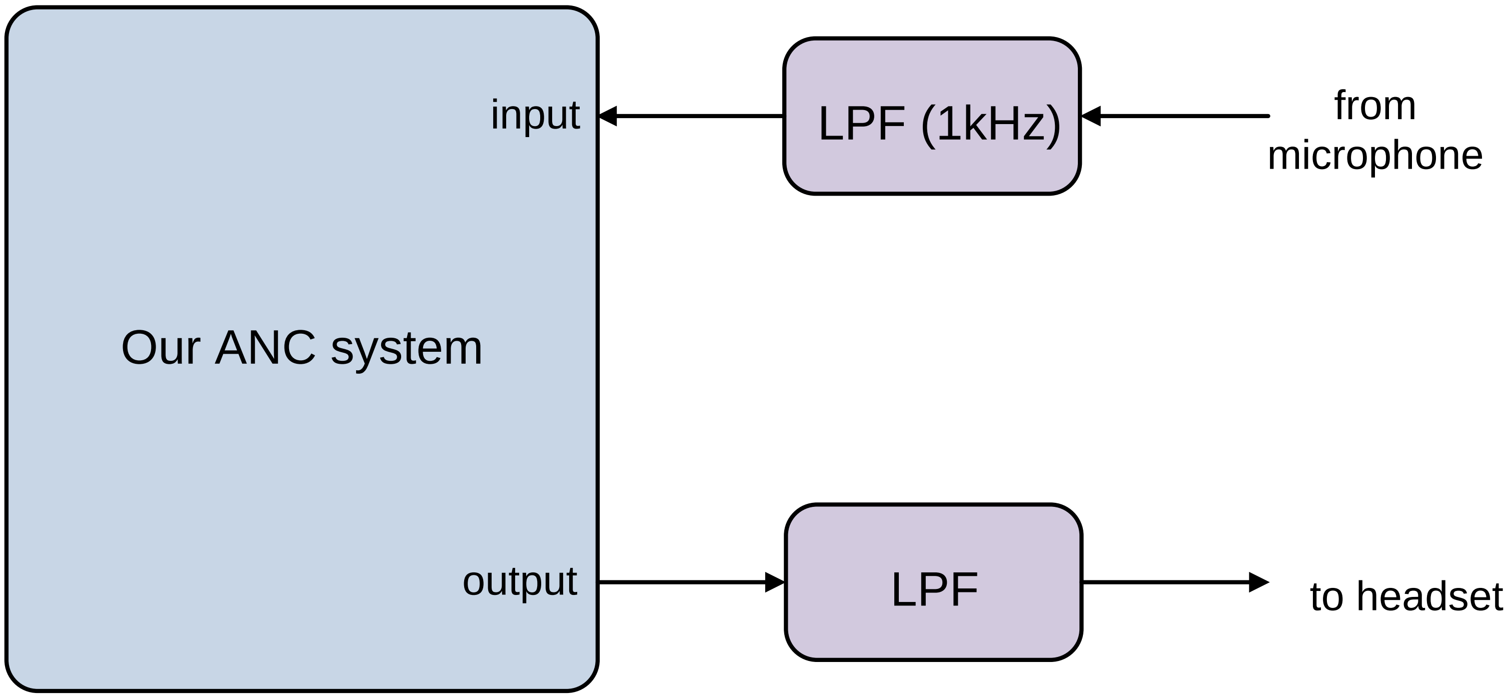
ANC system demonstration part 2:

Real engine noise

ANC system demonstration part 3:

Noise with music source

Future work (1)



Future work (2)

- Use more precise microphone and ADC, DAC to acquire more accurate measurement.
- Integrate the design components into a build-in embedded system to avoid feedback interference.
- Implementation in assembly language to save computation time.

Conclusion

- A workable ANC headset for both artificial and real world noise.
- Works for noise frequency ranging from 100 to 800 Hz.
- Incorporate music source.
- Implemented and compared LMS, FxLMS, Feedback, FuLMS and Hybrid algorithms:
  - For stability, Hybrid is the best.
  - For simplicity, FxLMS is recommended.

Thank you

References

- S.M. Kuo, D.R. Morgan, Active noise control: a tutorial review, Proc. IEEE 87 (6) (June 1999) 943-975.
- S. M. Kuo and D. R. Morgan, Active Noise Control Systems – Algorithms and DSP Implementations. New York: Wiley, 1996.
- A. Miguez-Olivares, M. Recuero-Lopez, Development of an Active Noise Controller in the DSP Starter Kit. TI SPRA336. September 1996.
- S. Haykin, Adaptive Filter Theory, 2nd ed. Englewood Cliffs, NJ: Prentice-Hall, 1991.