Chapter

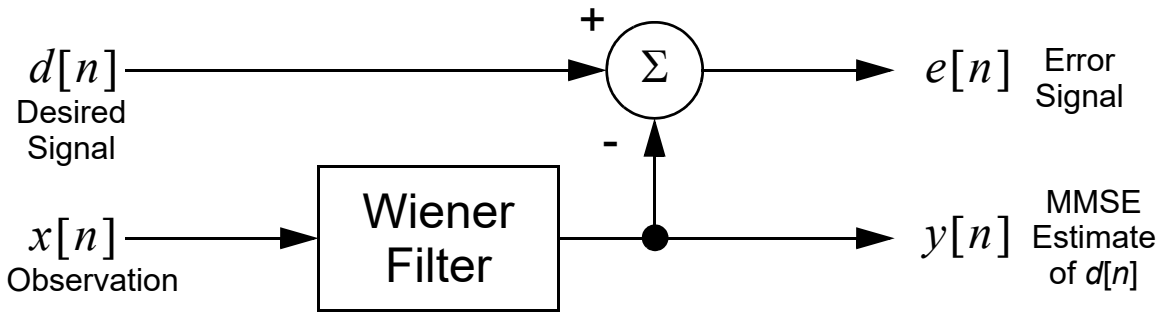
8

Adaptive Filters

Introduction

The term adaptive filter implies changing the characteristic of a filter in some automated fashion to obtain the *best* possible signal quality in spite of changing signal/system conditions. Adaptive filters are usually associated with the broader topic of statistical signal processing. The operation of signal filtering by definition implies extracting something desired from a signal containing both desired and undesired components. With linear FIR and IIR filters the filter output is obtained as a linear function of the *observation* (signal applied) to the input. An optimum linear filter in the minimum mean square sense can be designed to extract a signal from noise by minimizing the error signal formed by subtracting the filtered signal from the *desired signal*. For noisy signals with time varying statistics, this minimization process is often done using an *adaptive filter*.

For statistically stationary inputs this solution is known as a *Wiener* filter.[1]



1. Simon Haykin, *Adaptive Filter Theory,* fourth edition, Prentice Hall, 2002.

Wiener Filter

- An M tap discrete-time Wiener filter is of the form

$$y[n] = \sum_{m=0}^{M-1} w_m x[n-m] \tag{8.1}$$

  where the w_m are referred to as the filter weights

  – Note: (8.1) tells us that the Wiener filter is just an M-tap FIR filter

- The quality of the filtered or estimated signal $y[n]$ is determined from the error sequence $e[n] = d[n] - y[n]$
- The weights w_m, $m = 0, 1, \ldots, M-1$ are chosen such that

$$E\{e^2[n]\} = E\{(d[n] - y[n])^2\} \tag{8.2}$$

  is minimized, that is we obtain the minimum mean-squared error (MMSE)
- The optimal weights are found by setting

$$\frac{\partial}{\partial w_m} E\{e^2[n]\} = 0, m = 0, 1, \ldots, M-1 \tag{8.3}$$

- From the orthogonality principle[1] we choose the weights such that the error $e[n]$ is orthogonal to the observations (data), i.e.,

1. A. Papoulis, *Probability, Random Variables, and Stochastic Processes*, third edition, McGraw-Hill, 1991.

$$E\{x[n-k](d[n]-y[n])\} = 0, k = 0, 1, \ldots, M-1 \quad (8.4)$$

– This results in a filter that is optimum in the sense of minimum mean-square error

- The resulting system of equations

$$\sum_{m=0}^{M-1} w_m E\{x[n-k]x[n-m]\} = E\{x[n-k](d[n])\} \quad (8.5)$$

or

$$\sum_{m=0}^{M-1} w_m \phi_{xx}[m-k] = \phi_{xd}[-k] \quad (8.6)$$

for $k = 0, 1, \ldots, M-1$ are known as the Wiener-Hopf or normal equations

– Note: $\phi_{xx}[k]$ is the autocorrelation function of $x[n]$ and $\phi_{xd}[k]$ is the cross-correlation function between $x[n]$ and $d[n]$

- In matrix form we can write

$$\mathbf{R}_{xx}\mathbf{w}_o = \mathbf{p}_{xd} \quad (8.7)$$

where $\mathbf{R}_{xx}$ is the $M \times M$ correlation matrix associated with $x[n]$

$$\mathbf{R}_{xx} = \begin{bmatrix} \phi_{xx}[0] & \cdots & \phi_{xx}[M-1] \\ \vdots & \ddots & \vdots \\ \phi_{xx}[-M+1] & \cdots & \phi_{xx}[0] \end{bmatrix} \tag{8.8}$$

$\mathbf{w}_o$ is the optimum weight vector given by

$$\mathbf{w}_o = \begin{bmatrix} w_{o0} & w_{o1} & \cdots & w_{oM-1} \end{bmatrix}^T \tag{8.9}$$

and $\mathbf{p}_{xd}$ is the cross-correlation vector given by

$$\mathbf{p}_{xd} = \begin{bmatrix} \phi_{xd}[0] & \phi_{xd}[-1] & \ldots & \phi_{xd}[1-M] \end{bmatrix}^T \tag{8.10}$$

- The optimal weight vector is given by

$$\mathbf{w}_o = \mathbf{R}_{xx}^{-1}\mathbf{p}_{xd} \tag{8.11}$$

- As a matter of practice (8.11) can be solved using sample statistics, that is we replace the true statistical auto- and cross-correlation functions with time averages of the form

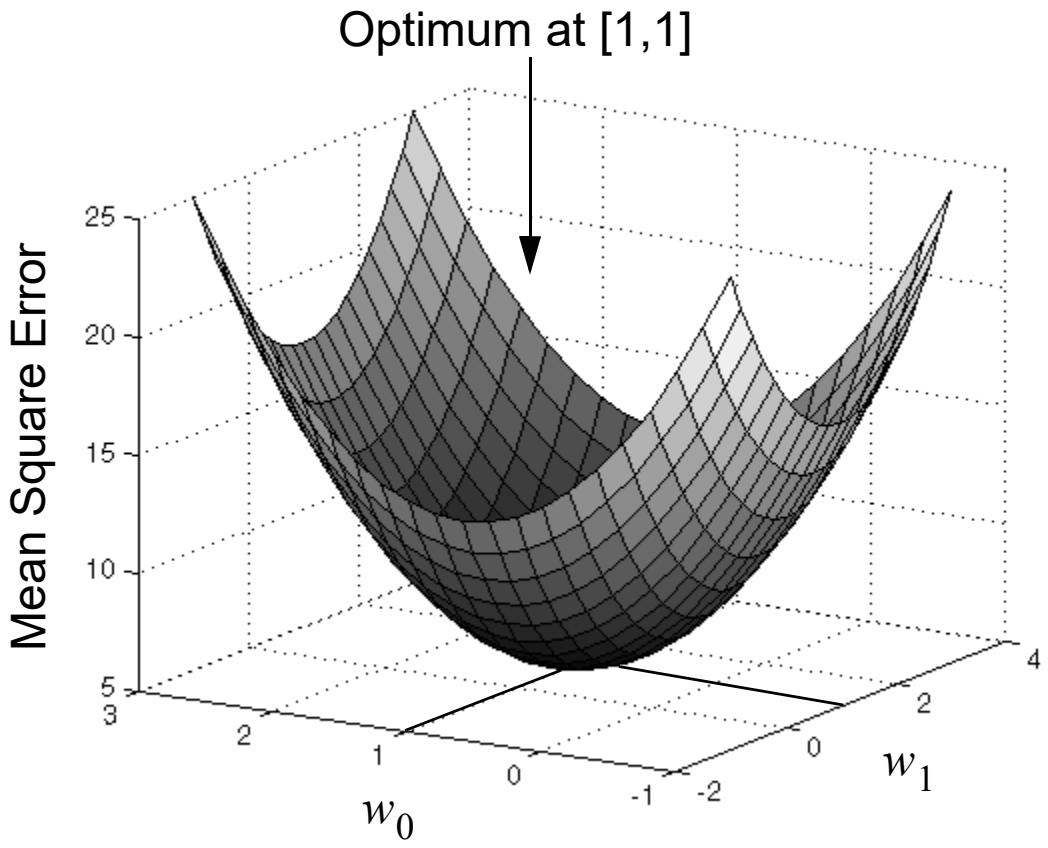
$$\phi_{xx}[k] \cong \frac{1}{N}\sum_{n=0}^{N-1} x[n+k]x[n] \tag{8.12}$$

$$\phi_{xd}[k] \cong \frac{1}{N}\sum_{n=0}^{N-1} x[n+k]d[n] \tag{8.13}$$

where N is the sample block size

Adaptive Wiener Filter

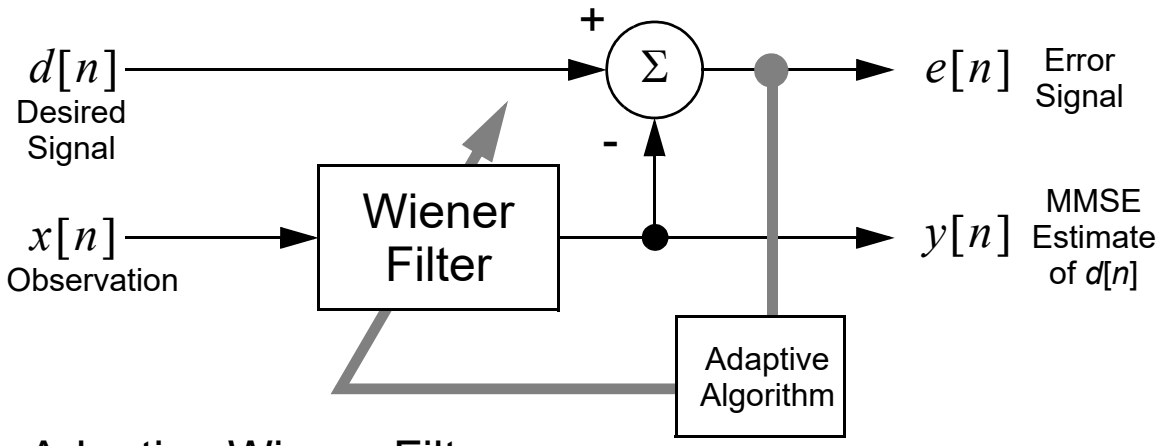
- In an adaptive Wiener filter the error signal $e[n]$ is fed back to the filter weights to adjust them using a *steepest-descent algorithm*
- With respect to the weight vector $\mathbf{w}$, the error $e[n]$ can be viewed as an M dimensional error surface, that due to the squared error criterion, is convex cup (a bowl shape)



Error Surface for M = 2

- The filter decorrelates the output error $e[n]$ so that signals in common to both $d[n]$ and $x[n]$ in a correlation sense are canceled

- A block diagram of this adaptive Wiener (FIR) filter is shown below



Adaptive Wiener Filter

Least-Mean-Square Adaptation

- Ideally the optimal weight solution can be obtained by applying the steepest descent method to the error surface, but since the true gradient cannot be determined, we use a *stochastic gradient*, which is simply the instantaneous estimate of $\mathbf{R}_{xx}$ and $\mathbf{p}_{xd}$ from the available data, e.g.,

$$\mathbf{R}_{xx} = \mathbf{x}[n]\mathbf{x}^{T}[n] \tag{8.14}$$

$$\mathbf{p}_{xd} = \mathbf{x}[n]d[n] \tag{8.15}$$

where

$$\mathbf{x}[n] = \begin{bmatrix} x[n] & x[n-1] & \ldots & x[n-M+1] \end{bmatrix}^{T} \tag{8.16}$$

- A practical implementation involves estimating the gradient from the available data using the *least-mean-square* (LMS) *algorithm*

- The steps to the LMS algorithm, for each new sample at time n, are:
  - Filter $x[n]$ to produce:

$$y[n] = \sum_{m=0}^{M-1} \hat{w}_m[n]x[n-m] = \hat{\mathbf{w}}^T[n]\mathbf{x}[n] \tag{8.17}$$

  - Form the estimation error:

$$e[n] = d[n] - y[n] \tag{8.18}$$

  - Update the weight vector using step-size parameter μ:

$$\hat{\mathbf{w}}[n+1] = \hat{\mathbf{w}}[n] + \mu\mathbf{x}[n]e[n] \tag{8.19}$$

- For algorithm stability, the step-size μ must be chosen such that

$$0 < \mu < \frac{2}{\text{tap-input power}} \tag{8.20}$$

  where

$$\text{tap-input power} = \sum_{k=0}^{M-1} E\{|x[n-k]|^2\} \tag{8.21}$$

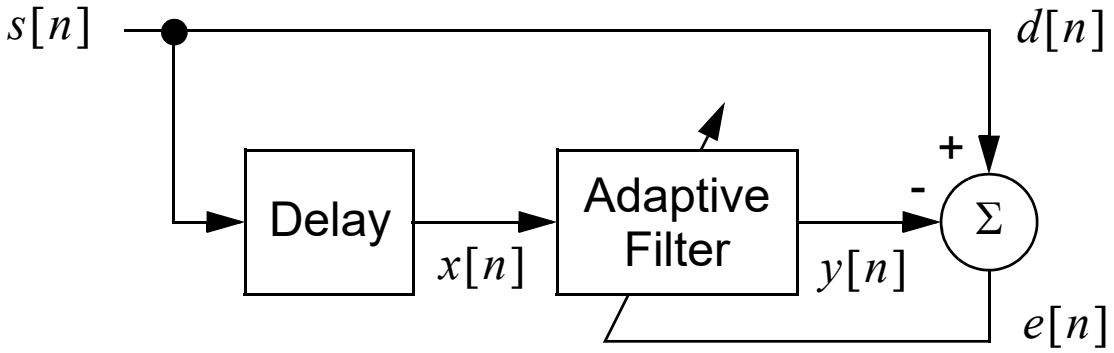
- In theory, (8.20) is equivalent to saying

$$0 < \mu < \frac{2}{\lambda_{max}} \tag{8.22}$$

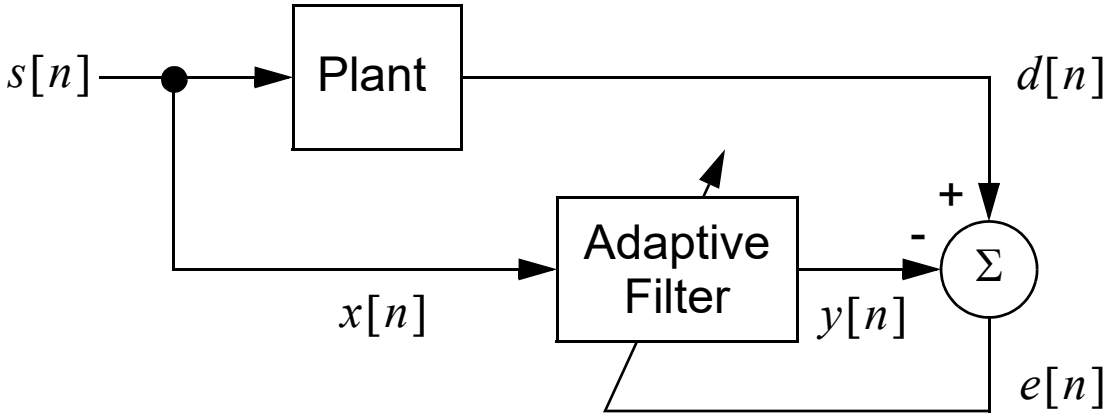
  where λ_{max} is the maximum eigenvalue of $\mathbf{R}_{xx}$

Adaptive Filter Variations[1]

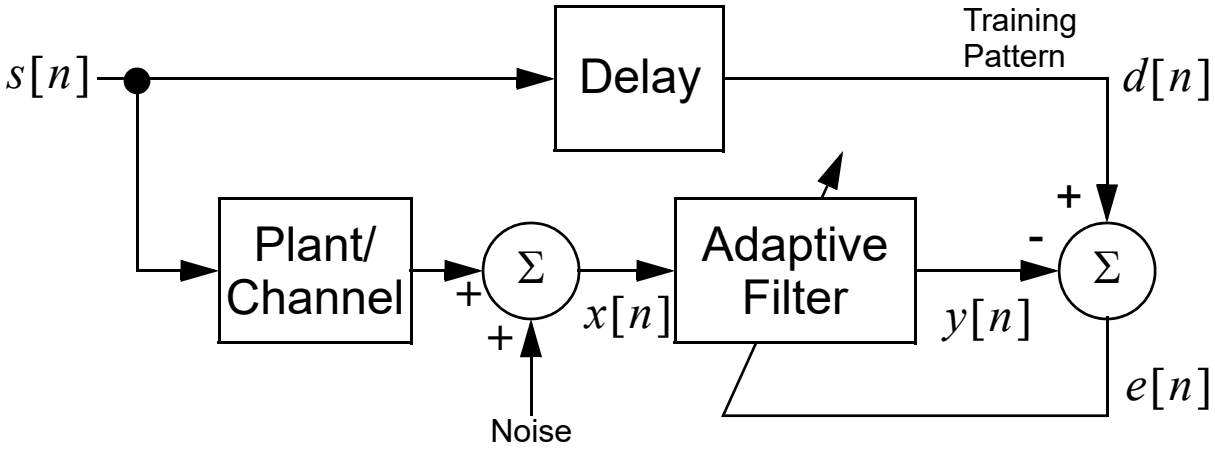
- **Prediction**



- **System Identification**

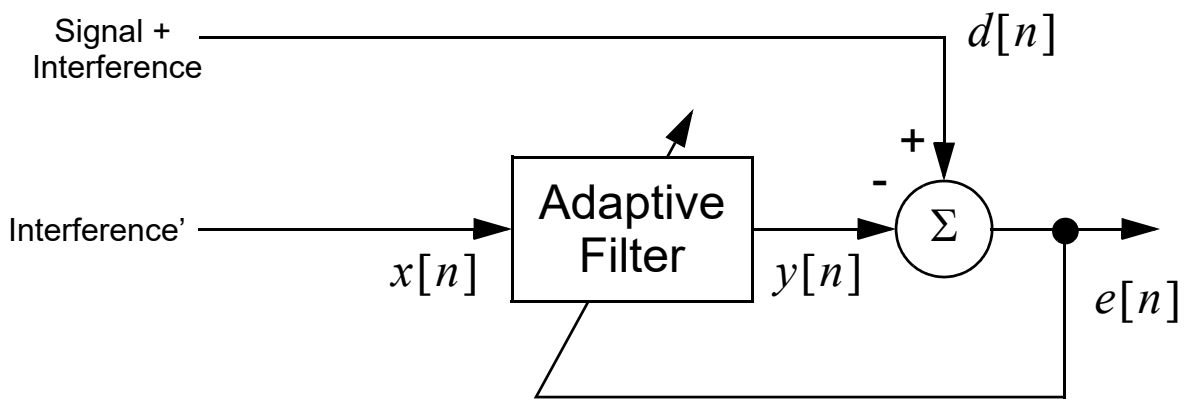


- **Equalization**



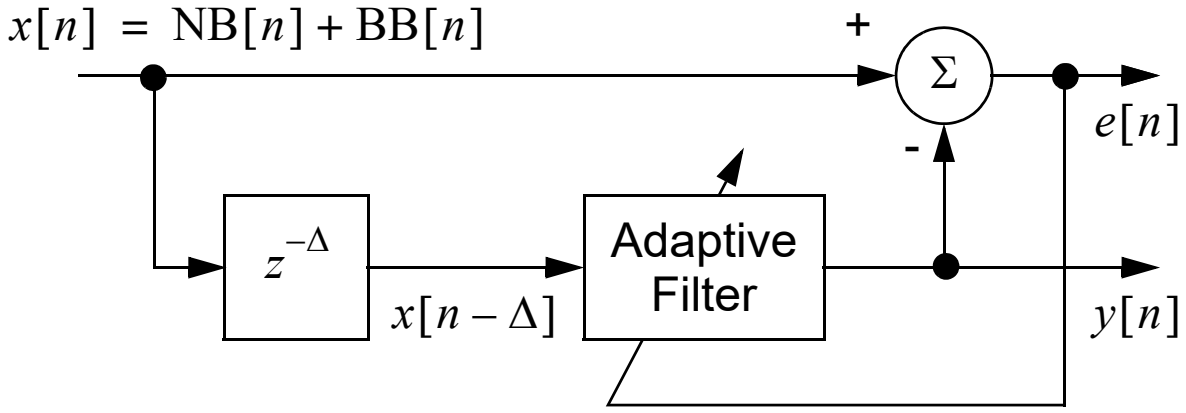
1. B. Widrow and S. Stearns, *Adaptive Signal Processing*, Prentice Hall, New Jersey, 1985.

- **Interference Canceling**



Adaptive Line Enhancement

- A relative of the interference canceling scheme shown above, is the *adaptive line enhancer* (ALE)
- Here we assume we have a narrowband signal (say a sinusoid) buried in broadband additive noise



- The filter adapts in such a way that a narrow passband forms around the sinusoid frequency, thereby suppressing much of the noise and improving the signal-to-noise ratio (SNR) in $y[n]$

Python ALE Simulation

- A simple Python simulation is constructed using a single sinusoid at normalized frequency $f_o = 1/20$ plus additive white Gaussian noise

$$x[n] = A\cos[2\pi f_o n] + w[n] \tag{8.23}$$

- The SNR is defined as

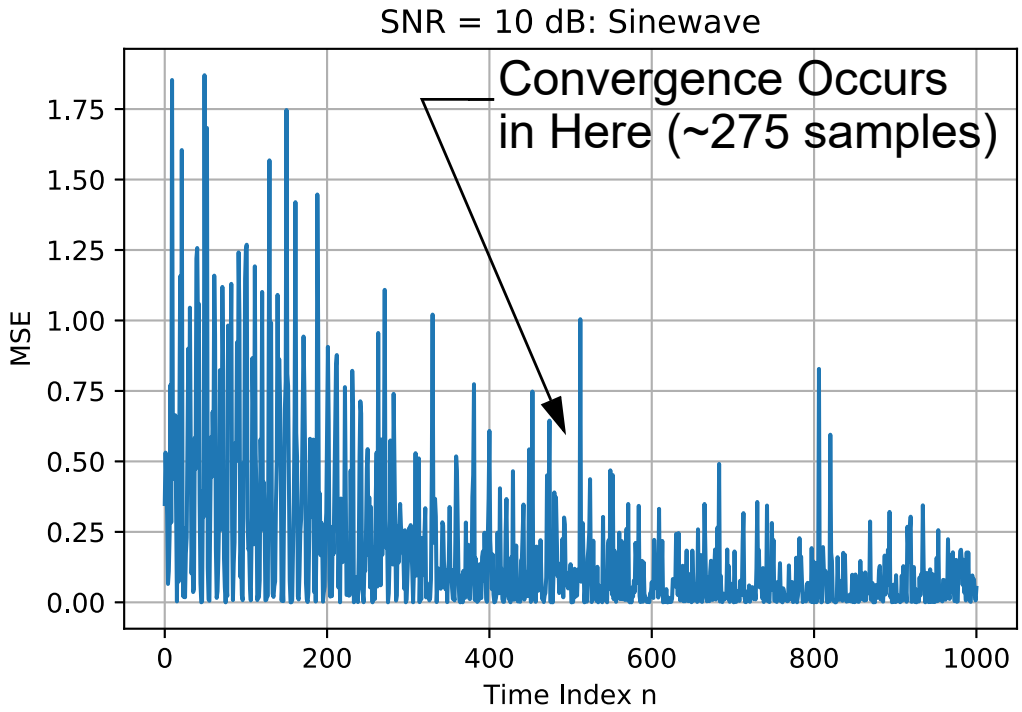
$$\text{SNR} = \frac{A^2}{2\sigma_w^2} \tag{8.24}$$

```
def lms_ale(SNR,N,M,mu,sqwav=False):
    """
    lms_ale  lms ALE adaptation algorithm using an IIR filter.
            n,x,x_hat,e,ao,F,Ao = lms_ale(SNR,N,M,mu)

    *******LMS ALE Simulation************
       SNR = Sinusoid SNR in dB
         N = Number of simulation samples
         M = FIR Filter length (order M-1)
        mu = LMS step-size
      mode = 0 <=> sinusoid, 1 <=> squarewave

         n = Index vector
         x = Noisy input
     x_hat = Filtered output
         e = Error sequence
        ao = Final value of weight vector
         F = Frequency response axis vector
        Ao = Frequency response of filter in dB
    ***************************************
    Mark Wickert, November 2014
    """

    # Sinusoid SNR = (A^2/2)/noise_var
    n = arange(0,N+1) # length N+1
    if not(sqwav):
        x = 1*cos(2*pi*1/20*n) # Here A = 1, Fo/Fs = 1/20
        x += sqrt(1/2/(10**(SNR/10)))*randn(N+1)
    else: # Squarewave case
        x = 1*sign(cos(2*pi*1/20*n)); # Here A = 1, Fo/Fs = 1/20
        x += sqrt(1/1/(10**(SNR/10)))*randn(N+1)

    # Normalize mu
    mu /= M + 1
```

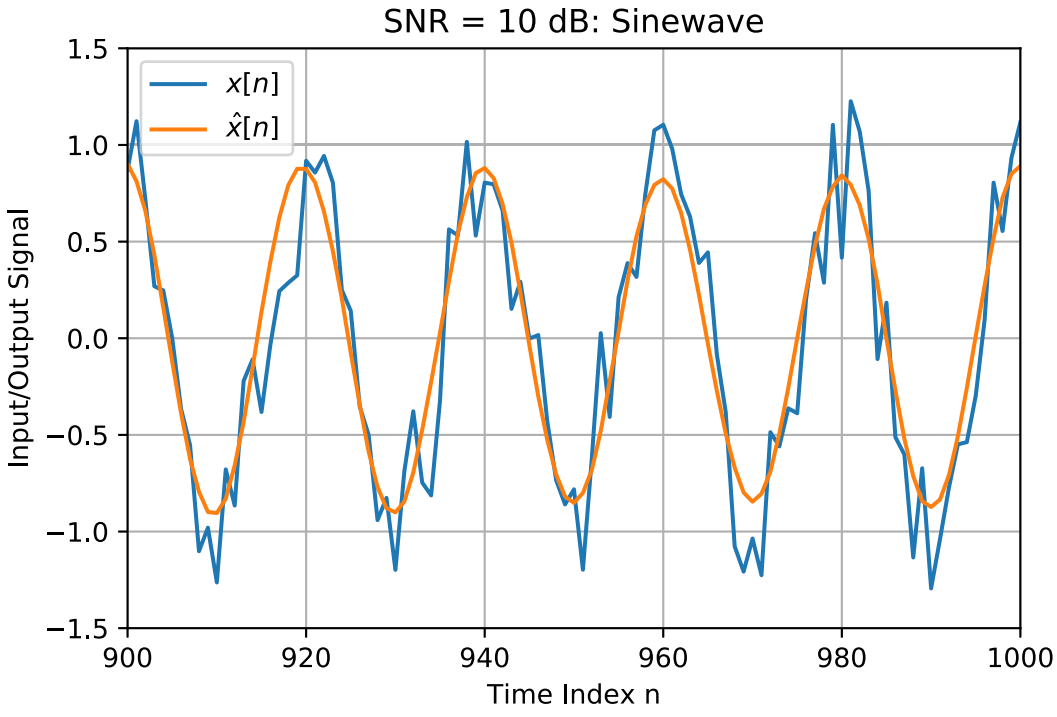
```
    # White Noise -> Delta = 1, so delay x by one sample
    y = signal.lfilter([0, 1],1,x)
    # Initialize output vector x_hat to zero
    x_hat = zeros_like(x)
    # Initialize error vector e to zero
    e = zeros_like(x)
    # Initialize weight vector to zero
    ao = zeros(M+1)
    # Initialize filter memory to zero
    zi = signal.lfiltic(ao,1,y=0)
    # Initialize a vector for holding ym of length M+1
    ym = zeros_like(ao)
    for k,yk in enumerate(y):
       # Filter one sample at a time
       x_hat[k],zi = signal.lfilter(ao,1,[yk],zi=zi)
       # Form the error sequence
       e[k] = x[k] - x_hat[k]
       # Update the weight vector
       ao = ao + 2*mu*e[k]*ym
       # Update vector used for correlation with e[k]
       ym = hstack((array(yk), ym[0:-1]))
    # Create filter frequency response
    F = arange(0,0.5,1/512)
    w,Ao = signal.freqz(ao,1,2*pi*F)
    Ao = 20*log10(abs(Ao))
    return n,x,x_hat,e,ao,F,Ao
```

- A simulation is run using 1000 samples, SNR $=$ 10 dB, $M =$ 64, and $\mu = 0.01/64$

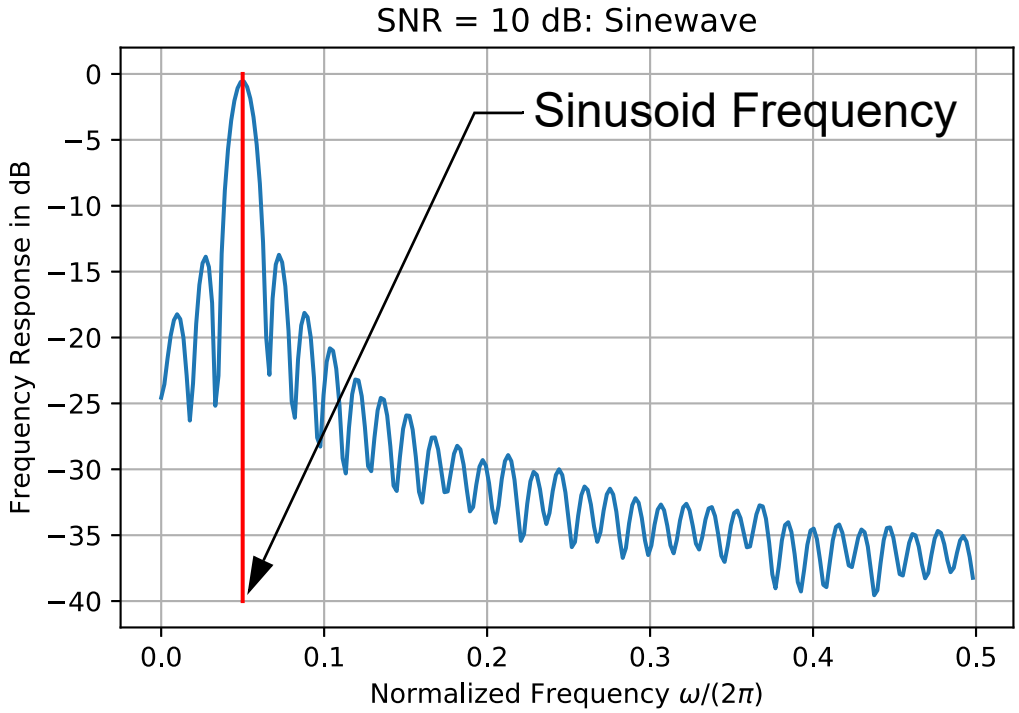
```
n,x,x_hat,e,ao,F,Ao = lms_ale(10,1000,64,0.005,False)

plot(n,e**2)
#xlim([800,1000])
ylabel(r'MSE')
xlabel(r'Time Index n')
title('SNR = 10 dB: Sinewave')
grid();
```




```
plot(n,x)
plot(n,x_hat)
xlim([900,1000])
legend((r'$x[n]$',r'$\hat{x}[n]$'),loc='best')
ylabel(r'Input/Output Signal')
xlabel(r'Time Index n')
title('SNR = 10 dB: Sinewave')
ylim([-1.5,1.5])
grid();
```

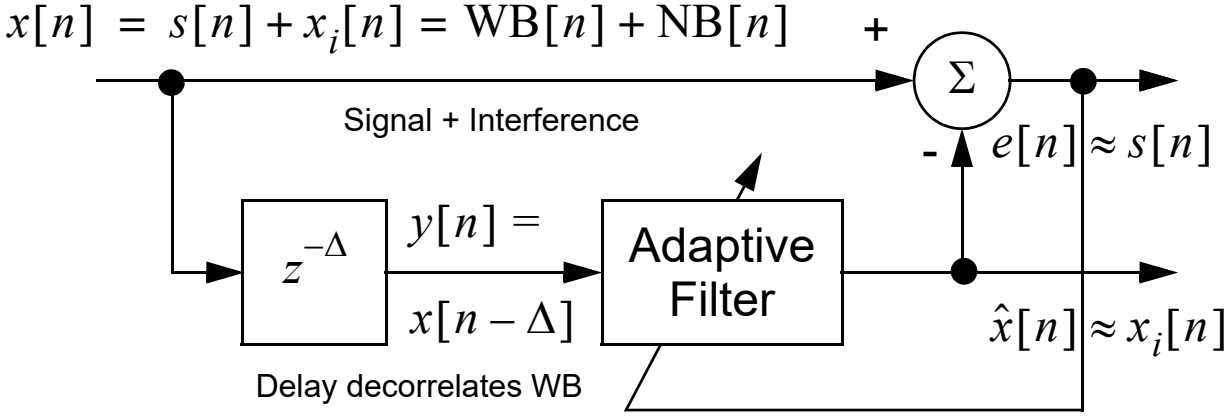


```
plot(F,Ao)
plot([0.05,0.05],[-40,0],'r')
ylabel(r'Frequency Response in dB')
xlabel(r'Normalized Frequency $\omega/(2\pi)$')
title('SNR = 10 dB: Sinewave')
grid();
```



- A C version of the above Python code will be very similar except all of the vector operations are replaced by `for` loops

Adaptive Interference Cancellation



- With the adaptive interference canceler the interference, $x_i[n]$, is formally present in two locations:
  - On the upper signal path additive with the signal of interest
  - Isolated on the lower signal path as possibly observed by a separate sensor, e.g., a microphone sensing outside the ear cup of noise canceling headphones)
- If a separate interference signal is not available it is possible to derive one from $s[n] + x_i[n]$ by decorrelating the wide and signal from narrow band interference as shown above

Python AIC Simulation

- An interference canceler can be obtained with a little bit of rework of the ALE code presented previously
- Here we consider narrow band interference in the form of a single sinusoid with the wide band signal being speech at 8 ksps

```
def lms_ic(s,SIR,N,M,delta,mu):
    """
```

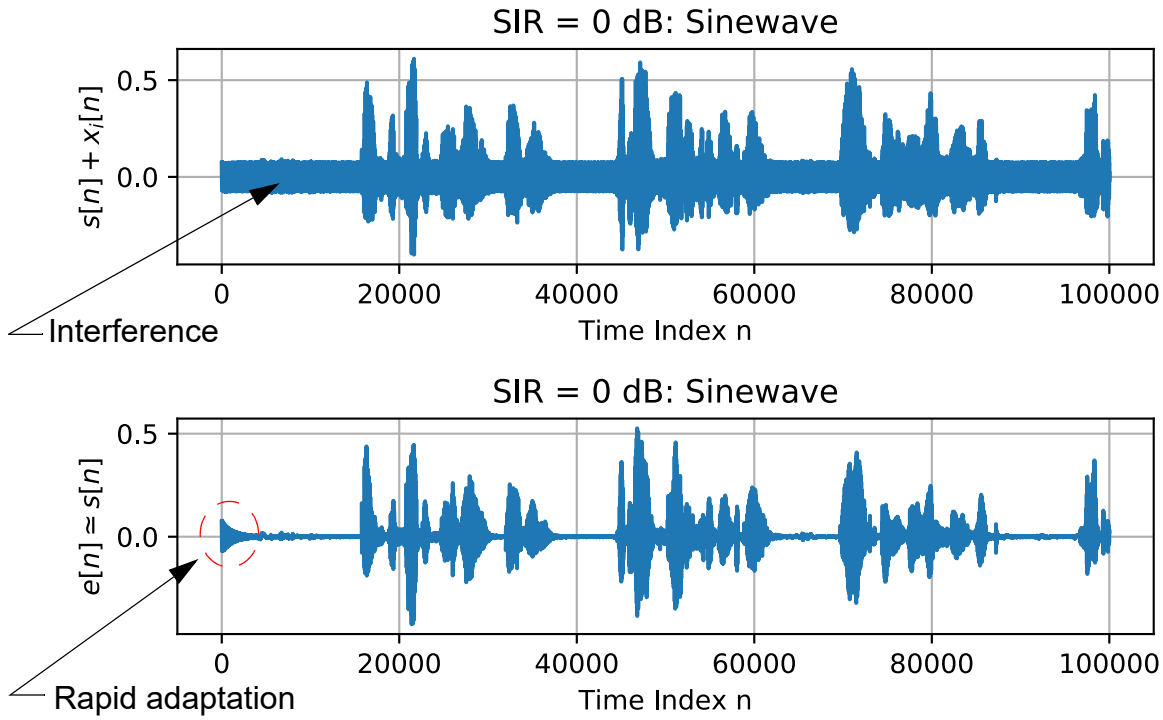
```
Adaptive interference canceller using LMS and FIR
n,x,x_hat,e,ao,F,Ao = lms_ic(s,SIR,N,M,delta,mu)

*******LMS Interference Cancellation Simulation************
     s = Input speech signal
   SIR = Speech signal power to sinusoid interference level in dB
     N = Number of simulation samples
     M = FIR Filter length (order M-1)
 delta = Delay used to generate the reference signal
    mu = LMS step-size

     n = Index vector
     x = Noisy input
 x_hat = Filtered output
     e = Error sequence
    ao = Final value of weight vector
     F = Frequency response axis vector
    Ao = Frequency response of filter
**************************************
Mark Wickert, November 2014
"""

# Input signal SIR = var(s)/(A^2/2)
n = arange(0,N+1) # actually length N+1
x_i = cos(2*pi*1/20*n) # Here A = 1, Fo/Fs = 1/20
s = s[:N+1] # the input speech vector truncated to the length N+1
Ps = var(s) #estimate the AC power in s
x = s + sqrt(2*Ps*10**(-SIR/10))*x_i
# Form the reference signal y via delay delta
y = signal.lfilter(hstack((zeros(delta), [1])),1,x)
# Initialize output vector x_hat to zero
x_hat = zeros_like(x)
# Initialize error vector e to zero
e = zeros_like(x)
# Initialize weight vector to zero
ao = zeros(M+1)
# Initialize filter memory to zero
zi = signal.lfiltic(ao,1,y=0)
# Initialize a vector for holding ym of length M+1
ym = zeros_like(ao)
for k,yk in enumerate(y):
   # Filter one sample at a time
   x_hat[k],zi = signal.lfilter(ao,1,array([yk]),zi=zi)
   # Form the error sequence
   e[k] = x[k] - x_hat[k]
   # Update the weight vector
   ao = ao + 2*mu*e[k]*ym
   # Update vector used for correlation with e[k]
   ym = hstack((array(yk), ym[0:-1]))
# Create filter frequency response
F = arange(0,0.5,1/512)
w,Ao = signal.freqz(ao,1,2*pi*F)
Ao = 20*log10(abs(Ao))
return n,x,x_hat,e,ao,F,Ao
```

- Running in the Jupyter notebook, we import a speech test vector

```
fs,s = ss.from_wav('OSR_us_000_0030_8k.wav')
from IPython.display import Audio, display
Audio('OSR_us_000_0030_8k.wav')
```

- We now run the simulation

```
n,x,x_hat,e,ao,F,Ao = lms_ic(s,0,100000,64,2,.005)

subplot(211)
plot(n,x)
ylabel(r'$s[n] + x_i[n]$')
xlabel(r'Time Index n')
title('SIR = 0 dB: Sinewave')
grid();
subplot(212)
plot(n,e)
ylabel(r'$e[n] \simeq s[n]$')
xlabel(r'Time Index n')
title('SIR = 0 dB: Sinewave')
grid();
tight_layout()
```



Cortex-M4 Implementation

- The CMSIS-DSP library contains adaptive LMS filters

Least Mean Square (LMS) Filters

Filtering Functions

Functions

void **arm_lms_f32** (const **arm_lms_instance_f32** *S, **float32_t** *pSrc, **float32_t** *pRef, **float32_t** *pOut, **float32_t** *pErr, uint32_t **blockSize**)
Processing function for floating-point LMS filter.

void **arm_lms_init_f32** (**arm_lms_instance_f32** *S, uint16_t numTaps, **float32_t** *pCoeffs, **float32_t** *pState, **float32_t** mu, uint32_t **blockSize**)
Initialization function for floating-point LMS filter.

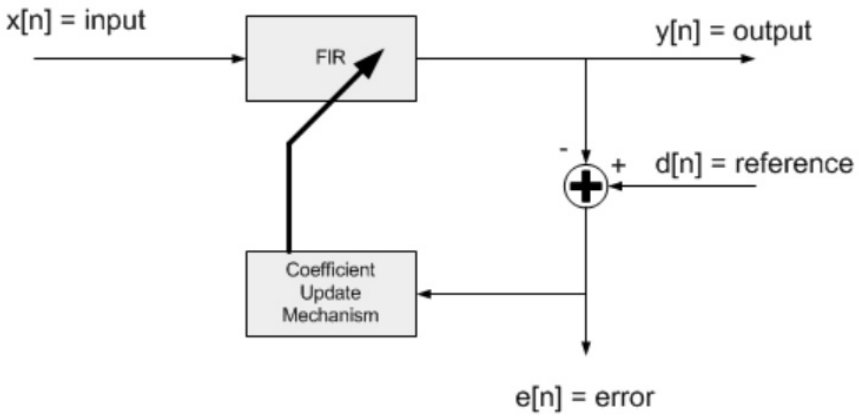
void **arm_lms_q15** (const **arm_lms_instance_q15** *S, **q15_t** *pSrc, **q15_t** *pRef, **q15_t** *pOut, **q15_t** *pErr, uint32_t **blockSize**)
Processing function for Q15 LMS filter.

void **arm_lms_q31** (const **arm_lms_instance_q31** *S, **q31_t** *pSrc, **q31_t** *pRef, **q31_t** *pOut, **q31_t** *pErr, uint32_t **blockSize**)
Processing function for Q31 LMS filter.

Description

LMS filters are a class of adaptive filters that are able to "learn" an unknown transfer functions. LMS filters use a gradient descent method in which the filter coefficients are updated based on the instantaneous error signal. Adaptive filters are often used in communication systems, equalizers, and noise removal. The CMSIS DSP Library contains LMS filter functions that operate on Q15, Q31, and floating-point data types. The library also contains normalized LMS filters in which the filter coefficient adaptation is indepedent of the level of the input signal.

An LMS filter consists of two components as shown below. The first component is a standard transversal or FIR filter. The second component is a coefficient update mechanism. The LMS filter has two input signals. The "input" feeds the FIR filter while the "reference input" corresponds to the desired output of the FIR filter. That is, the FIR filter coefficients are updated so that the output of the FIR filter matches the reference input. The filter coefficient update mechanism is based on the difference between the FIR filter output and the reference input. This "error signal" tends towards zero as the filter adapts. The LMS processing functions accept the input and reference input signals and generate the filter output and error signal.



Internal structure of the Least Mean Square filter

The functions operate on blocks of data and each call to the function processes `blockSize` samples through the filter. `pSrc` points to input signal, `pRef` points to reference signal, `pOut` points to output signal and `pErr` points to error signal. All arrays contain `blockSize` values.

The functions operate on a block-by-block basis. Internally, the filter coefficients `b[n]` are updated on a sample-by-sample basis. The convergence of the LMS filter is slower compared to the normalized LMS algorithm.

Instance Structure

The coefficients and state variables for a filter are stored together in an instance data structure. A separate instance structure must be defined for each filter and coefficient and state arrays cannot be shared among instances. There are separate instance structure declarations for each of the 3 supported data types.

Initialization Functions

There is also an associated initialization function for each data type. The initialization function performs the following operations:

- Sets the values of the internal structure fields.
- Zeros out the values in the state buffer. To do this manually without calling the init function, assign the follow subfields of the instance structure: numTaps, pCoeffs, mu, postShift (not for f32), pState. Also set all of the values in pState to zero.

Use of the initialization function is optional. However, if the initialization function is used, then the instance structure cannot be placed into a const data section. To place an instance structure into a const data section, the instance structure must be manually initialized. Set the values in the state buffer to zeros before static initialization. The code below statically initializes each of the 3 different data type filter instance structures

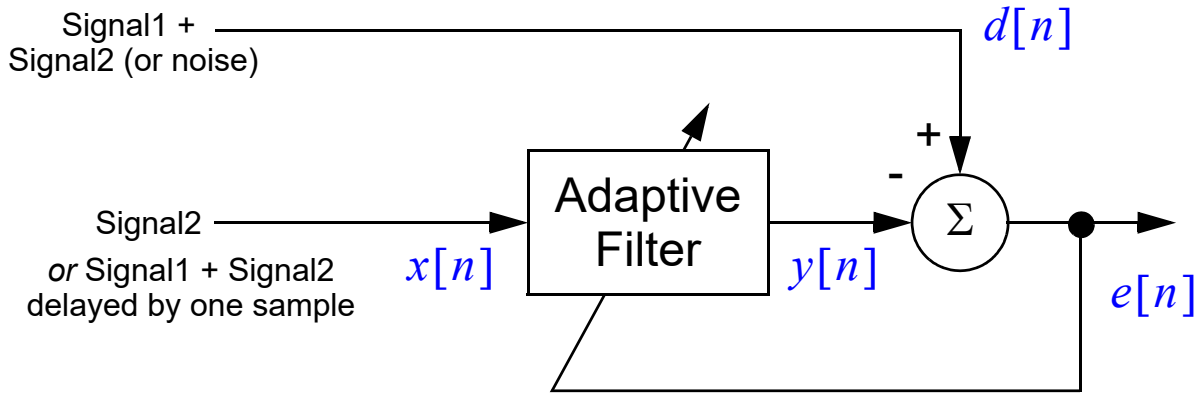
```
arm_lms_instance_f32 S = {numTaps, pState, pCoeffs, mu};
arm_lms_instance_q31 S = {numTaps, pState, pCoeffs, mu, postShift};
arm_lms_instance_q15 S = {numTaps, pState, pCoeffs, mu, postShift};
```

where `numTaps` is the number of filter coefficients in the filter; `pState` is the address of the state buffer; `pCoeffs` is the address of the coefficient buffer; `mu` is the step size parameter; and `postShift` is the shift applied to coefficients.

- The next steps are to develop some examples using custom code and using the CMSIS-DSP library for comparison

Adaptive Line Enhancer and Interference Cancellor on the FM4

- A combination adaptive line enhancer and interference cancellor example is available inside `Lab_6_UART_Adaptive.zip`
- The source file `FM4_Adaptive_intr.c` uses the GUI slider control to allow a single application file to implement different adaptive filter implementations:
  - Interference canceling
  - Adaptive line enhancement (ALE)



- The CMSIS-DSP function `arm_lms_f32()` is used as the adaptive filter kernel in both cases with the notation of that function configured in code as follows:

$$d[n] \Leftarrow \begin{cases} \text{left\_in\_sample} \cdot \text{P\_vals}[0] \\ \quad + \text{right\_in\_sample} \cdot \text{P\_vals}[1], & \text{P\_vals}[3] = 0 \\ \text{left\_in\_sample} \cdot \text{P\_vals}[0] \\ \quad + \text{noise} \cdot \text{P\_vals}[1], & \text{P\_vals}[3] = 1 \end{cases} \tag{8.25}$$

$$x[n] \Leftarrow \begin{cases} \text{left\_in\_sample}, & \text{P\_vals}[4] = 0 \\ d[n-1], & \text{P\_vals}[4] = 1 \end{cases} \tag{8.26}$$

$$y[n] \Rightarrow \text{left\_output\_sample} \tag{8.27}$$

$$e[n] \Leftarrow \text{right\_out\_sample} \tag{8.28}$$

Change app with Filter Path = P_vals[3]

- For the interference canceling scenario the input $x[n]$ is a version of just interference portion of $d[n]$ which is composed of both the desired signal plus the interference
- For the adaptive line enhancer the input $x[n]$ is a copy of $d[n]$ delayed by one sample
- Delaying $d[n]$ by one sample uncorrelates the broadband component of $d[n]$ from itself, meaning that the adaptive filter will be ignoring this input
- The outputs for both algorithms need some interpretation too:
  - With the interference canceler the error signal $e[n]$ should contain the desired signal with the interference removed
  - For the ALE the broadband component, e.g., noise or speech, is returned on $e[n]$ and the narrowband component is recovered on $y[n]$
- Main module code listing:

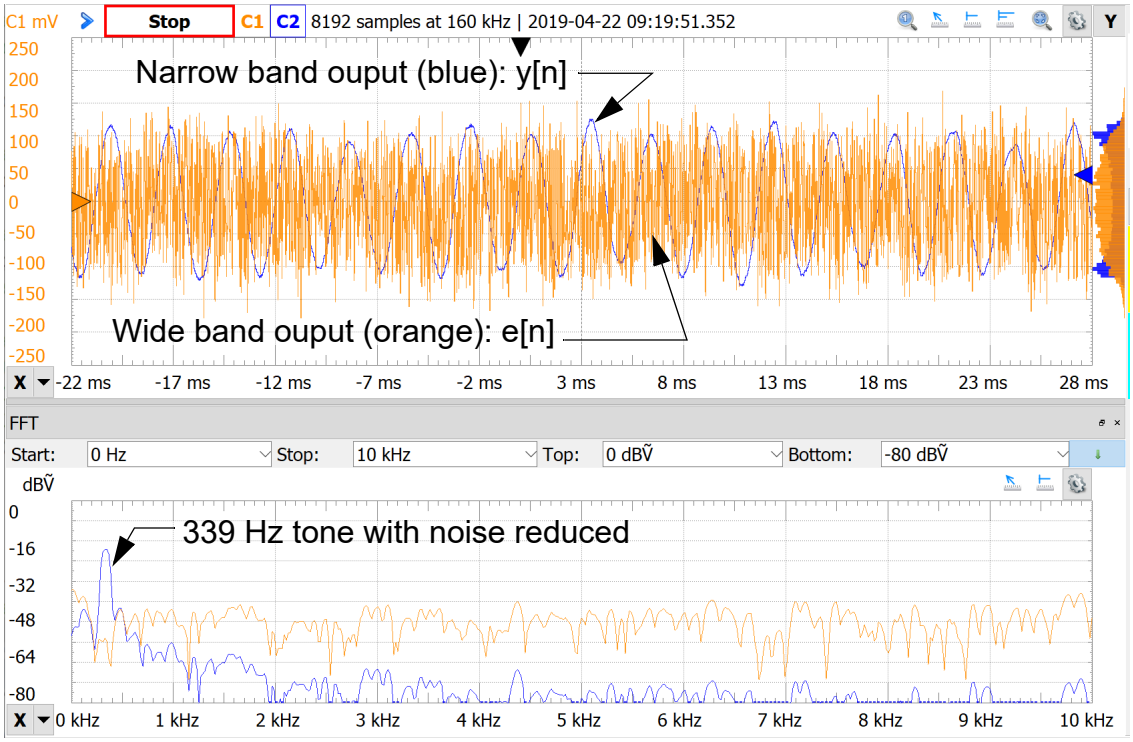
```
// fm4_adaptive_intr_GUI.c

#include "fm4_wm8731_init.h"
#include "FM4_slider_interface.h"

int32_t rand_int32(void); // prototype for random number generator

// Create (instantiate) GUI slider data structure
struct FM4_slider_struct FM4_GUI;

//CMSIS-DSP adaptive filter structure
arm_lms_instance_f32 LMS1;
//arm_lms_norm_instance_f32 LMS1;
uint16_t Ntaps = 100;
float32_t a_coeff[100];
float32_t states[100];
float32_t mu = 1e-13;

float32_t x_inter, x_noise, x_speech;
float32_t y, y_hat, error;
float32_t y_del = 0.0f;
```

```
void PRGCRC_I2S_IRQHandler(void)
{
  union WM8731_data sample;
  //int16_t xL, xR;

  gpio_set(DIAGNOSTIC_PIN,HIGH);
  // Get L/R codec sample
  sample.uint32bit = i2s_rx();

  // Map L & R inputs to adaptive filter variable names
  x_noise = (float32_t)(((short)rand_int32())>>2);
  x_inter = (float32_t)sample.uint16bit[LEFT];
  x_speech = (float32_t)sample.uint16bit[RIGHT];
  if (FM4_GUI.P_vals[3] < 1)
  {
    // Used for interference canceller
    y = FM4_GUI.P_vals[0]*x_inter + FM4_GUI.P_vals[1]*x_speech;
  }
  else
  {
    // Used for ALE (note noise is generated internally)
    y = FM4_GUI.P_vals[0]*x_inter + FM4_GUI.P_vals[1]*x_noise;
  }
  if (FM4_GUI.P_vals[3] < 1) // For interference cancelling
  {
    // input/src  ref  output  error  blk size
    arm_lms_f32(&LMS1, &x_inter, &y, &y_hat, &error, 1);
  }
  else // ALE where input is tone + noise
  {
    // input/src  ref  output  error  blk size
    arm_lms_f32(&LMS1, &y_del, &y, &y_hat, &error, 1);
  }
  //arm_lms_norm_f32(&LMS1, &y_del, &y, &y_hat, &error, 1);
  y_del = y; // update one sample delayed version of the reference input

  // Return L/R samples to codec via C union
  sample.uint16bit[LEFT] = (int16_t) y_hat;
  sample.uint16bit[RIGHT] = (int16_t) error;
  i2s_tx(sample.uint32bit);

  NVIC_ClearPendingIRQ(PRGCRC_I2S_IRQn);

  gpio_set(DIAGNOSTIC_PIN,LOW);
}

int main(void)
{
  // Initialize the slider interface by setting the baud
  // rate (460800 or 921600)
  // and initial float values for each of the 6 slider parameters

  init_slider_interface(&FM4_GUI,460800, 1.0, 1.0, 1.0, 1.0, 0.0, 0.0);
```

```
  // Send a string to the PC terminal
  write_uart0("Hello FM4 World!\r\n");

  // Initialize LMS
  arm_lms_init_f32(&LMS1,Ntaps,a_coeff,states,mu,1);
  //arm_lms_norm_init_f32(&LMS1,Ntaps,a_coeff,states,mu,1);

  // Some #define options for initializing the audio codec interface:
  // FS_8000_HZ, FS_16000_HZ, FS_24000_HZ, FS_32000_HZ, FS_48000_HZ,
  // FS_96000_HZIO_METHOD_INTR, IO_METHOD_DMA
  // WM8731_MIC_IN, WM8731_MIC_IN_BOOST, WM8731_LINE_IN
  fm4_wm8731_init (FS_48000_HZ,                // Sampling rate (sps)
                   WM8731_LINE_IN,             // Audio input port
                   IO_METHOD_INTR,             // Audio samples handler
                   WM8731_HP_OUT_GAIN_0_DB,    // Output hphone jack Gain (dB)
                   WM8731_LINE_IN_GAIN_0_DB); // Line-in input gain (dB)
  while(1){
    // Update slider parameters
    update_slider_parameters(&FM4_GUI);
    // Update LMS mu if slider parameter changes
    if(FM4_GUI.P_idx == 2)
    {
      mu = FM4_GUI.P_vals[2]*1e-13f;
      arm_lms_init_f32(&LMS1,Ntaps,a_coeff,states,mu,1);
    }
  }
}

int32_t rand_int32(void)
{
  static int32_t a_start = 100001;

  a_start = (a_start*125) % 2796203;
  return a_start;
}
```

- Capture some screen-shots of the running application

- ALE - fully adapted



- AIC - fully adapted