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Design and development of an adaptive prediction filter for cancellation of narrowband noise interference in wideband signal

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***Abstract*-Adaptive filters are used in cases where signal conditions, system parameters change and the design should be such that its parameters will be adjusted to compensate for this chance. The Least Mean Square (LMS) criterion is a search algorithm that can be used to provide the strategy for adjusting the filter coefficients. In conventional FIR and IIR filters, the process parameters that determine the filter characteristics are known. In many real time problem, the parameters change with respect to time and un-predictive in nature. The coefficients of an adaptive filter are adjusted to compensate for changes in input signal, output signal and system parameters. A number of adaptive structures have been used for different applications in adaptive filtering . Some of these are used in narrowband noise cancellation and identification processing using LMS algorithm are performed under MATLAB and TMS320C6713DSK environments. The software and hardware implementation are discussed.**

Keywords-Adaptive filter, LMS, Narrowband interference cancellation, DSP Processor

I. INTRODUCTION

Signal processing has developed enormously due to increase of technology for implementing the different algorithms. The term adaptive is defined as the ability of the system to adjust parameters according to its state and the environment of surroundings[1]. The filter is used to designed for the extract the desired information which is contained in a signal. It has a relation between two signals in real time and realized either as a set of programming instructions running on a arithmetical processing device as microprocessor, DSP chip, set of logical operations ehich are implemented in FPGA or VLSI circuits[3]. Adaptive filters are mostly used where the signal conditions or system parameters are changing then the filters are adjusted to compensate the change. A filter is a system which is used for retaining all the frequency components which belongs to particular frequencies. The Least Mean Square(LMS) is a serch algorithm which is used to adjust the filter coefficients.

Historically adaptive filters represents a part of statistical signal processing in which they have found the parametric approach is a main engineering approach for the signal processing which is based on a “Priori” model which is derived from the scientific knowledge which mean the problem. Adaptive filter applications in diverse fields are included as a communication, controls, robotics, Sonar, radar, seismology and biomedical engineering.[2]

II. ADAPTIVE FILTERS

Adaptive filters are best used in cases where signal conditions or system parameters are slowly changing and the adaptive filter are adjusted to compensate for this change. The Least Mean Square (LMS) is a search algorithm which can be used to provide the strategy for adjusting the coefficients.

In conventional FIR and IIR filters, it is given that processor parameters are determined the filter characteristics are known which may vary by time but the environment of variations are assumed to be known. In practical problems there is a uncertainty in some parameters because of inadequate prior test data about the process. Some parameters might be expected to change with time, but the exact nature of the change is not predictable. In this cases it’s highly desirable to design the adaptive filter to be self-learning and it can adapt itself to the situation at hand.

The coefficients of adaptive filter are adjusted to compensate for changes in input signal, output signal, or system parameters. An adaptive system can learn the system characteristics and track slow changes. It can be very useful when there will be uncertainty about the characteristics of a signal or the environmental changes.

The adaptive filter are defined in four steps:

1. The filter is processing the “signals”
2. The ‘structure’ defines how the output signal of the filter is computed with its input signal
3. pThe parameters within the structure that can be iteratively changed to alter the filter input output relation
4. The adaptive algorithm which describes the parameters are adjusted from one time to another

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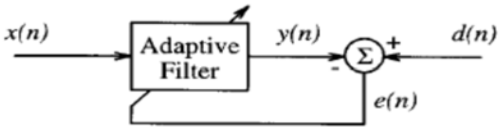

Figure 1. Adaptive Filter

From the fig.1 the digital filter computes the output y(n) in response to the input signal x(n) which generates the error signal e(n) by comparing the y(n) with desired response d(n) which is known as reference signal shown in fig.1 and the feedback signal is known as error signal e(n)[2]. which is used for adaptive algorithm for adjusting the tap weight of digital filter the output signal is compared to the second signal d(n) called desired response signal, by subtracting two samples at time t, difference signal is given by[1,2,3]

$$e(n) = d(n) - y(n) \quad (1)$$

The LMS searching algorithm with a linear combiner (FIR filter) there are several strategies for performing adaptive filtering the output of the adaptive filter is

$$y(n)=\sum_{k=0}^{N-1} w_k(n)x(n-k) \quad (2)$$

$w_k(n)$ represents N weights for a specific time n. It is common practice to use the terminology of weights w for the coefficients associated with the topics in adaptive filtering and neural network

Equ 1. Is the difference between the desired signal d(n) and the adaptive filters output y(n). the weights $w_k(n)$ are adjusted such that a mean squared error function is minimized. This mean square error function is $E[e^2(n)]$ where E is expected value.since there are k weights a fradient of the mean square error function is required. An estimation can be found instead of using the gradient of $e^2(n)$ [3]

$$w_k(n+1)=w_k(n)+2\beta_e(n)x(n-k) \quad (3)$$

where k=0,1,. N-1

From LMS algorithm [2,3] and equ 3. This provides a simple and powerful efficient weights or coefficients without differentiating and will be used for implementing adaptive filters. The input of adaptive filter is x(n), and the rate of convergence and accuracy of the adaption process which step size is β.

For each specific time *n*, each coefficient, or weight, *wk*(*n*) is updated or replaced by a new coefficient, based on (3), unless the error signal *e*(*n*) is zero. After the filter's output *y*(*n*), the error signal *e*(*n*) and each of the coefficients *wk*(*n*) are updated for a specific time *n*, a new sample is acquired
(from an ADC) and the adaptation process is repeated for a different time. Note that from (3), the weights are not updated when *e*(*n*) becomes zero.

The linear adaptive combiner is one of the most useful adaptive filter structures and is an adjustable FIR filter. Whereas the coefficients of the frequency-selective FIR filter are fixed, the coefficients, or weights, of the adaptive FIR filter can be adjusted based on a changing environment such as an input signal. Adaptive IIR filters (not discussed here) can also be used. A major problem with an adaptive IIR filter is that its poles may be updated during the adaptation process to values outside the unit circle, making the filter unstable.

III. ADAPTIVE STRUCTURES

A number of adaptive structure have been used for different applications in adaptive filtering.

1. For noise cancellation: The desired signal d is corrupted by uncorrelated additive noise n. the input to the adaptive filter is a noise ń that is correlated with the noise n. the noise ń could come from the same source as n but modified by the environment. The adaptive filter output y is adpted to the noise n. when this happrns, the error signal approaches the desired signal d. the overall output is this error signal and not the adaptive filters output y.

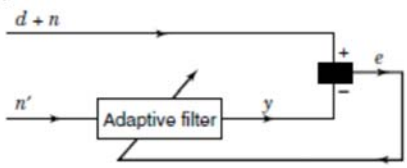

Figure 2: Noise cancellation

2. For system identification. Figure 3 shows an adaptive filter structure that can be used for system identification or modeling. The same input is to an unknown system in parallel with an adaptive filter. The error signal e is the difference between the response of the unknown system d and the response of the adaptive filter y. This error signal is fed back to the adaptive filter and is used to update the adaptive filter's coefficients until the overall output *y*=*d*. When this happens, the adaptation process is finished, and *e* approaches zero. In this scheme, the adaptive filter models the unknown system.

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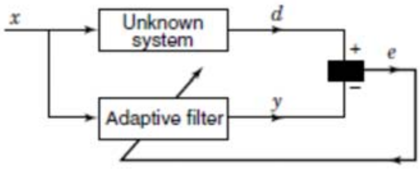

Figure 3: System Identification

3. Adaptive predictor. The desired signal d(n) is assumed to have predictable signal components[3] this signal is delayed by Δ samples to form the input signal u(n)=d(n-Δ) for the adptive filter to minimize the error signal e(n).

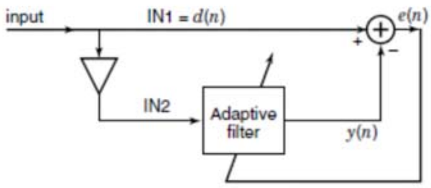

Figure 4: adaptive predictor

4. Additional structures have been implemented, such as:
   a) Notch with two weights, which can be used to notch or cancel/reduce a sinusoidal noise signal. This structure has only two weights.
   b) Adaptive channel equalization, used in a modem to reduce channel distortion resulting from the high speed of data transmission over telephone channels.

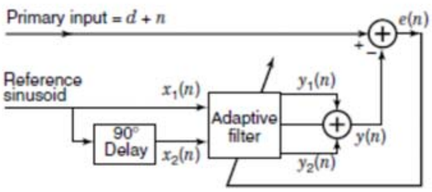

Figure 5: adaptive notch structure with two weights

IV. LEAST MEAN SQUARE (LMS) ALGORITHM

The LMS algorithm will be adjusting the filter coefficients to decrease the cost functions. When compared to the RLS algorithm it does not involve matrix operation so that, LMS require few computational recourses and memory than the RLS algorithm. LMS is less complicated when compared to RLS

Standard LMS algorithm: The LMS algorithm follows some operations for changing the coefficients of adaptive filter.

- It calculates the output signal y(n)
- It calculates the error signal e(n)
- Updates the coefficients

$$\overline{w}(n+1) = \overline{w}(n) + \mu.e(n).\overline{u}(n) \qquad (4)$$

μ is step size, $\overline{w}(n)$ is filter coefficient, $\overline{u}(n)$ filter input

Normalized LMS: Normalized LMS is the modified version of LMS algorithm it updates the coefficient by using the equation

$$\overline{w}(n+1) = \overline{w}(n) + \mu.e(n).\frac{\overline{u}(n)}{\|\overline{u}(n)\|^2} \qquad (5)$$

$$\overline{w}(n+1) = \overline{w}(n) + \mu.e(n).\overline{u}(n) \qquad (6)$$

Where $\mu(n) = {}^{\mu}/_{\|\overline{u}(n)\|^2}$ within the previous equation, the NLMS rule becomes constant because the standard LMS rule except that the NLMS algorithm in corporate a time-varying step size μ(n). This step size will improve the convergence speed of the adaptive filter.

Leaky LMS: The cost perform of the leaky LMS rule is outlined by the subsequent equation:

$$j(n) = e^2(n) + a\sum_{i=0}^{N-1} w_i^2(n) \qquad (7)$$

where α is that the leaky issue with a spread of (0, 0.1). Owing to the presence of α, the value perform of the leaky LMS rule is completely different from that of the standard LMS algorithm. The leaky LMS rule mitigates the coefficients overflow downside, as a result of the value perform of this rule accounts for each $e^2(n)$ and therefore the filter coefficients. The leaky LMS rule updates the coefficients of associate degree accommodative filter by mistreatment the subsequent equation:

$$j(n) = e^2(n) + a\sum_{i=0}^{N-1} w_i^2(n) \qquad (8)$$

$$\overline{w}(n+1) = (1-\mu c).\overline{w}(n) + \mu.e(n).\overline{u}(n) \qquad (9)$$

If α = 0, the leaky LMS algorithm becomes constant because the common place LMS an outsized leaky issue leads to a large steady state error. Use the AFT produce FIR LMS VI associate degreed specify associate degree acceptable worth for the leak parameter to make an accommodative filter with the leaky LMS rule.

Normalized Leaky LMS: The normalized leaky LMS rule could be a changed style of the leaky LMS algorithm. This updates the coefficients of associate degree accommodative adaptive filter by mistreatment the subsequent equation:

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$$\bar{w}(n+1) = (1-\mu c).\bar{w}(n) + \mu.e(n).\frac{u(n)}{\|u(n)\|^2}$$
(10)

The LMS is well suited for a number of applications, including adaptive echo and noise cancellation, equalization and prediction. Other variants of the LMS algorithm have been employed, such as the sign-error LMS the sign-data and sign-sign LMS

(i) For the sign-error LMS algorithm
$w_k(n+1) = w_k(n) + \beta sgn[e(n)]x(n-k)$(11)
Where sgn is the signum function,

$$\text{Sgn}(u)=\begin{cases}1 & if\ u \geq 0\\ -1 & if\ u < 0\end{cases} \qquad (12)$$

(ii) For the sign-data LMS algorithm
$w_k(n+1) = w_k(n) + \beta e(n) sgn[x(n-k)]$(13)
(iii) For the sign-sig LMS algorithm
$w_k(n+1) = w_k(n) + \beta sgn[e(n)]x(n-k)$(14)
Which reduces to
$w_k(n+1)=$
$$\begin{cases} w_k + \beta & if\ sgn[e(n)] = sgn[x(n-k)] \\ w_k - \beta & otherwise\end{cases} \qquad (15)$$

V. ERROR MEASUREMENTS

Adaptation of the filter coefficients follows a decrease procedure of a selected objective or value perform. This perform is often outlined as a norm of the error signal e(k). The 3 most typically utilized norms are the mean-square error (MSE), the instant sq. error (ISE), and also the weighted least-squares (WLS), that are introduced below.

The mean-square error

The MSE is defined as

$$\xi(k)=E[e^2(k)]=E[d(k)-y(k)^2] \qquad (16)$$
Writing the output signal y(k) obtains
$$\xi(k) = E[|d(k)-w^Tx(k)|^2] \qquad (17)$$

$$=E[d^2(k)]-2w^TE[d(k)x(k)]+w^TE[x(k)x^T(k)]w$$
$$=E[d^2(k)]-2w^Tp+w^TRw \qquad (18)$$

where R and p are the input-signal correlation matrix and the cross-correlation vector between the reference signal and the input signal, respectively, and are defined as
$$R = E[x(k)xT(k)], \qquad (19)$$
$$p = E[d(k)xT(k)]. \qquad (20)$$
Note, from the above equations, that R and p are not representing as a purpose of the iteration k or not time-varying, due to the assumed inactive of the input and reference signals. From Equation (2.5), the grade vector of the MSE function with respect to the adaptive filter coefficient vector is given as
$$\nabla w\xi(k) = -2p+2Rw. \qquad (21)$$
So it is called as a Wiener solution wo, that decreases the MSE cost function, which is obtained by a equation of the gradient vector in zero. Assuming that R is non-singularize;
$$wo = R-1p. \qquad (22)$$

The instantaneous square error

The MSE is the cost function which requires information about the error function e(k) at the time k. For that purpose, so that MSE cannot be determined exactly in practice and is commonly have the approximation by other cost functions. The easy form for estimating the MSE function is to work with the ISE which is given by
$$\xi(k)=e^2(k) \qquad (23)$$
The gradient vector with respect to the coefficient is determined as
$$\begin{aligned}\nabla_w \xi(k)&=2e(k)\, \nabla_w e(k)\\ &=2e(k)\, \nabla_w[d(k)-w^Tx(k)]\\ &=-2e(k)x(k) \qquad (24)\end{aligned}$$
This vector can be seen as a noisy estimate of the MSE gradient vector defined in Equation (30) or as a precise gradient of the ISE function, which, in its own turn, is a noisy estimate of the MSE cost function

VI. HARDWARE AND SOFTWARE ANALYSYS

The hardware used in this project is TMS320C6713 DSK which is low priced standalone development plotform that allow the users to develop the TI C6XX DSP family[11]. Therse are used in large kind og applications

- A TX Instruments TMS320C6713 DSP operative at 225 MHz.
- An AIC23 stereo codec
-
- eight Mbytes of synchronous DRAM
- 512 Kbytes of non-volatile nonvolatile storage (256 Kbytes usable in default configuration)
- Four user accessible LEDs and DIP switches
- software system board configuration through registers enforcedin CPLD
- Configurable boot choices
- customary enlargement connectors for girl card use
- JTAG emulation through on-board JTAG mortal with USB host interface or external mortal
- Single voltage power provide (+5V) [11]

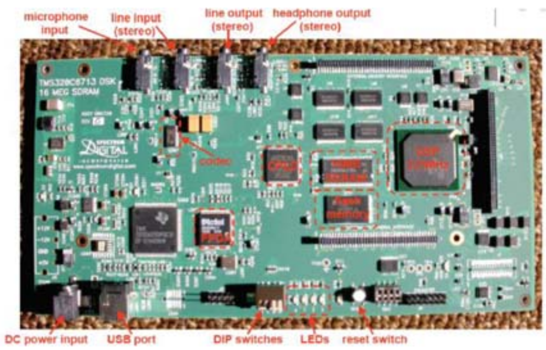

Figure 6: TMS320C6713 DSP kit

The software we use in this project is CODE COMPILER STUDIO (CCS) code. It provides an IDE to include the software package tools which has tools for code generation like a C compiler, an assembly program and a linker[4].

CCS communication with the board through the on-board JTAC emulator. Once all the documents are installed in code composer the DSK is connected to the laptop with the USB cable enclosed to DSK kit

Setup of adaptive interference cancellation:

For hardware implementation, the DSK board is initial high-powered up and connected to the computer via USB cable provided. CCS is interfaced with the board by clicking Debug>Connect among the program. Once connected, the steps in making a brand new project in Section s square measure taken. during this project, a stereo cable with 2 connecters at the top is created to get desired and unwanted signals from left and right channels. A stereo cable with BNC at the top is connected to the board to send output signals from codec to the CRO

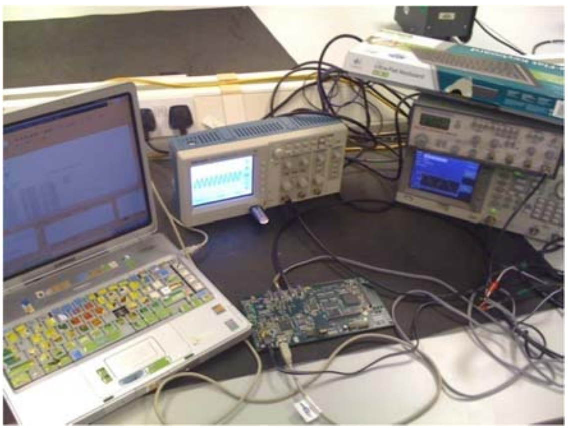

Figure 7 Experimental setup

VII. RESULT ANALYSIS

To create the simulation model of LMS algorithm a new matlab file is created. In the editor window the MATLAB code of LMS algorithm should be wrriten and saved The adding of desired signal and interference the output of the desired+noise signal is as

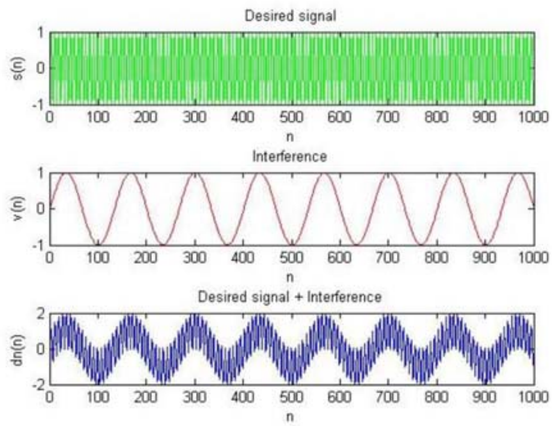

Figure 8 : Desired+Noise signal

The MATLAB implementation for system identification, system prediction and cancellation

1. System identification

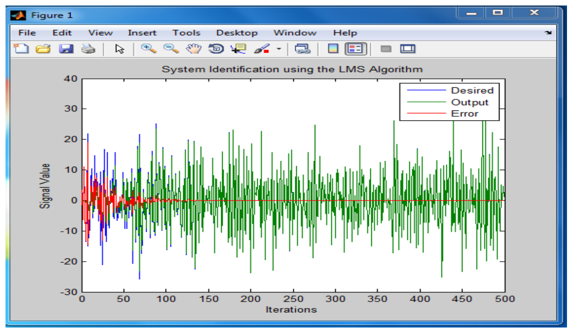

Figure 9 system identification

This picture shows the value of the desired response *d(n)*, the filter output *y(n)* and the estimation error *e(n)* varying according to the number of iterations. From the plot the track characteristics of the adaptive filter can be verified. It starts trying to identify the system, and after about 130 iterations over time, the error starts with a large disturbance until the filter reaches a good tracking of the system and the error starts to be near to its optimum value (zero).

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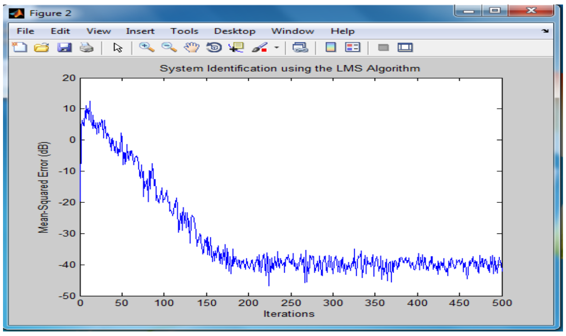

Figure 10 Mean square error of the LMS algorithm

The mean-squared error of the algorithm can be seen in the figure 10. The cost function of the LMS algorithm has as aim to minimize the MSE. From this figure it can be detected that after about 150 iterations of the filter, the MSE converges to the noise variance 0.01 or – 40 dB.

2. Linear Prediction

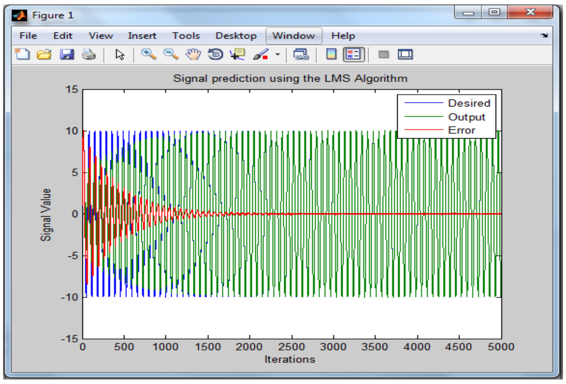

Figure 11 Desired signal output error of the LMS algorithm for the predicyion problem

The desired response *d(n)* (blue line) being tracked for the filter output *y(n)* (green line) and the error *e(n)* (red line), resultant of this comparison. It can be noticed that the algorithm presents a small error, near to its optimum value, about 2000 iterations after the initialization. The step-size μ was chosen to be equal to 0.01 after tests analysing the mean-squared error.

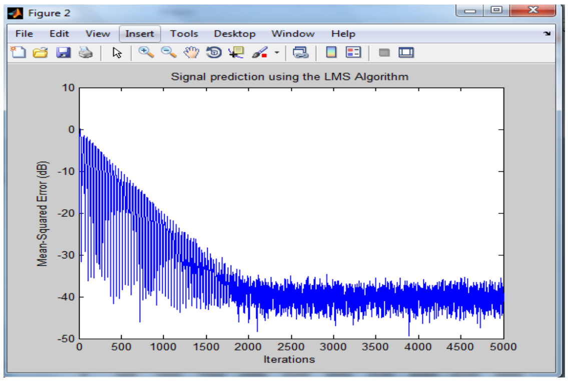

Figure 12: Mean Square error of the LMS algorithm

The figure 12 depicts the mean-squared error of the algorithm. By studying this figure, it can be detected that the algorithm converges after about the 2000th iteration, converging to the variance of the noise *n(n)* 0.01 or – 40dB.

3. LMS algorithm for cancellation results

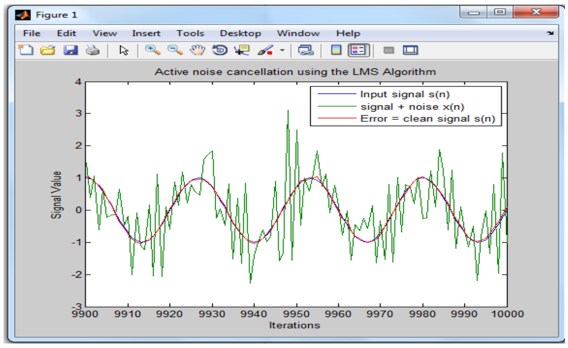

Figure 13 Result for LMS algorithm to the give problem

The figure 13 depicts the results obtained by applying the LMS algorithm for the given problem, containing the input signal *s(n)*, the desired signal *x(n)=s(n) + n2(n)* and the error signal, which should be equal to the input signal *s(n)*. The step-size parameter was chosen to be equal to 0.0002 and the adaptive filter has length 5. It can be seen in blue, the signal *s(n)*, the input signal. In green color it is presented the input signal after the noise corruption *s(n) + n2(n)*, and in red, the error signal *e(n)*.

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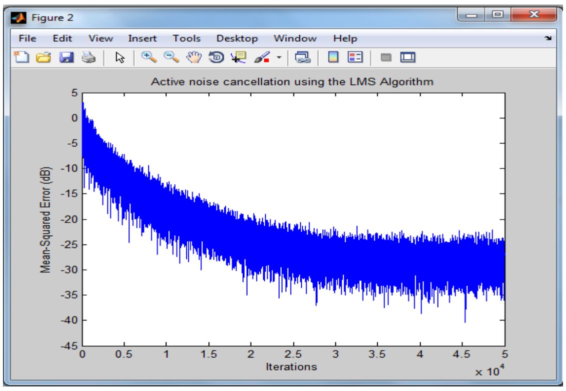


Figure 14 Mean Square error using LMS algorithm

The Experimental results by Hardware using DSP Kit

Filter Length

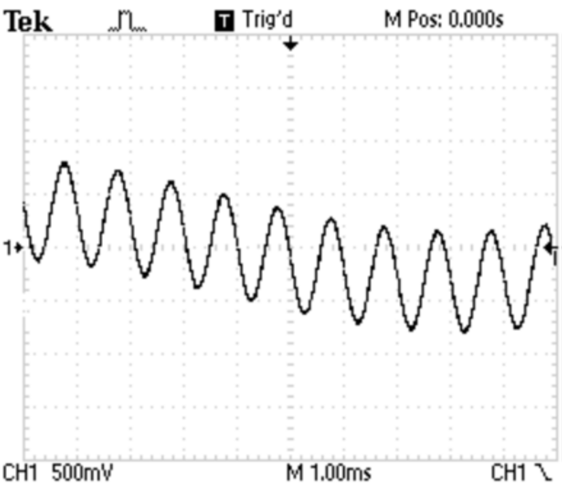
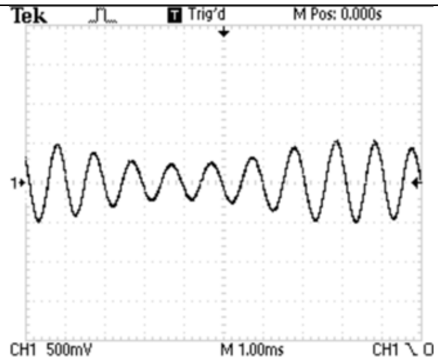
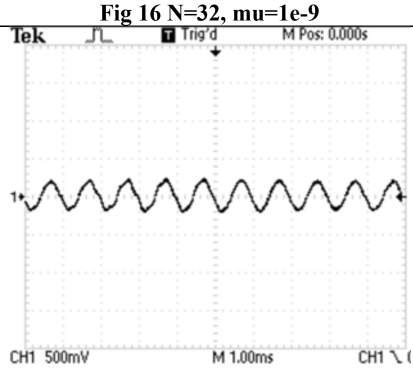


Figure 15 dn(n)=1KHz sinewave+1.5 Vpp 60KHz sinewave

To investigate the effect of filter length on the adaptive system performance, the desired signal s(n) and interference v(n) are applied to the system as shown in Figure 15. The experiment is carried with chosen step size mu=1e-9 while filter length is varied at N=32 and 64.

Filter length N	Output
32	 Fig 16 N=32, mu=1e-9
64	 Fig 17 N=64,mu=1e-9

Based on the waveforms above, it can be seen that with the same input parameters, the output signals are more alike with the desired signal when the filter length increases from 32 to 64. However, it is observed that the amplitude of the output signal is half to that of the desired signal. The convergence rate has close relationship with other system parameters such as the step size, filter length and input noise. The results above show that with the chosen step size, the performance of the adaptive filter is improved when filter length increases.

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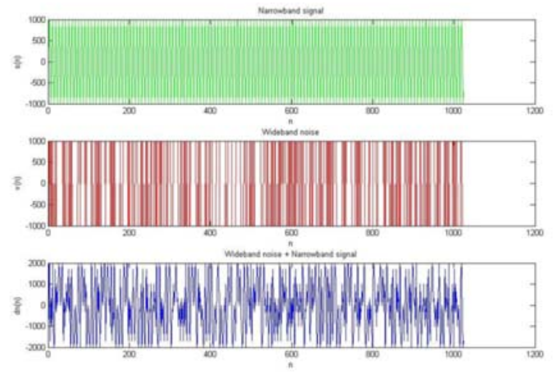

Figure 18 Narrowband +wideband

A 1kHz narrowband signal s(n) is added into a wideband signal v(n) to form a combined signal dn(n) as shown in Figure 65. Using an empirically chosen step size of 1e-9, the simulation model is tested based on various SNRs with fixed filter length of 64.

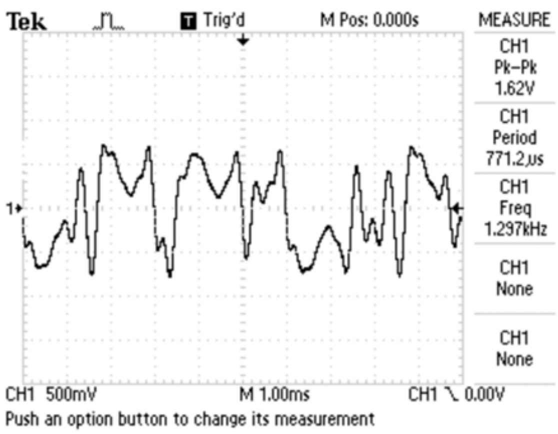

Figure 19 Wideband +Narrowband

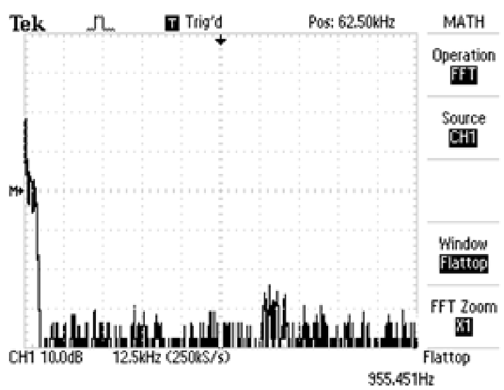

Figure 20 FFT of wideband+Narrowband

An external MATLAB file is created to generate a wideband signal. As for narrowband signal, it is sourced from an external function generator. These two signals are combined in the C code and processed by the adaptive FIR filter. A 2kHz narrowband signal is sourced to the left channel and the adaptive system step size and filter length are set to 1e-14 and 64 respectively. The experiment is tested under varying input power. By changing the SNR values when the narrowband signal is innreases the wideband signal will be decresed.

VIII. CONCLUSION

The main aim of this project is to design and develop an LMS based adaptive narrowband interference cancellation The main aim of the project is to design and development of an using a LMS algorithm for narrowband interference cancellation form wideband noise. In this we have implemented in different environments

First we have implemented a LMS algorithm cancellation in MATLAB code the results which are obtained are taken a screen shot and kept the results. The we have written the C code and implemented in the CCS software by interfacing the DSK kit, CRO and DSO to it. The results, which are saved in the DSO through pen drive, have been analyzed and outputs are placed.

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