

Development of an Adaptive Filter for Signal Processing

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Summary

Adaptive filters play an important role in digital signal processing. In this paper, a suitable MATLAB signal was provided for the experiment and our task is to develop an adaptive filter to process the provided signal. Critical investigation and analysis of the effectiveness of the filter were carried out and we also investigated how the filter's parameters affect its performance and the interpretations of the inferences were critically stated.

Key words:

Adaptive filter, input signal, LMS, Noise canceller

1. Introduction

Filtering is a process of altering the spectral content of an input signal (or data sequence) in a specified manner, i.e it is a process of removing noise from a measured process in order to enhance information about some quantity of interest. Any signal measuring process includes some degree of noise from various possible sources which means the desired signal may have added noise due to thermal or physical effects. Therefore, filtering process is done by filters whose magnitude or phase responses satisfy certain specifications in the frequency domain. Filter can be classified as either linear or non-linear, linear filter is a filter whose output is a linear function of the input and it is designed to minimize the effect of noise on the signal [1-2]. The term "Adaptive Filters" means the filters parameters like bandwidth and notch frequency change with time.

The contamination of a signal by noise is a problem often encountered in many situations. If the signal and noise occupy fixed and separate frequency bands then conventional filters are suitable but when signal or noise spectra vary with time, adaptive filters may be more suitable [3].

2. Application for Adaptive filters

Adaptive filters have been widely used in communication systems, control systems and various other systems in which the statistical characteristics of the signals to be filtered are either unknown in some cases. Some of the application includes:

- Adaptive antenna systems in which adaptive filters are used for beam steering.
- System modelling, in which adaptive filters is used as a model to estimate the characteristic of unknown system.
- Adaptive filter can be used as a Noise canceller.
- Adaptive filters can offer performance improvements over the more conventional parametrically bases filter design [4-5].

In this work, an adaptive filter was developed to process an input signal and the investigation of the effectiveness of filter's performance was examined. We did set the system up for proper equalization of inter symbol interference and for channel identification in digital communications receivers. And also for estimation and elimination of a noise component in some desired signals.

3. Principle of Adaptive Filters

The filter consists of an ordinary FIR subsection that generates an output $y(n)$ in response to an input $x(n)$. This output $y(n)$ is then compared with ideal reference signal $d(n)$ and error signal $e(n)$ is generated. The magnitude or this error is proportional to the difference between $y(n)$ and $d(n)$. The error signal is used in feedback configuration to modify the filter taps $h(k)$ where $k = 0 \dots 4$ until the difference between $y(n)$ and $d(n)$ is minimized. In order to obtain the optimum filter coefficients, if the autocorrelation function of $x(n)$ and cross-correlation function between $d(n)$ and $x(n)$ are known, the most suitable technique used to iterate towards an optimum solution is Least Mean Square (LMS). But before talking about LMS, we would like to use one of the Adaptive filters applications to explain its principle in details i.e. Adaptive filters as a Noise canceller.

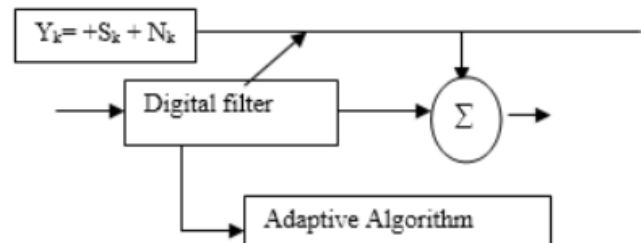


Fig. 1. Adaptive filters as a noise canceller

Please note the following:

- X_k : noise
- Y_k : Signal + Noise
- e_k : signal estimate
- \hat{n}_k : noise estimate
- $e_k = y_k - \hat{n}_k$

The processing element is a digital filter with adjustable coefficients (weight) and the adaptive algorithm adjusts the coefficients of the digital filter to achieve the best.

The adaptive filter inputs are: y_k : This represents contaminated signal which contains both the desired signal s_k and contaminating noise n_k ; therefore, $y_k = s_k + n_k$. x_k : This is a measure of the contaminating noise, n_k . Adaptive Filter output is $e_k = \hat{s}_k$: This represents estimated desired signal.

The two conditions that need to be met for adaptive filters to work well are:

1. Contaminated noise (n_k) is assumed not to be correlated with desired signal (S_k).
2. Measured of contaminated noise n_k is assumed to be correlated with noise estimate.

The estimate of the desired signal is then obtained by subtracting the digital filter output (i.e. \hat{n}_k) from the contaminated signal (y_k). i.e

$$e_k = y_k - \hat{n}_k = (s_k + n_k) - \hat{n}_k \tag{1}$$

The main function of an echo canceller is to produce an optimum estimate of the noise in contaminated signal and hence an optimum estimate of desired signal.

The output signal e_k serves two purposes:

1. Is an estimate of desired signal i.e \hat{s}_k
2. It is an error signal use to adjust the digital filter coefficients.

4. Implementation of Noise Canceller

The digital filter part of noise canceller can be implemented with a Finite Impulse Response (FIR) filter or Infinite Impulse Response (IIR) structure. The FIR structure is the most widely used because of its simplicity and guaranteed stability.

The adaptive algorithm part of the noise canceller is used to adjust the digital filter coefficients in such a way that the error signal e_k is minimized. The most common adaptive algorithm Least Mean Square (LMS).LMS is the most efficient in terms of computation and storage requirements and this does not suffer from numerical instability inherent in other algorithm [9-10].

5. Design of LMS Algorithm

LMS is based on the steepest descent algorithm where the weight vector is updated sample by sample. The aim of the steepest descent algorithm is to move along the error surface progressively toward optimum solution (minimum J). The error surface represents the mean square error (J) and this is given as

$$J = E(e^2_k) \tag{2}$$

Using the steepest technique, the change in weight from one iteration to the next can be expressed as $-\mu\Delta k$ or $W_{k+1} = w_k - \mu\Delta k$

- Where w_k = the current weight vector
- W_{k+1} is updated weight vector
- Δk is the gradient weight vector
- μ controls the stability and rate of convergence

Note that the weights obtained by LMS algorithm are only estimate, but the estimates improve gradually with time as the weight is adjusted and filter learns the characteristics of the signal [6-9].

6. Implementation of Least Mean Square

The computational procedure for the implementation of Least Mean Square can be illustrated in a flowchart below:

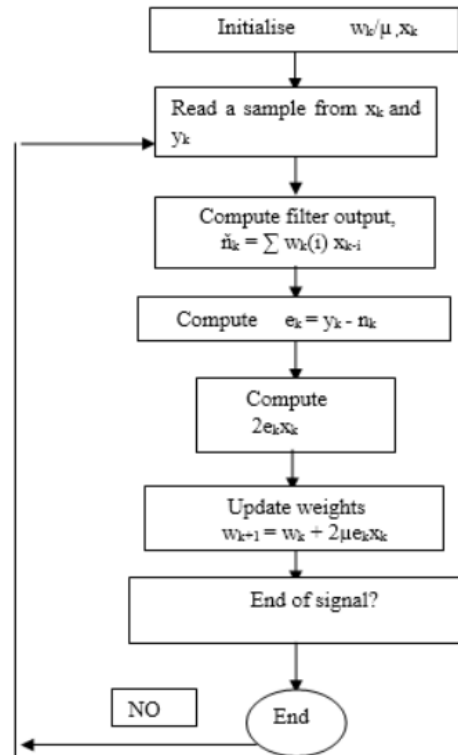


Fig. 2 Flowchart for adaptive algorithm

6. Discussion and Results

Toolbox can be described by changing its operating parameters like learning rate of the LMS in order to view the filter coefficient as this determines the results. All signals were plotted to indicate these effects. Changing of the filters coefficient indicates the difference between the output signal and desired signal by altering their filter coefficients.

A. Experiment 1

Set the LMS Filter block parameters to model the output of the Digital Filter Design block. Open the LMS Filter dialog box by double-clicking the block. Set the block parameters as follows:

- Algorithm = Normalized LMS
- Filter length = 40
- Specify step size via = input port
- Step size (μ) = 0.1
- Leakage factor (0 to 1) = 1.0
- Initial value of filter weights = 0
- Select the Adapt port check box.
- Reset port = none
- Select the Output filter weights check box.

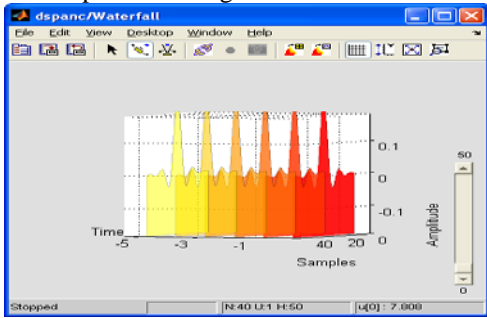


Fig 3. First Waterfall Graph

From the above waterfall block graph, the filtered signal contains some errors when simulate with the above parameters and this can further be explained with the signal browser below

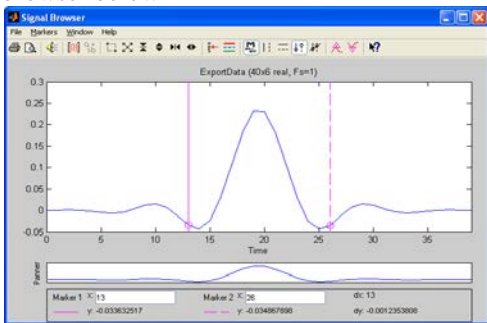


Fig 4.. Second Waterfall Graph

Looking at this export data sp tools graph, the filtered coefficient has not reach its steady state but according to the behaviour of the filter coefficient of the signal, some noise has been filtered but not well enough.

B. Experiment 2

Using the same LMS parameters above but clear adapt port check box and changed the specify step size via input dialog; let's look at difference from the graph below:

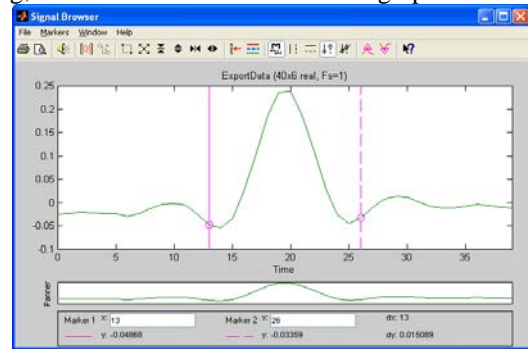


Fig 5. Third Waterfall Graph

Here, the performance of the LMS filter has increased because the behaviour of the filter coefficient is better compared to the previous parameters.

C. Experiment 3

Here, we only changed the filter length from 40 to 43 and this has really made the waterfall blocks to run faster than the one in experiment 2, the rate of execution of the block is very fast and hence made the signal to be more accurate as we can see from the graph below, The filter coefficient has reached its peak and looks almost the same as the original signal as noisy signal becomes very negligible.

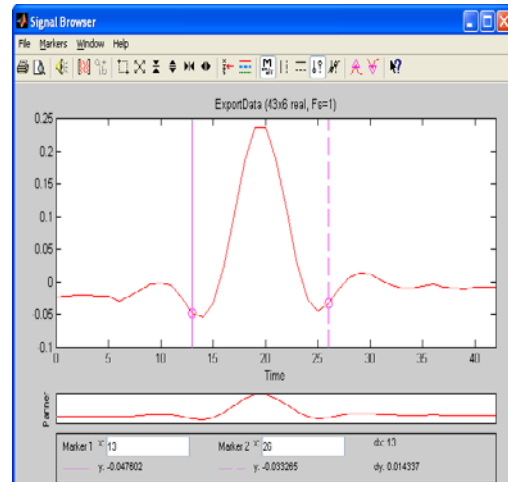


Fig6. Forth Waterfall Graph

D. Experiment 4

Now we try to reduce the filter length from 43 to 30 and it is observed that the filter coefficient moved away from steady state which generated an error into the filter signal. See below:

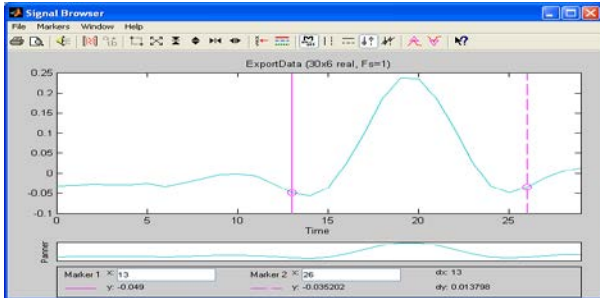


Fig 7. Fifth Waterfall Graph

E. Experiment 5

But when the filter length is increased to 45, It is noted that the LMS algorithm optimizes the filter performance and the filter coefficients reach their steady state.

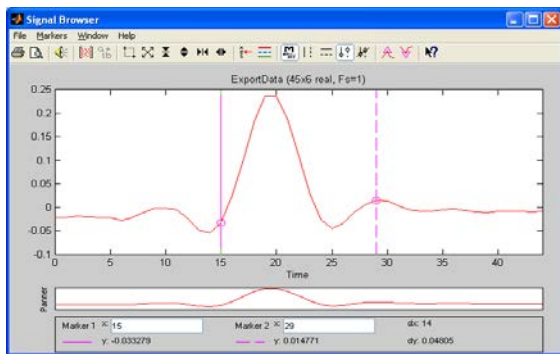


Fig 8. Sixth Waterfall Graph

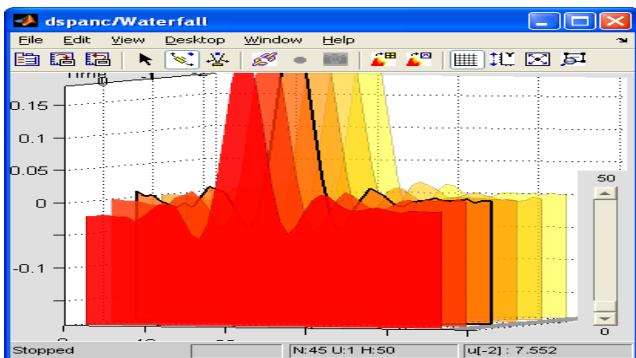


Fig 8. Seventh Waterfall Graph

This seems to be the best result so far and at this juncture, we shall plot all our signals i.e. noisy signal, filtered signal

and original signal to confirm the results. This is done by using command plot (y_org) in the MATLAB command line. Please see the following graphs

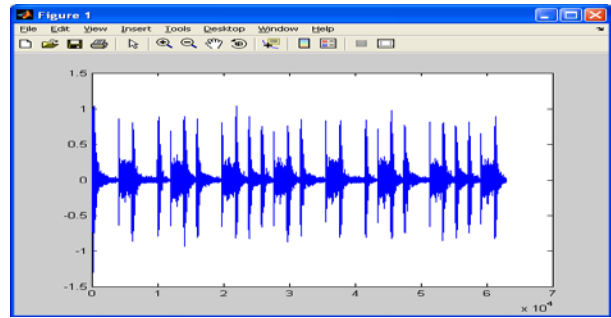


Fig 9. Filtered signal

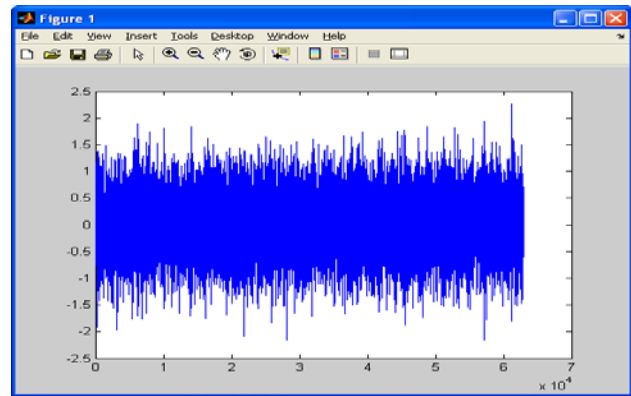


Fig. 10 Noisy signal

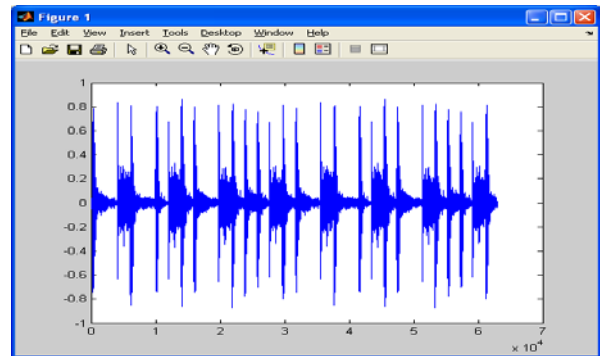


Fig 11. Original Signal

Conclusion

These graphs are the clear indication that the LMS algorithm subtracts the noise from the input signal which uses the desired port to match the filter response as it converges to the right filter model, the filter noise is deducted and filtered signal contains only the original signal as this has been proved above. The filter signal is almost the same as original signal because the error signal contains only original signal and this implies that the performance of the LMS algorithm is fantastic in the design of adaptive filters.

REFERENCES

- [1] Emmanuel C. Ifeakor, Barrie W. Jervis, Digital Signal Processing (A practical Approach), second Edition, 2007.
- [2] Haykin, S. Adaptive Filter Theory. 3rd ed. Englewood Cliffs, NJ: Prentice Hall, 2008.
- [3] N.B. Jones and J.D. McK. Watson, Digital Signal Processing Principles, Devices and applications, 2008.
- [4] Saheed V. Vaseghi. Advanced Digital Signal Processing and Noise Reduction. Third Edition. Brunel University UK, 2009.
- [5] Warren Yates PhD (university of Technology), Andrew Bateman PhD (university of Bristol) Digital Signal Processing design, Sidney, 2009.
- [6] Ababarnel H., D., I., Brown R., Sidorowich J., L. and Tsimring L., S., 2010, the analysis of observed chaotic data in physical systems. Reviews of Modern Physics, Vol. 65, No. 4 Pp1331-1392
- [7] Bishop, C.M. (2009) Neural Networks for Pattern Recognition, Oxford [online]Accessed 19th march, 2010 at:<http://www.inference.phy.cam.ac.uk/>
- [8] Bengio, S., Fessant F., Collobert D. A Connectionist System for Medium-Term Horizon Time Series Prediction. In Proc. Intl. Workshop Application Neural Networks to Telecoms Pp308-315, 2010.
- [9] Dorffner, G. 2010, Neural Networks for Time Series Processing. Neural Network World 4/96, 447-468.