Comparative Study of Adaptive Filter in Noise Cancellation

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Declaration

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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Acknowledgement

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I would also like to thank Mr. Wan Mohd Amri Wan Mamat Ali for assisting me in the research by providing me ideas, and supplying me with equipment and appliances.

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WONG POOI MUN

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List of Symbols

Symbols	**Description**
R	Autocorrelation matrix
p	Cross-correlation vector
$u(n)$	Reference input (noise-correlated)
$y(n)$	Estimated noise output
$d(n)$	Primary input
$e(n)$	Error output
$w(n)$	Filter coefficient
μ	Convergence step-size
M	Filter length

List of Abbreviations

Notations	**Description**
SD	Steepest descent
LMS	Least mean square
ANC	Active noise cancellation
MSE	Mean square error
SNR	Signal-to-noise ratio

Abstrak

Penapis penyesuaian telah luas diguna dalam aplikasi penyesuaian pembatalan bunyi (ANC), termasuklah telekomunikasi. Pelbagai penapis penyesuaian yang berasas dari algoritma least mean square (LMS) boleh didapati, malah prestasi setiap penapis adalah berbeza dari segi kadar penumpuan dan ketepatan dalam anggaran bunyi bising untuk pembatalan bunyi. Kertas ini mengaji perbezaan parameter prestasi tiga jenis penapis: LMS tunggal, LMS melata dan LMS silang tambah dengan pengajian mean square error (MSE), penambahbaikkan signal-to-noise ratio (SNR) dan kadar penumpuan. Model simulasi bagi setiap penapis dibina dalam LabVIEW. Dengan menggunakan model tersebut, simulasi pembatalan bunyi daripada ucapan yang dicemar dijalankan pada nilai saiz-langkah yang optima. Keputusan simulasi dikesahkan dengan pengukuran dalam masa sebenar yang dijalankan dengan myRIO 1900 platform real time (RT). Keputusan yang didapati menjelaskan bahawa penapis LMS melata menunjukkan penambahbaikkan SNR yang tertinggi, purata MSE yang terkecil pada size langkah yang optima dan kadar penumpuan yang tertinggi pada size langkah yang same bagi semua penapis. Walaupun LMS silang tambah boleh berfungsi apabila input bunyi bising tercampur dengan ucapan, penapis ini menunjukkan penambahbaikkan SNR yang terrendah, purata MSE yang tertinggi dan kadar penumpuan yang terrendah. Ini bermaksud penapis yang paling tepat dan efektif dalam susunan menaik adalah LMS silang tambah, LMS tunggal dan seterusnya LMS melata.

Abstract

Adaptive filters have been widely used in adaptive noise cancellation (ANC) applications, including telecommunication. Various adaptive filters that uses least mean square (LMS) algorithm as basis are available with each performance varies in terms of convergence rate and accuracy in estimation of noise for noise reduction. This paper compares the performance parameters between three adaptive filters: single LMS, cascaded LMS and cross-coupled LMS by evaluating the mean square error (MSE), improved signal-to-noise ratio (SNR) and convergence rate. Simulation models of the respective adaptive filter were built in LabVIEW. Using these models, ANC was simulated by cancelling noise from corrupted speech at the optimum step-size of each respective adaptive filter. The simulation results are validated through measurements carried out in real-time using myRIO 1900 real time (RT) platform. It was found that cascaded LMS filter has the highest improved SNR, smallest average MSE at its respective optimum step-size and the fastest convergence rate at the same step-size as the other adaptive filter. Cross-coupled LMS albeit able to perform when the noise reference input was corrupted by the desired speech, has the lowest improved SNR, largest average MSE and the lowest convergence rate. This meant that the ascending order of the most accurate and effective adaptive filter was cross-coupled LMS, single LMS and cascaded LMS.

1 Introduction

From the standpoint of noise cancellation, noise is the unwanted signal that either corrupts a desired signal or produces disturbing effect on human comfort, and is to be reduced to a minimal audible signal. For example, a study conducted by Marit Skogstad showed an association between occupational noise and hypertension disease. [1]

There are two main types of acoustic noise cancellation, namely passive noise cancellation and active noise cancellation. Passive noise cancellation uses physical object to isolate noise through transmission loss, where according to [2], for most materials, transmission loss is mostly effective for mid to high frequency range. Active noise cancellation uses electro-acoustic system to generate secondary noise source which is of equal amplitude but antiphase to the noise and thereby attenuates the noise by destructive superposition, where, it is mostly effective for low frequency range [3][4].

Another method of noise cancellation is through signal processing, known as adaptive noise cancellation (ANC). In ANC, adaptive filter is used to estimate additive noise signals in the corrupted signal without complete apriori information on noise-to-be-filtered [5]. The estimated noise signal is subtracted from the corrupted signal to reduce noise.

There are previous studies conducted to compare the common adaptive filters: least mean square (LMS), normalized least mean square (NLMS) and recursive least square (RLS). Mugdha M. [6], Jyoti Dhiman [7] and Shruti R Patel [8] mainly compared these algorithms based on convergence rate and accuracy. Their papers found that LMS has relatively high convergence rate and mean square error (MSE). However, due to its low complexity and low computational memory requirement, LMS was chosen to be the subject of study for ANC application in this paper.

Cascaded LMS –ANC for real-time was proposed by Shubhra Dixit in 2016 [10]. Cascaded LMS filter was found to predict signals better than single LMS, a type of linear predictor [9]. In [10], cascaded filter also resulted in higher convergence rate and signal-to-noise ratio (SNR) output, and lesser MSE compared to single LMS in ANC.

Cross-coupled LMS filter was brought up in IEEE Conference in 1999 [11] where it was reported for application in quadratic constrained maximization which could also be used to model audio waveform signals. From [11], cross-coupled LMS was found to have a better dynamic control of weight which benefits the noise cancellation results when the signal varies with time. Cross-coupled LMS algorithm is also used in crosstalk-resistant adaptive decorrelator (CRANC). [12][13]

This paper aims to compare the performance parameters between three adaptive filters: single LMS, cascaded LMS and cross-coupled LMS based on average MSE, improved SNR and convergence rate. ANC is done by reducing noise from a corrupted speech. Models were built in LabVIEW for each respective adaptive filter to be simulated to obtain the interested performance parameters. Experiments were carried out using myRIO 1900 real time (RT) platform to validate the simulated results.

2 Theoretical Background of Adaptive Noise Cancellation

Two inputs, primary input and reference input, are fed into the noise canceller system which consists of an adaptive filter to produce filtered output, as shown in Fig. 1 [5]. The primary input $d = s + u$ contains the speech signal corrupted by noise. The reference input u contains noise that is correlated with primary input. The noise signal to be cancelled y is estimated from the inputs of adaptive filter. The output of the canceller e is the subtraction of the signal to be cancelled from the primary input $e = d - y$ [5].

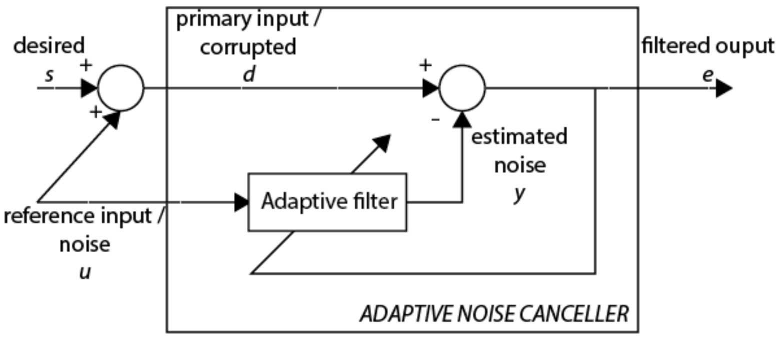


Fig. 1 Adaptive noise canceller

2.1 Single LMS algorithm

LMS is a *stochastic gradient* algorithm based on the gradient of the mean square error of the signal processed. The statistics of the signals are not known and are estimated recursively, resulting in noisy gradient until convergence is obtained. The block diagram of single LMS is represented by Fig. 1 and can be summarized as the following [6].

a) Weight adaptation is the main factor in the algorithm used to predict the noise signal in the corrupted signal:

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu e(n)\boldsymbol{u}(n) \tag{1}$$

$$\begin{bmatrix} w_0(n+1) \\ w_1(n+1) \\ \vdots \\ w_{M-1}(n+1) \end{bmatrix} = \begin{bmatrix} w_0(n) \\ w_1(n) \\ \vdots \\ w_{M-1}(n) \end{bmatrix} + \mu e(n) \begin{bmatrix} u(n) \\ u(n-1) \\ \vdots \\ u(n-M+1) \end{bmatrix} \tag{2}$$

where $M$is filter length, the limit to step-size parameter is given by $0 < \mu < \frac{2}{MS_{max}}$ and S_{max} is the maximum value of power spectral density of $\boldsymbol{u}(n)$. The filter length was set as a constant $M = 1$ as lower filter length gives a better MSE [6].

b) Output of the adaptive filter is the estimated noise signal:

The initial condition of the filter coefficient matrix is $\boldsymbol{w_0}(n) = 0$.

$$y(n) = \boldsymbol{w}(n)^T \boldsymbol{u}(n) = \boldsymbol{w}(n) \cdot \boldsymbol{u}(n) \tag{3}$$

$$y(n) = \begin{bmatrix} w_0(n) \\ w_1(n) \\ \vdots \\ w_{M-1}(n) \end{bmatrix} \cdot \begin{bmatrix} u(n) \\ u(n-1) \\ \vdots \\ u(n-M+1) \end{bmatrix} \tag{4}$$

c) Error signal is the filtered speech, whereby noise is cancelled from the corrupted speech:

$$e(n) = d(n) - y(n) \tag{5}$$

2.2 Cascaded LMS algorithm

Cascaded LMS algorithm consists of two stages, one LMS algorithm in each stage, arranged in cascading order as shown in Fig. 2. One advantage of cascaded LMS is its ability to filter the corrupted speech twice.

The components and inputs of stage 1 are exactly the same as a single LMS. Stage 2 is different from single LMS, such that, the primary input is the error signal of stage 1 and the reference input is the subtraction of the estimated noise of stage 1 from the reference input in stage 1. The total estimated noise of the cascaded LMS filter is the sum of output of filter of both stages.

a) Reference input of stage 2:

$$u_2(n) = u_1(n) - y_1(n) \tag{6}$$

b) Total filter output or total estimated noise:

$$y(n) = y_1(n) + y_2(n) \tag{7}$$

c) Final error signal is the filtered speech:

$$e_2(n) = d(n) - y(n) \tag{8}$$

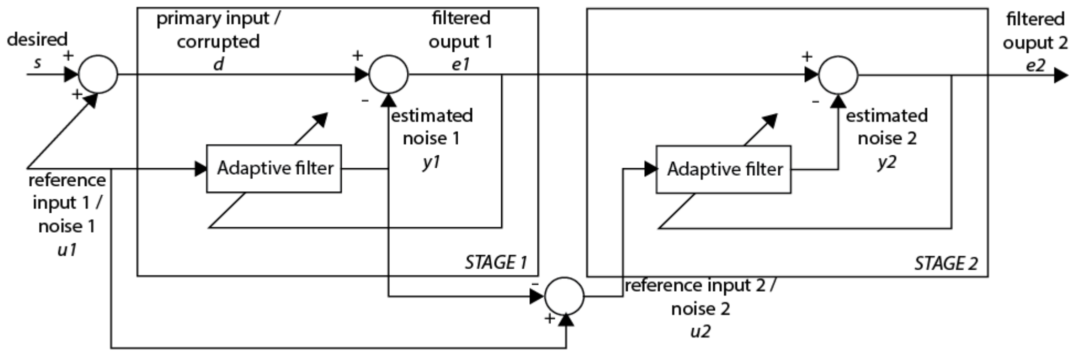


Fig. 2 Cascaded LMS structure

2.3 Cross-coupled LMS algorithm

Cross-coupled LMS algorithms consists of two LMS algorithms arranged in parallel as shown in Fig. 3. One advantage of cross-coupled LMS algorithm is its ability to split the overall filter of order into two cascaded filters of order (M-1)/2 [12]. This increases the convergence rate especially when parallelism is allowed.

Cross-coupled LMS algorithm has two weight adaptations, two filter outputs but only one error signal as the filtered speech. The algorithm can be summarized as the following.

a) Weight adaptation:

$$\boldsymbol{w_1}(n+1) = \boldsymbol{w_1}(n) + \mu \boldsymbol{eu}(n)\boldsymbol{e}(n) \tag{9}$$

$$\boldsymbol{w_2}(n+1) = \boldsymbol{w_2}(n) + \mu \boldsymbol{e}(n)\boldsymbol{eu}(n) \tag{10}$$

b) Filter output or estimated noise signal:

The initial condition of the filter coefficient matrix is $\boldsymbol{w_0}(n) = 0$.

$$ys(n) = \boldsymbol{w}(n)^T \boldsymbol{e}(n) = \boldsymbol{w}(n) \cdot \boldsymbol{e}(n) \tag{11}$$

$$y(n) = \boldsymbol{w}(n)^T \boldsymbol{eu}(n) = \boldsymbol{w}(n) \cdot e\boldsymbol{u}(n) \tag{12}$$

c) Error signal:

$$e(n) = d(n) - y(n) \tag{13}$$

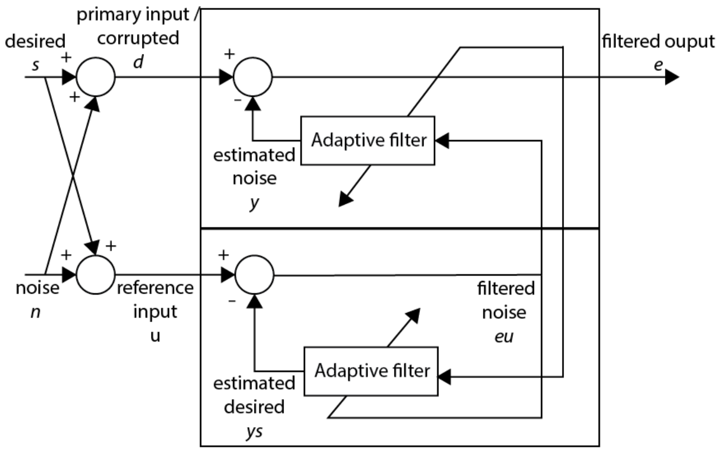


Fig. 3 Cross-coupled LMS structure

2.4 Performance parameter

Mean square error (MSE) of an adaptive filter is the average of the squares of the errors between the estimated noise and the acquired reference noise signal. MSE represents the accuracy of the filter, meaning that filters that give low MSE is more accurate.

$$MSE = (u - y)^2 \tag{14}$$

Signal-to-noise ratio (SNR) is the ratio of average desired signal power to average noise signal power. Improved SNR measures the amount of noise attenuated in the filtered output. [7][6]

$$Input\ SNR = 10 \log \frac{P_d}{P_u} \tag{15}$$

where, $P_d = \frac{1}{N}\sum_{n=0}^{N} d^2$ and $P_u = \frac{1}{N}\sum_{n=0}^{N} u^2$.

$$Output\ SNR = 10 \log \frac{P_d}{P_n} \tag{16}$$

where, $P_n = \frac{1}{N}\sum_{n=0}^{N}(u-y)^2$.

Thus,

$$Improved\ SNR = Output\ SNR - Input\ SNR \tag{17}$$

Convergence rate is determined based on the speed where MSE approaches a limit. Lastly, statistical analysis is done to compare the percentage difference in noise reduction between the filters. Root mean square (RMS) is used to represent the data of the audio signal.

$$Percentage\ of\ noise\ reduced = \frac{RMS(U) - RMS(U-Y)}{RMS(U)} \times 100\% \tag{18}$$

3 Methodology

The studied ANC in this paper requires a primary input and a reference input. Three audio files were prepared: speech of a male counting from 1 to 20, monotone noise at 500Hz and air-conditioner noise. The speech corrupted by noise was used as the primary input while the noises were used as the reference inputs. ANC was carried out in two cases. Case 1 involves having the speech corrupted by monotone (500Hz) noise which represents a simple waveform. Case 2 involves having the speech corrupted by air-conditioner noise which represents a complex waveform.

ANC was first simulated in LabVIEW, and then the simulation results were validated by experiments conducted using myRIO 1900 real time (RT) platform. The simulated and experimental data related to the interested performance parameters was collected and compared.

3.1 Simulation

Simulation models were built as VI using Sound and Vibration Toolkit. The audio files were opened in the model as primary and reference inputs, and then data converted to arrays. The output array was converted back to audio format as audio file.

For each case, two scenario were created. In the first scenario, pure noise signal were fed as reference input to represent the ideal case. In the second scenario, noise signal infiltrated by desired signal were fed as reference input to mimic the real case. In reality, complete isolation of desired signal from the reference input is not possible as the reference microphone is located nearby the primary microphone on a device. Since the presence of uncorrelated noise at the reference input reduces SNR at the output [5], it is desired to investigate the effect of the presence of desired signal in the reference input on the performance of the adaptive filters.

ANC in each scenario within each case was simulated at different step-sizes. Data on average MSE was recorded and plotted onto graph of average MSE against step-size values. The step-size value which gives the minimum average MSE, called the optimum solution, was selected as the optimum step-size and was used in the subsequent performance evaluations.

Since there were two scenarios for two cases, a total of four tests has to be conducted. Using the optimum solution, simulations were ran for each test and the improved SNR was calculated and compared. Convergence rate was observed from the convergence of the MSE curve plotted at each step-size values.

3.2 Experiment

Experiment was used to validate the comparative results obtained from simulation.

The experiment was conducted for each case, giving a total of two tests. The experiment set-up consisted of two microphones, three speakers, two internally insulated boxes, a myRIO 1900 and a computer.

Microphones used were BSWA array microphones MPA 201 with preamplifier MA211, which functioned as primary and reference input sensors. Two speakers used were CLIPTEC BMS350, which functioned as audio sources for reference noise and corrupted speech. The speaker used for filtered speech output was BOOMPODS downdraft.

The following criteria has to be fulfilled in the physical design of the set-up:

1. The sound sources must be insulated from uncontrolled external noises.
2. Interior of the chamber must be lined with sound absorbent materials.
3. Noise input must be insulated from desired speech signal.

The experiment was set-up as shown in Fig. 4 and Fig. 5. The microphones were connected to myRIO analog audio input port directly and the BOOMPODS downdraft speaker was connected to the analog audio output port directly. The speaker which played the corrupted speech and the primary input microphone were placed in an internally insulated box. The speaker which played the reference noise and the reference input microphone were placed in the other insulation box. Both CLIPTEC BMS350 were connected to the computer to acquire the prepared audio files.

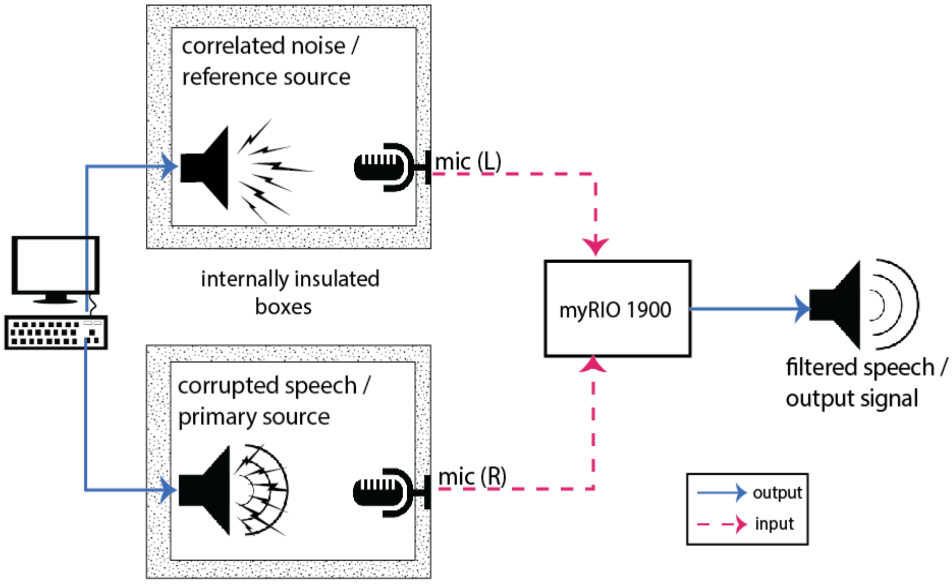


Fig. 4 Schematic diagram of experimental set-up design

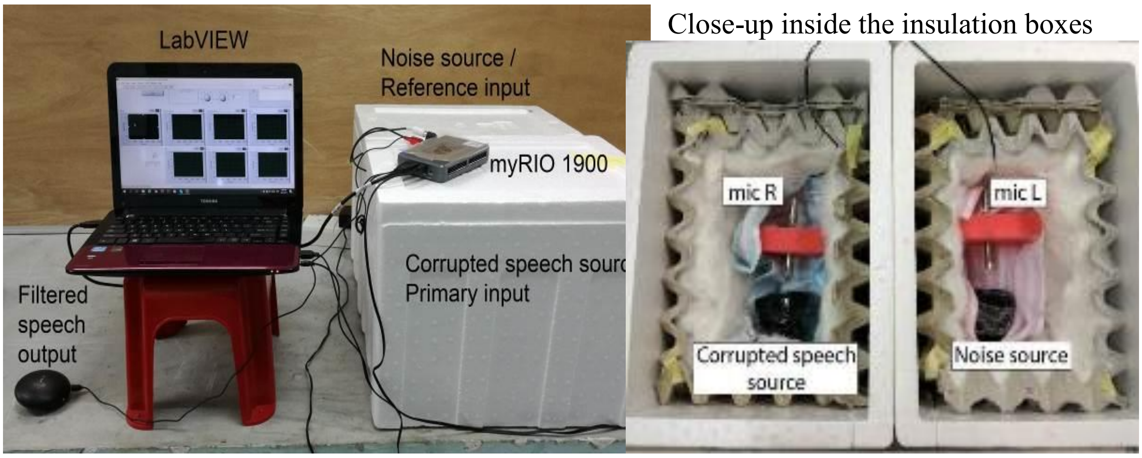
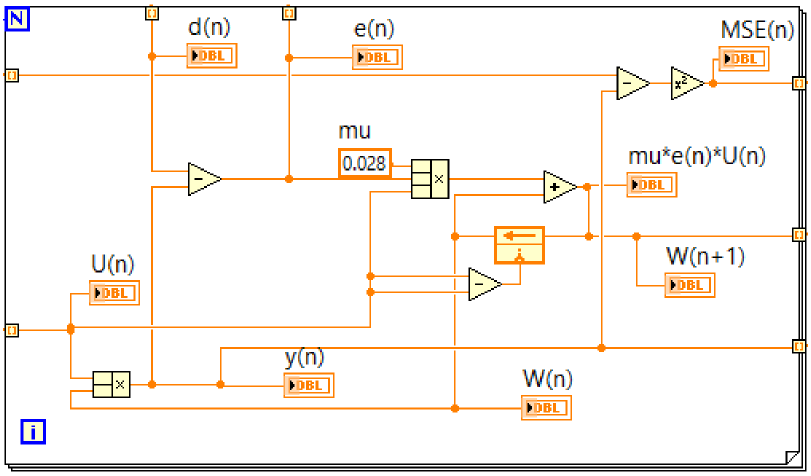


Fig. 5 View of experimental set-up

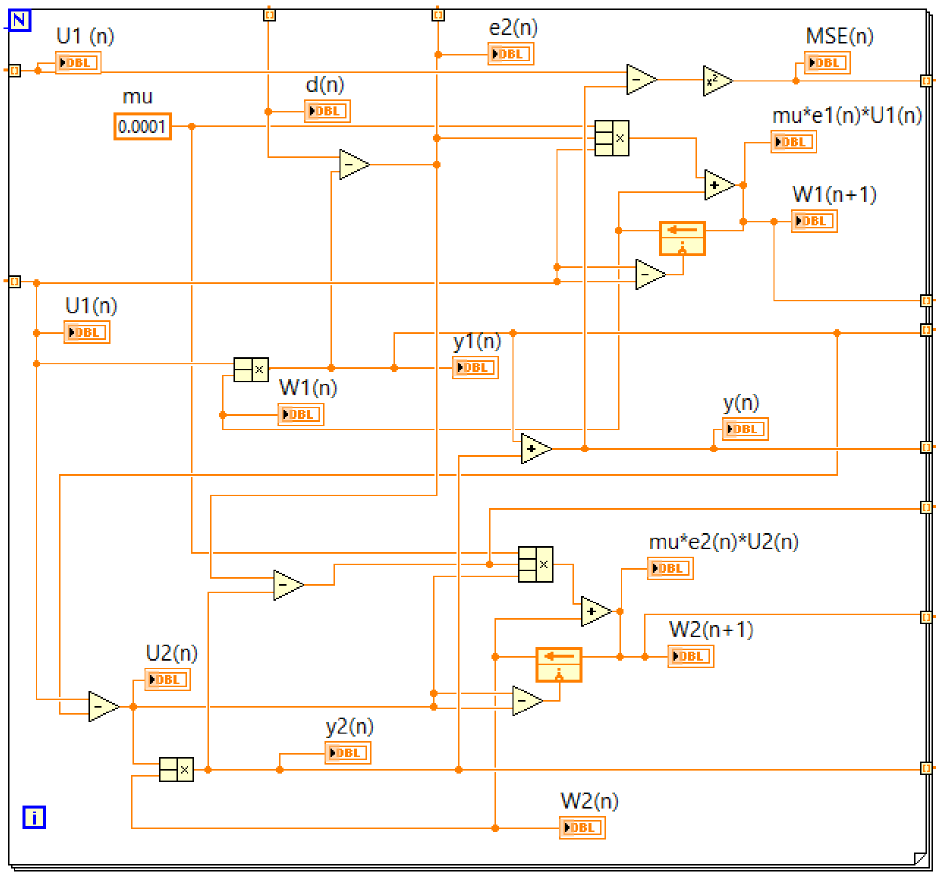
LabVIEW modelling was done in RT platform which maximum clock is 1kHz. Producer-consumer design was used in the model with sampling frequency of 1kHz. The adaptive filter code was the same as used in simulation code. Only the input and output signals were adapted to the analog I/O ports of myRIO 1900. Low band-pass filter was used on the acquired signals to reduce external noise that was unrelated to the tests.

4 Results and Discussion

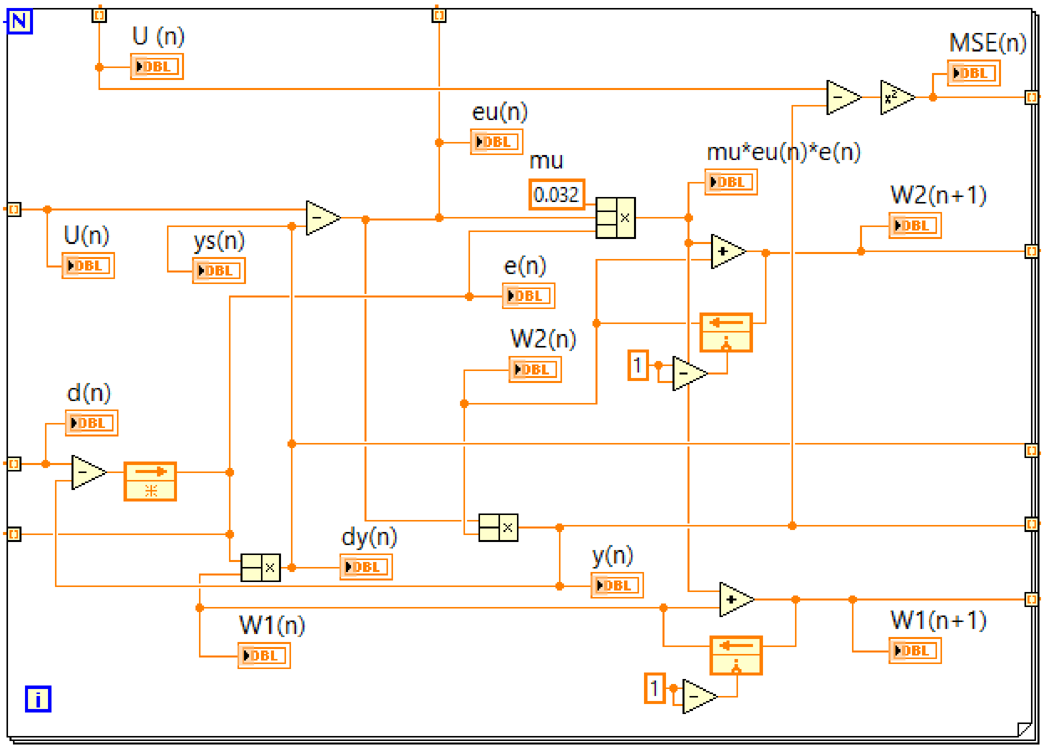
The developed LabVIEW models for the adaptive filters were shown in Fig. 6. The models were developed based on the equations (1) to (13) and Fig. 1 to Fig. 3.



(a) Single LMS filter



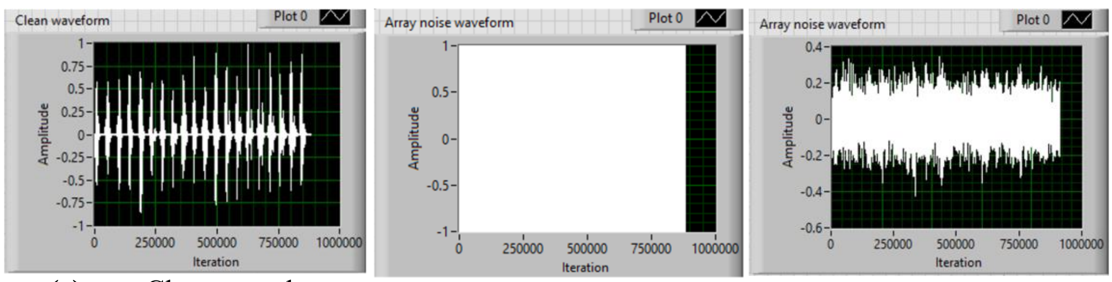
(b) Cascaded LMS filter



(c) Cross-coupled LMS filter

Fig. 6 Block diagram for adaptive filters

The arrays of audio waveform obtained in simulation at sampling rate of 44,100Hz are shown in Fig. 7. The total number of iterations is 882,000. The array of clean speech waveform acquired in experiment at sampling rate of 1,000Hz is shown in Fig. 8. The total number of iterations is 20,000.



(a) Clean speech (b) Monotonous noise (c) Air-conditioner noise

Fig. 7 Arrays of audio waveform

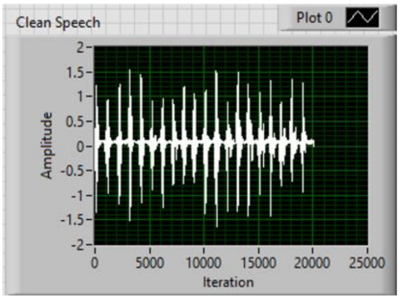


Fig. 8 Waveform of clean speech acquired in the experiment at sampling rate of 1kHz

4.1 Case 1: Speech corrupted by monotone signal

Table 1 and Table 2 showed the optimum step-size in bolded font when pure monotone noise signal was used as the reference input (scenario 1) and when there was infiltration of desired signal in the monotone noise signal for reference input (scenario 2). Both scenarios exhibited the same optimum step-size values for their respective filters.

The average MSE for all filters in scenario 2 were larger than the results obtained in scenario 1. For monotone noise, the degree of infiltration of desired signal into the noise signal has little effect on the filters. In real cases, this infiltration is unavoidable as the location of the reference microphone would have to be placed nearby, albeit further from the desired signal on the device, for example, a headset. This showed a better understanding that the infiltration has little effect when the studied adaptive filters filter simple sine waveform at 500Hz from desired signal.

Table 1 Pure monotone 500Hz (scenario 1)

Single				
Step-size (μ)	0.003	0.004	**0.005**	0.006
Average MSE	2.92E-04	2.73E-04	**2.71E-04**	2.78E-04
Cascaded				
Step-size (μ)	0.003	**0.004**	0.005	0.006
Average MSE	1.63E-04	**1.50E-04**	1.51E-04	1.60E-04
Cross-coupled				
Step-size (μ)	0.001	**0.002**	0.003	0.004
Average MSE	7.77E-02	**7.71E-02**	7.76E-02	7.85E-02

Table 2 Monotone 500Hz infiltrated by desired signal (scenario 2)

Single				
Step-size (μ)	0.004	0.005	**0.006**	0.007
Average MSE	2.576E-03	2.567E-03	**2.57E-03**	2.568E-03
Cascaded				
Step-size (μ)	0.003	**0.004**	0.005	0.006
Average MSE	2.436E-03	**2.43E-03**	2.425E-03	2.430E-03
Cross-coupled				
Step-size (μ)	0.001	**0.002**	0.003	0.004
Average MSE	5.78E-02	**5.77E-02**	5.84E-02	5.94E-02

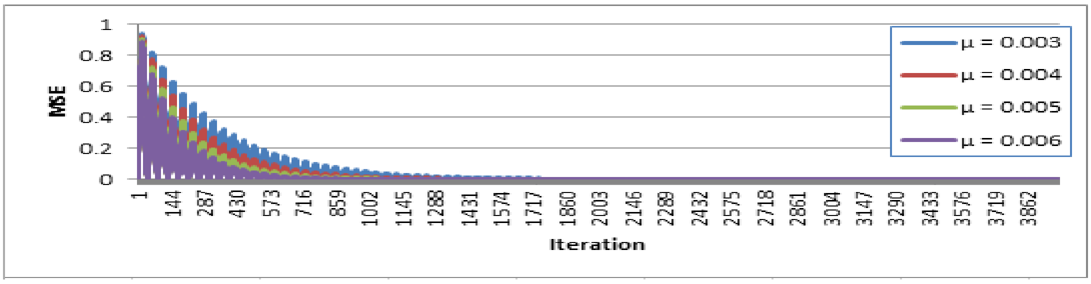
The percentage of noise reduction and improved SNR were tabulated in Table 3. In scenario 1, the noise reduction of cascaded LMS filter was 87.2%, which is 2.0% and 49.7% better than the noise reduction of single LMS filter and cross-coupled LMS filter respectively. In scenario 2, the noise reduction of the cascaded LMS filter was 74.4% which was 0.3% and 32.5% better than the noise reduction of single LMS filter and cross-coupled LMS filter respectively. The experiment has successfully validated that cascaded LMS filter gives the highest percentage of noise reduction among the three filters. In the experiment, cascaded LMS filter has reduced 56.1% of noise which was 3.0% and 61.8% better than the noise reduction of single LMS filter and cross-coupled LMS filter respectively. Negative improved SNR indicated increased in noise instead of reducing it. In overall, for case 1, the filtered speech from cascaded LMS has at least 0.3% more noise reduced than single LMS, and at least 32.5% more noise being reduced than cross-coupled LMS. Cascaded LMS filter was able to produce a filtered speech with the least simple waveform noise among the three adaptive filters.

Table 3 Improved SNR of filters when used to filter monotone noise from speech

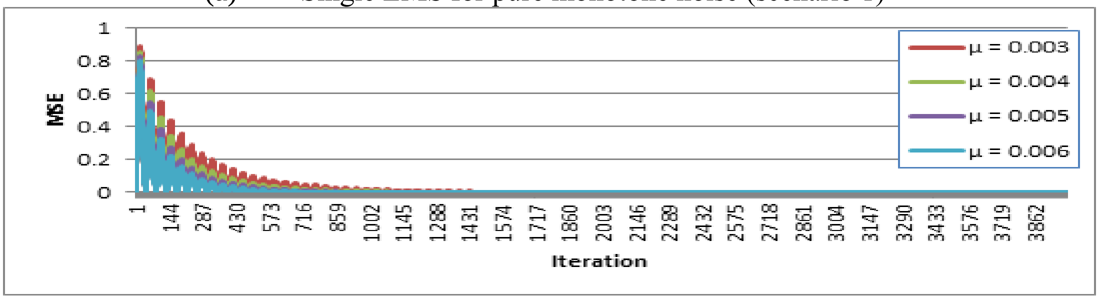
Filter type	Single	Cascaded	Cross-coupled
Monotone 500Hz pure noise (scenario 1)			
Optimum Step-size	0.005	0.004	0.002
MSE	2.71E-04	1.50E-04	7.71E-02
Improved SNR	33.203	35.760	6.397

% noise reduced	85.2%	87.2%	39.3%
Monotone 500Hz infiltrated by desired signal (scenario 2)			
Optimum Step-size	0.006	0.004	0.002
MSE	2.57E-03	2.43E-03	5.77E-02
Improved SNR	23.444	23.688	9.423
% noise reduced	74.1%	74.4%	41.9%
Experimental results			
Optimum Step-size	0.005	0.004	0.002
MSE	2.10E-03	7.17E-03	9.84E-03
Improved SNR	6.583	7.143	-0.485
% noise reduced	53.1%	56.1%	-5.7%

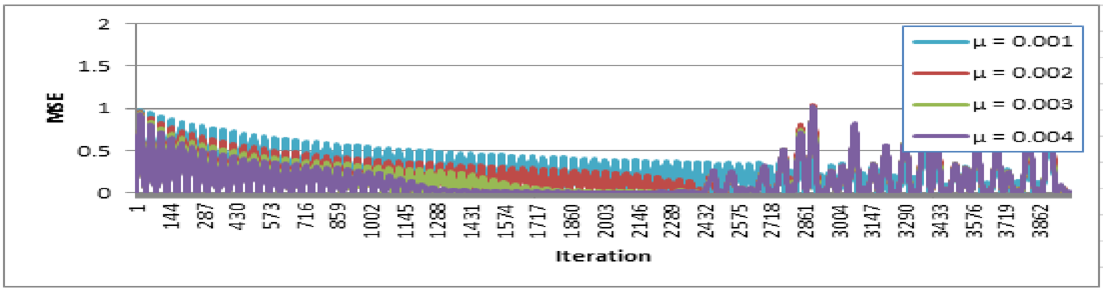
Fig. 9 and Fig. 10 focused on the MSE values of the initial 4000 iterations as the curve converged beyond this value. Convergence rate was the highest for as step-size value increases regardless of the filter type. Cross-coupled LMS was the most ineffective filter in estimating the error signal, while cascaded LMS converged faster than single LMS filter. The trend of weight described the convergence of the algorithm. Single and cascaded LMS filters are able to reach a convergence point. The weight in cross-coupled LMS filter fluctuated from negative value to positive value which caused the average MSE to fluctuate, not reaching a convergence.



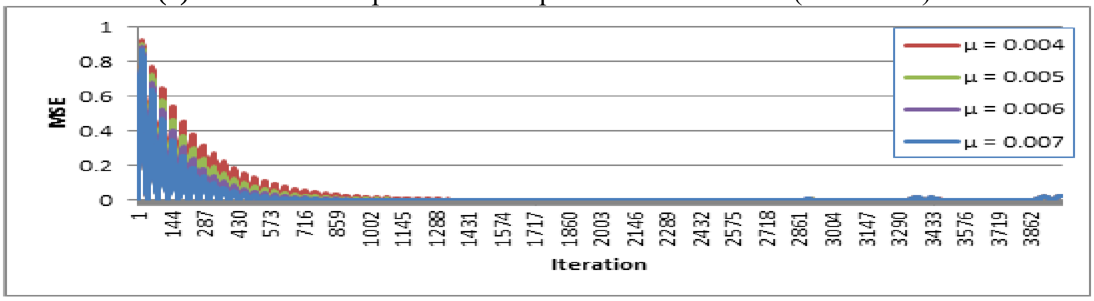
(a) Single LMS for pure monotone noise (scenario 1)



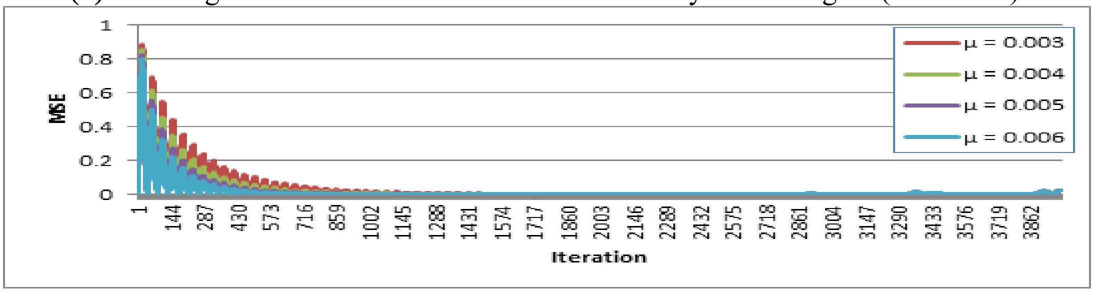
(b) Cascaded LMS for pure monotone noise (scenario 1)



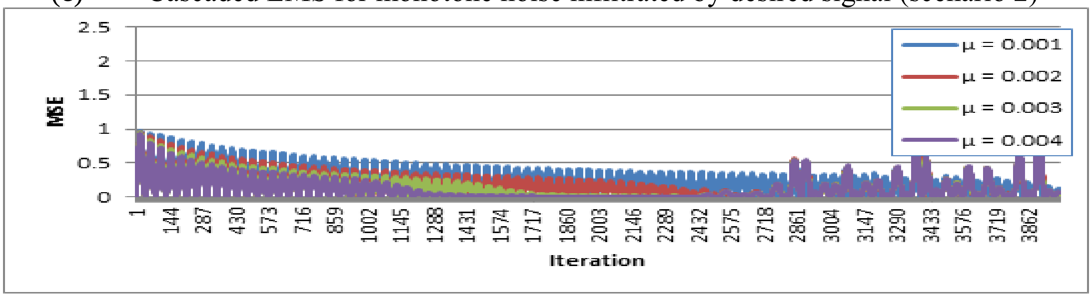
(c) Cross-coupled LMS for pure monotone noise (scenario 1)



(d) Single LMS for monotone noise infiltrated by desired signal (scenario 2)

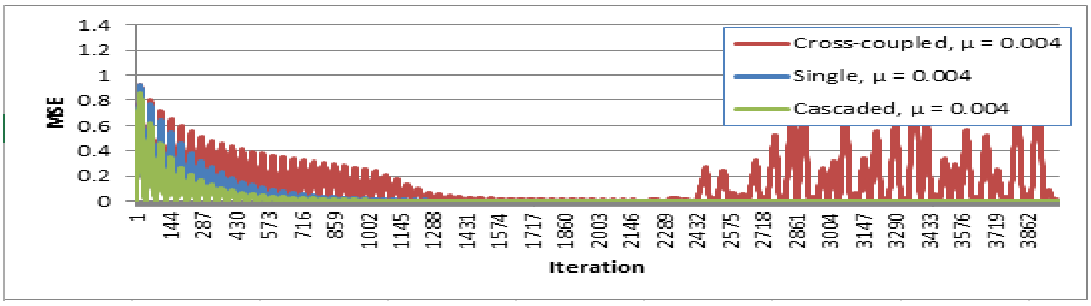


(e) Cascaded LMS for monotone noise infiltrated by desired signal (scenario 2)



(f) Cross-coupled LMS for monotone noise infiltrated by desired signal (scenario 2)

Fig. 9 MSE of adaptive filters of monotonous noise (500Hz)



(a) Pure monotone noise (scenario 1)