Adaptive filters have been widely used in adaptive noise cancellation (ANC) applications, including telecommunication. Various adaptive filters that use 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.

Keywords: adaptive filter comparison, noise cancellation

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, that 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 prior 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 [6], Jyoti [7] and Shruti [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 in year 2016 [9]. Cascaded LMS filter was found for predicting signals better than single LMS, a type of linear predictor [10]. In [9], 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 reported in year 1999 for the application in quadratic constrained maximization, which could also be used to model audio waveform signals [11]. From [11], cross-coupled LMS was found to have a better dynamic control of weight that benefits the noise cancellation results when the signal varies with time. Cross-coupled LMS algorithm is also been used in crosstalk-resistant adaptive de-correlator. [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 for validation.

2. Theoretical background of adaptive noise cancellation

Two inputs (primary and reference input) are fed into the noise canceller system that consists of an adaptive filter to produce filtered output, as shown 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].

![Figure 1: Adaptive noise canceller.](image)

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 explained as below. Weight adaptation is the main factor in the algorithm used to predict the noise signal in the corrupted signal:

\[
\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n) \mathbf{u}(n)
\]

(1)

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

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

Output of the adaptive filter is the estimated noise signal:

\[
y(n) = w(n)^T u(n) = w(n) \cdot u(n)
\] (3)

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

\[
e(n) = d(n) - y(n)
\] (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 the same as 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.

Reference input of stage 2: \( u_2(n) = u_1(n) - y_1(n) \) (6)

Total filter output or total estimated noise: \( y(n) = y_1(n) + y_2(n) \) (7)

Final error signal is the filtered speech: \( e_2(n) = d(n) - y(n) \) (8)

![Figure 2: Cascaded LMS structure.](image)

### 2.3 Cross-coupled LMS algorithm

Cross-coupled LMS algorithm 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.

Weight adaptation:

\[
w_1(n+1) = w_1(n) + \mu e_1(n)e(n)
\] (9)

\[
w_2(n+1) = w_2(n) + \mu e_2(n)e(n)
\] (10)

Filter output or estimated noise signal:

\[
y_{\text{s}}(n) = w(n)^T e(n) = w(n) \cdot e(n)
\] (11)

\[
y(n) = w(n)^T e_1(n) = w(n) \cdot e_1(n)
\] (12)

Similar to single LMS, the error signal could be calculated by Eq. (5).
2.4 Performance parameter

MSE of an adaptive filter is the average of the squares of the errors between the estimated noise and the acquired reference noise signal, which is \( \text{MSE} = (u - y)^2 \). MSE represents the accuracy of the filter, meaning that filters that give low MSE is more accurate.

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 [6-7].

\[
\text{Improved SNR} = \text{Output SNR} - \text{Input SNR} = 10 \log \frac{P_d}{P_n} - 10 \log \frac{P_d}{P_u} \tag{13}
\]

where, \( P_d = \frac{1}{N} \sum_{n=0}^{N} d^2 \), \( P_u = \frac{1}{N} \sum_{n=0}^{N} u^2 \) and \( P_n = \frac{1}{N} \sum_{n=0}^{N} (u - y)^2 \)

Convergence rate is determined based on the speed where MSE approaches a limit. Lastly, percentage differences in between the performance of different filters are compared.

3. METHODOLOGY

Three audio files were used in this study, which are 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. Two case studies are used, which case 1 involves the speech corrupted by monotone (500Hz) that represents a simple waveform and case 2 involves the speech corrupted by air-conditioner noise that represents a complex waveform.

ANC was simulated in LabVIEW, and then the simulation results were validated by experiments conducted using myRIO 1900 real time (RT) platform.

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 scenarios were created. For first scenario, pure noise signal was fed as reference input to represent the ideal case. In the second scenario, noise signal infiltrated by desired signal was 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. Simulation was done at different step-sizes. The step-size that gives the minimum average MSE was selected as the optimum step-size and been used in the subsequent simulation. Based on the optimum step size, simulations were performed 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

The experiment was conducted for each case. The 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 experiment was set-up as shown in Fig. 4. The microphones were connected to myRIO analogue audio input port directly and the BOOMPODS downdraft speaker was connected to the analogue audio output port directly. The speaker that played the corrupted speech and the primary input microphone were placed in an internally insulated box. The speaker that 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. The sampling frequency of 1kHz was used and also low band-pass filter was used on the acquired signals to reduce external noise that was unrelated to the tests.

![Figure 4](image)

Figure 4: (a) Schematic diagram and (b) overall view of the physical experimental set-up

4. RESULTS AND DISCUSSION

4.1 Case 1: Speech corrupted by monotone signal

Table 1 showed the optimum step-size for both scenarios and the average MSE. The percentage of noise reduction and improved SNR are included in Table 1. 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 shows that the noise reduction of cascaded LMS filter in scenario 1 was 87.2%, which is 2.0% and 49.7% better than single LMS filter and cross-coupled LMS filter respectively. For scenario 2, the noise reduction of the cascaded LMS filter was 74.4%, which is 0.3% and 32.5% better than single LMS filter and cross-coupled LMS filter respectively.

The simulation results are validated by the experiment results that cascaded LMS filter gives the highest percentage of noise reduction among the three filters as shown in Table 2. From Table 2, the cascaded LMS filter has achieved 56.1% of noise reduction which was 3.0% and 61.8% better than single LMS filter and cross-coupled LMS filter respectively. In overall, for case 1, cascaded LMS has at least 0.3% more noise reduction than single LMS, and at least 32.5% more 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 1: Comparison of scenario 1 and scenario 2 for case 1

<table>
<thead>
<tr>
<th>Filter type</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimum Step-size</td>
<td>Single</td>
<td>Cascaded</td>
<td>Cross-coupled</td>
</tr>
<tr>
<td>MSE</td>
<td>2.71E-04</td>
<td>1.50E-04</td>
<td>7.71E-02</td>
</tr>
<tr>
<td>Improved SNR</td>
<td>33.203</td>
<td>35.760</td>
<td>6.397</td>
</tr>
<tr>
<td>% noise reduced</td>
<td>85.2%</td>
<td>87.2%</td>
<td>39.3%</td>
</tr>
</tbody>
</table>

Table 2: Experimental results for case 1

<table>
<thead>
<tr>
<th>Filter type</th>
<th>Single</th>
<th>Cascaded</th>
<th>Cross-coupled</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimum Step-size</td>
<td>0.005</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>MSE</td>
<td>2.10E-03</td>
<td>7.17E-03</td>
<td>9.84E-03</td>
</tr>
<tr>
<td>Improved SNR</td>
<td>6.583</td>
<td>7.143</td>
<td>-0.485</td>
</tr>
<tr>
<td>% noise reduced</td>
<td>53.1%</td>
<td>56.1%</td>
<td>-5.7%</td>
</tr>
</tbody>
</table>

Table 3: Differences in between clean and filtered speech from monotone noise

<table>
<thead>
<tr>
<th>Single</th>
<th>Cascaded</th>
<th>Cross-coupled</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pure monotone noise (scenario 1)</td>
<td><img src="image1.png" alt="Waveform" /></td>
<td><img src="image2.png" alt="Waveform" /></td>
</tr>
<tr>
<td>Monotone noise infiltrated by desired signal (scenario 2)</td>
<td><img src="image4.png" alt="Waveform" /></td>
<td><img src="image5.png" alt="Waveform" /></td>
</tr>
</tbody>
</table>

Table 3 shows the residue simple waveform noise from the ANC. Cascaded LMS able to cancel the most noise whereas cross-couple LMS able to cancel the least noise for both scenarios. There was electrical noise emitted from myRIO that fluctuated the input signals acquired. The monotone waveform was supposed to have constant amplitude throughout the experiment. The acquired waveform shaped in random increasing and decreasing trend in amplitude. This affected the comparison in between experimental and simulation results.

4.2 Case 2: Speech corrupted by air-conditioner signal

Table 4 showed the optimum step-size when pure air-conditioner noise signal was used as the reference input (scenario 1) and when there was infiltration of desired signal in the air-conditioner noise signal for reference input (scenario 2). Air-conditioner noise is represented complex waveform in the study. There were large differences in values of optimum solution obtained for both scenarios. In scenario 2, there was no optimum step-sizes found for single LMS and cascaded LMS filters. Only cross-coupled LMS filter was able to achieve an optimum value of 0.032 and cancelled significant amount of air-conditioner noise as in Table 4. This value was less than the optimum so-
olution of cross-coupled LMS obtained in scenario 1, which was 0.068. In addition, the increase average MSE from scenario 1 to scenario 2 indicated less accuracy in noise cancellation. The weight adaptation Eq. (9) and Eq. (10) contributed to this advantage of cross-coupled LMS as the correlated noise signal underwent noise-cancellation to filter out infiltration of desired signal before being fed into the other stage of the adaptive filter as reference input.

Table 4: Comparison of scenario 1 and scenario 2 for case 2

<table>
<thead>
<tr>
<th>Filter type</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single</td>
<td>Cascaded</td>
</tr>
<tr>
<td>Optimum Step-size</td>
<td>0.028</td>
<td>0.026</td>
</tr>
<tr>
<td>MSE</td>
<td>3.96E-05</td>
<td>2.21E-05</td>
</tr>
<tr>
<td>Improved SNR</td>
<td>21.609</td>
<td>24.137</td>
</tr>
<tr>
<td>% noise reduced</td>
<td>71.2%</td>
<td>75.1%</td>
</tr>
</tbody>
</table>

Table 5: Experimental results for case 2

<table>
<thead>
<tr>
<th>Filter type</th>
<th>Single</th>
<th>Cascaded</th>
<th>Cross-coupled</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimum Step-size</td>
<td>0.024</td>
<td>0.026</td>
<td>0.068</td>
</tr>
<tr>
<td>MSE</td>
<td>9.33E-04</td>
<td>7.06E-03</td>
<td>5.40E-03</td>
</tr>
<tr>
<td>Improved SNR</td>
<td>9.308</td>
<td>11.704</td>
<td>1.563</td>
</tr>
<tr>
<td>% noise reduced</td>
<td>65.8%</td>
<td>74.0%</td>
<td>16.5%</td>
</tr>
</tbody>
</table>

From table 4, the improved SNR between the three filters exhibited the same trend as case 1. In scenario 1, the noise reduction of cascaded LMS filter was 75.1%, which is 3.9% and 47.6% better than single and cross-coupled LMS filter respectively. In scenario 2, the noise reduction of the cascaded LMS filter was 22.2% which was 3.5% and 5.2% better than single and cross-coupled LMS filter respectively. The comparison by experimental results is shown in Table 5 where the cascaded LMS filter has the highest improved SNR among the three filters. In the experiment, cascaded LMS filter has achieved 74.0% of noise reduction which was 8.2% and 75.5% better than single and cross-coupled LMS filter respectively. For case 2, filtered speech from cross-coupled filter produced lowest improved SNR in positive value. The noise reduction of the filtered speech from cascaded LMS has at least 3.5% more than single LMS, and at least 5.2% more than cross-coupled LMS. However, the difference in performance between cascaded LMS and cross-coupled LMS could be as large as 75.5% which was obtained in the experimental results. Cascaded LMS filter able to produce a filtered speech with the least complex waveform noise among the three adaptive filters.

5. Conclusion

Three adaptive filters were compared in the application of adaptive noise cancellation: single LMS, cascaded LMS and cross-coupled LMS. It was observed that the convergence rate of adaptive filter increases with step-size value. Two cases were investigated: filtering monotone noise of 500Hz, which represented simple waveform, from corrupted speech, and filtering air-conditioner noise, which represented complex waveform, from corrupted speech. Cascaded LMS filter gave the lowest MSE and highest improved SNR for both cases. The effectiveness of the filter is improved by the range of 0.3% to 8.3% compared to single LMS. On the other hand, cross-coupled LMS filter gave the highest MSE and lowest improved SNR for both cases. The effectiveness of the filter is less by the range of 32.2% to 49.3%, while having an outlier of 1.7% less effective compared to single LMS. Thus, cascaded LMS filter was proven to have best performance in adaptive noise cancellation among the three adaptive filters in the studied cases.
Acknowledgement

The author would like to acknowledge Ministry of Higher Education Fundamental Research Grant Scheme, FGRS [account no. 6071345] for funding the project.

REFERENCES


