University of Balamand

Faculty of Engineering

ELCP392 - Undergraduate Project

ACTIVE NOISE CANCELLATION

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Abstract

Over the last two decades, urban noise has been increasing rapidly, primarily in urban areas, due to population growth and the increase of certain noise sources. Furthermore, while mild noise can be a nuisance, excessive noise can destroy a person's hearing.

As in many developing countries, noise pollution constitutes a major problem in Lebanon. While existing data on noise levels in Beirut is relatively limited, recent surveys indicate that current average noise levels exceed 75 dBA in many locations (Chaaban and Ayoub, 1996). This can be attributed to several problems, specifically the high usage of generators due to rationing of electricity.

Noise cancellation headphones provide a solution to the problem, but only on a small scale, person-to-person basis. In addition, good quality noise cancellation headphones cost about $300-$350 per set, thus posing a very impractical and costly solution to a problem suffered by over 80% of the Lebanese population.

Although noise cancellation headphones are already available, they are expensive and impractical on a large scale. A need exists for a more extensive design that could actively cancel noise over a larger scale. Ideally, the design should be economical, effective, and simple to use and maintain.

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Chapter 1: Introduction

The focus of the work of this project was Active Noise Cancelling technology in general. In particular, we looked at how this technology can be implemented and developed to effectively cancel variable frequency noise. Basing our research on previous work done by fellow university students, we developed a circuit that, through implementing an adaptive algorithm, was capable of performing variable frequency noise attenuation.

As part of the project pilot, we started by looking at a previously performed noise cancellation project, taking the time to reproduce its circuit on Multisim and test it to verify its function. It was important here to understand exactly how it works, i.e., the overall purpose of the design, the function of each component as well as the circuit's performance when fed with noise samples.

The second part of this project included the development of an active noise cancellation circuit capable of performing variable frequency noise attenuation. Developed using the LabView platform, the designed circuit was tested on multiple noise samples, each of different varying amplitude, frequency, and length.

One of the future goals of the previous project worked on by our colleagues was to build a system that can "give the circuit an adaptive nature where having a noise whose frequency varies is not a problem." It is our hope in this report to pick up where they left off, implement their design and enhance it into a more effective and applicable system.

Chapter 2: Literature Review

A comfortable environment is one in which there is little or no annoyance and distraction so that working or leisure tasks can be carried out unhindered either physically or mentally. Unfortunately, residential noise has become a serious problem in many countries, and it is difficult to regulate by physical means alone. It is well known that residential noise may affect sleep, attentiveness, problem solving, memory, conversation, academic work in terms of reading and learning, and cause annoyance as well as affect task performance. Noise has become a very significant stress factor in the environment, to the level that the term noise pollution has been used to signify the hazard of sound the consequences of which in modern day development is immeasurable Noise is intrusive and harmful. William H. Stewart, former US Surgeon General, stated, "Calling noise a nuisance is like calling smog an inconvenience. Noise must be considered a hazard to the health of people everywhere."

Exposure to excessive noise is a threat to many aspects of life. Loud sound is dangerous even when it is not painful. Noise as a polluting agent in the environment has been recognized for some time as a serious threat to the quality of life enjoyed by the populace. A link between residential noise and mental health problems is suggested by the demand for tranquillizers and sleeping pills, the incidence of psychiatric symptoms and the number of admissions to mental hospitals. The World Health Organization (WHO) classified the adverse effects of noise pollution on humans into seven categories which are hearing impairment, interference with spoken communication, sleep disturbances, cardiovascular disturbances, disturbance in mental health, impaired task performance and negative social behavior and annoyance reactions.

There are many noise cancellation headphones already out there, and they all work on the same principle. Active Noise Cancellation headphones aim to protect the ear from harmful noises, but instead of doing that through encapsulation or other “passive” means, they eliminate noise actively. This means that they create a noise that is of the same amplitude and opposite phase to the original noise, and play it thus making them cancel each other.

The first configuration for a noise cancellation headphone was suggested by Olson and May in 1953. Their aim was simply to remove noise in one small area, directly around the ear canal. This was, even then, a classic problem in Control and they simply aimed to apply it to the human ear. An Active Noise Cancellation headphone needs to be controlled by a feedback loop, for this reason Wheeler (1986) used control theory methods in order to shape the frequency response in the open-loop. Later on, Bai and Lee (1997) used more modern control theory optimization techniques to produce a more optimal, robust controller. Leitch and Tokhi (1987) have written an excellent review on the evolution of the algorithms used in Active Noise Cancellation.

The problem with most models is that they need an accurate prediction of what the noise is going to be like if they are to produce optimal results. There is a need to determine the parameters of the model, usually as a transfer function, which can be done based on observed/measured results. It is also important to know what is known for certain and what is an uncertainty. Once we know of uncertainties we can account and correct for them, in parametric or non-parametric form. Another thing that ANC headphone manufacturers have to keep in mind is that designs should carefully follow performance specifications, because the headphone itself will be producing noise very close to the human ear which can be bothersome or even harmful if it does not follow proper specifications.

Noise cancellation systems are known, in which an electronic noise signal representing ambient noise is applied to a signal processing circuit, and the resulting processed noise signal is then applied to a speaker, in order to generate a sound signal. In order to achieve noise cancellation, the generated sound should approximate as closely as possible the inverse of the ambient noise, in terms of its amplitude and its phase.

In particular, feedforward noise cancellation systems are known, for use with headphones or earphones, in which one or more microphones mounted on the headphones or earphones detect an ambient noise signal in the region of the wearer's ear. In order to achieve noise cancellation, the generated sound then needs to approximate as closely as possible the inverse of the ambient noise, after that ambient noise has itself been modified by the headphones or earphones. One example of modification by the headphones or earphones is caused by the different acoustic path the noise must take to reach the wearer's ear, travelling around the edge of the headphones or earphones.

However, noise cancellation systems are generally employed in applications where it is highly desirable to reduce power consumption. For example, portable music players and mobile phones have limited battery resources, and therefore efforts should be made in order to reduce the drain on these resources. Noise cancellation is one such drain, and therefore it is desirable to design a noise cancellation system that is as efficient as possible, while existing solutions oftentimes are not. A novel approach to active noise cancellation using two microphones also exists. The primary microphone is placed at the point where noise cancellation is desired, and the secondary microphone is placed at some other point. The cancelling signal is generated as the output of a two-input/single-output FIR (finite impulse response) filter which is driven by the outputs of the secondary and the primary microphones. The output of the primary microphone is not only used to adjust the coefficients of this filter but is also used as an input to the filter itself. The performance of the two-sensor algorithm is compared with that of an LMS (least mean square) algorithm and with that of a single-sensor algorithm. These three algorithms were applied to noise recordings made using a set of headphones worn inside the cabin of a propeller aircraft. The primary sensor was placed inside the headphones and the secondary sensor was attached to the outside of the headphones. Assuming that the transfer function between the cancelling speaker and the primary sensor was a pure delay of about 40 mu s, the new algorithm was able to attenuate the overall noise power 15 dB more than the LMS algorithm and 3 dB more than the single-sensor algorithm.

2.1 History of ANC

The first patent for active noise control systems was granted to Paul Lueg in Germany in 1934. In his patent, Lueg examined and showed the idea of noise cancellation by combining the sinusoidal tone with a phase shifted reproduction of itself. Though theoretically functional, the implementation of Lueg’s study was hindered by the absence of proper equipment to detect, process and generate sound. As a result, active noise cancellation technology remained theoretical for more than 20 years, finally transitioning from theory to implementation in 1957 when Willard Meeker developed the first working model of active noise control applied to circumoral earmuff. Meeker’s headset, boasting an attenuation bandwidth of 50 to 500 Hz, was capable of achieving a maximum attenuation of approximately 20 dB. However, ANC technology was not commercially available until 1989, when Dr. Amar Bose, MIT professor and founder of Bose Corporation, developed the first commercially available noise cancellation headphones in history.

Active Noise Cancellation technology has gone through countless stages of development throughout the years, thriving off research and experimentation to reach the complexity, efficiency and performance it boasts today. Furthermore, numerous works and documentations regarding ANC were studied in order to reach a complete understanding of active noise cancellation technology and its fields of implementation.

2.2 Evolution of ANC

Since Paul Lueg was the first to invent Noise cancelling methods, Active Noise Control systems have gained popularity years and their usage grew rapidly. The idea behind cancelling the Unwanted noise is to receive the noise through a microphone and reproduce the same noise through a speaker that is phase shifted by 180 degrees. He introduced several methods: If the sound is coming from one direction and the noise is sinusoidal the method can be simply done by placing a microphone in a certain distance between the source of the noise and a speaker where by the time the noise reaches the speaker it will have the opposite signal opposing it.

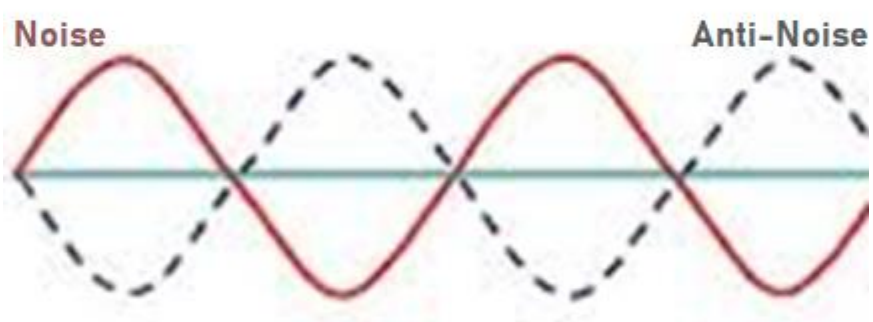


Figure 2.1: First ANC Model

Over the years, the Neonatal Intensive Care Units (NICU) has done several improvements to insure the safety of infants. Newborn infants in their critical period are very vulnerable to environmental impacts due their auditory systems being fragile. One issue is the noise of the incubator and its surroundings; in addition to other noise sources such as alarms, beeps, doors, and vibration sounds made by medical equipment which may cause hearing disorders. Therefore, having a noise coming from one direction with a constant frequency is no longer applicable in this case. This is where the LMS algorithm started to appear. It was first invented by Bernard Widrow and his PhD student Ted Hoff. The idea behind this algorithm is to mimic a desired filter by finding the filter coefficients that relate to producing the least mean square of the error signal (difference between the desired and the actual signal). This is done by updating the weights of adaptive filter according to the error detected. The weights are updated again and again until the error reaches its minimum value.

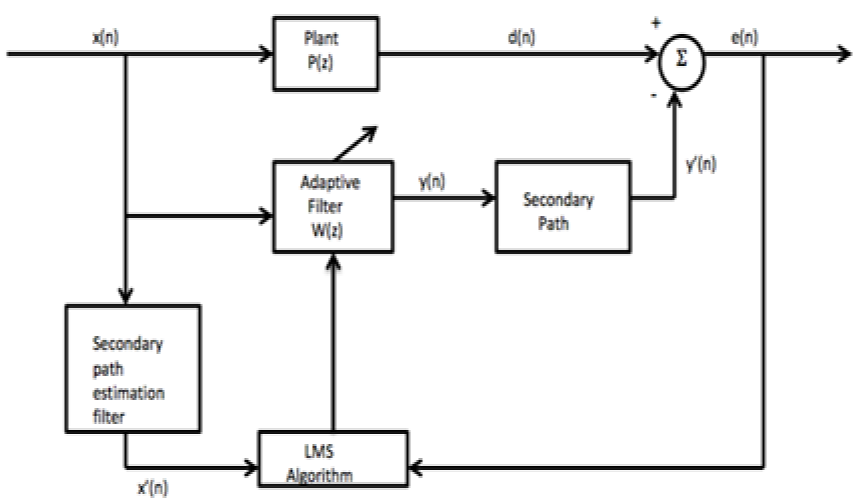


Figure 2.2: LMS Algorithm System

2.3 Problems and Solutions

The issues that need to be solved with ANC depend on its desired application. For example, in certain cases the goal is not to completely cancel out all the received sound, but rather to clean up an audio wave of noise while keeping the message signal audible. In cases like this, traditional noise cancellation technology may not be the best choice, and generally adaptive noise cancellation may be preferred. Nevertheless, the problem is not impossible for Active Noise Cancellation to overcome, for example Dieter Foller in 1991 proposed a solution and even received a patent for it. Foller's solution uses two microphones: The first of these, M1, is directed towards the unwanted noise source and connected to a circuit that will create the anti-noise wave. Placed next to it is Microphone M2 which is directed towards the desired sound source. M2 will only receive the desired sound because the emitter placed between the M1 and the noise source, will cancel out the noise before it can reach it.

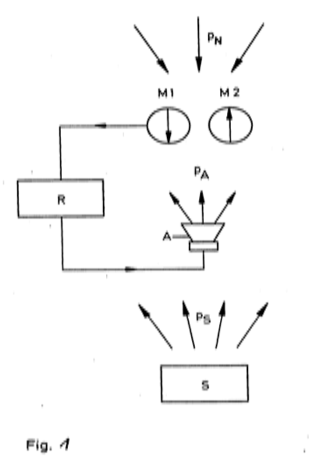


Figure 2.3: Foller's ANC Proposition

Another common problem is faced when using feed-forward technology in ANC headphones. The problem is that analog waves are much slower than electrical signals, so the natural noise will reach the ears much slower than the anti-noise generated by the headphones themselves, and therefore the noise and anti-noise will not overlap and cancel out. Here, the solution is to slow down the anti-noise with an all-pass filter. The all-pass filter consists of a series of capacitors and resistors that will affect a phase shift on any signal passing through it. To be able to configure it properly, we must know the desired phase shift, which will depend on the delay. To get the delay we assume the distance from the headphones to the ears to be 2cm, we can then use the formula: $Time\ Delay = \frac{distance}{speed\ of\ sound} = \frac{0.02m}{340m/s}$ = 60 µsec. Knowing this we find the phase shift with the formula: $Phase\ Shift = time\ delay * frequency * 360$. We can thus find the necessary phase shift for a 60 Hz frequency: 1.6 degrees and for a 100 Hz frequency it is 21.6 degrees. We could alternatively delay the anti-noise signal with a DPDT switch.

2.4 Applications of Active noise cancellation technology

There are many cases in which active noise cancellation is useful and desired. The one main requirement is that the source of noise must be predictable so that we may generate the opposite of it. One very common example is fan noise cancellation:

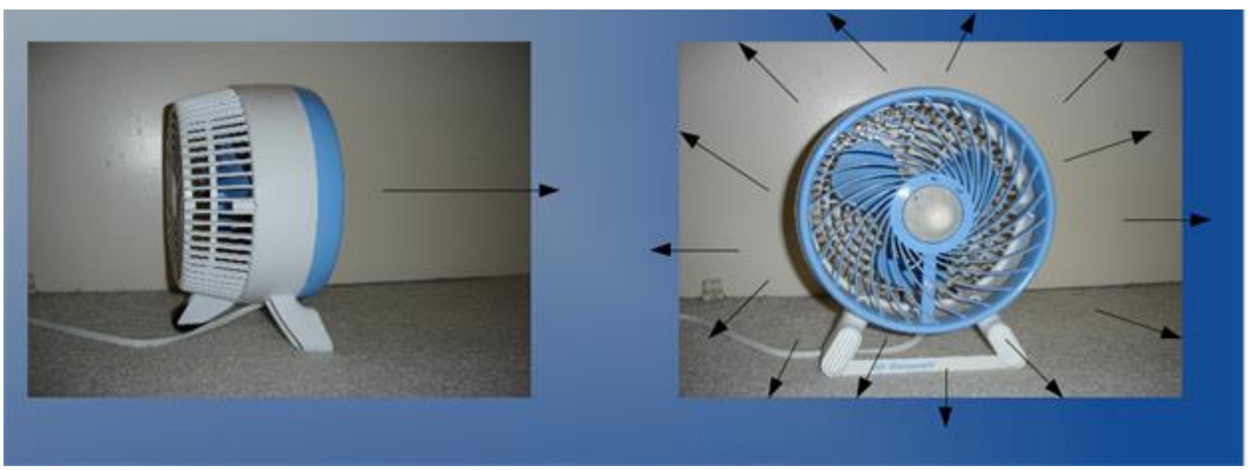


Figure 2.4: Fan's Noise Propagation

As can be seen, the noise from a fan does not spread forward, but it spreads in the direction of spin of the blades. To get a good signal to noise ratio, keeping this in mind during microphone placement is essential. With the proper microphones in the proper places we can analyze the frequency spectrum precisely, allowing us to generate the opposite soundwave, cancelling the sound waves coming from the fan in the following way:

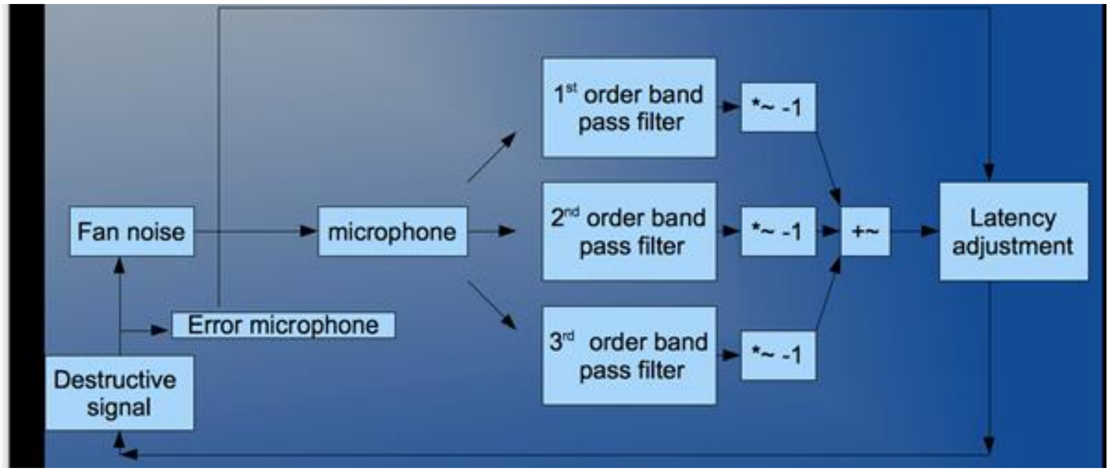


Figure 2.5: ANC for Fan Noise

In a similar way to that in which we can cancel large fan noise, it is also possible to cancel computer fan noise. This is obviously desirable since the noise from that can get rather large and bothersome, especially in the case of very powerful or numerous computers such as those used in server farms. The way to achieve this cancellation is generally to receive the noise through a microphone, determine its spectrum, then generate an airflow of opposite phase to destructively interfere with the fan noise. The graph below explains the procedure:

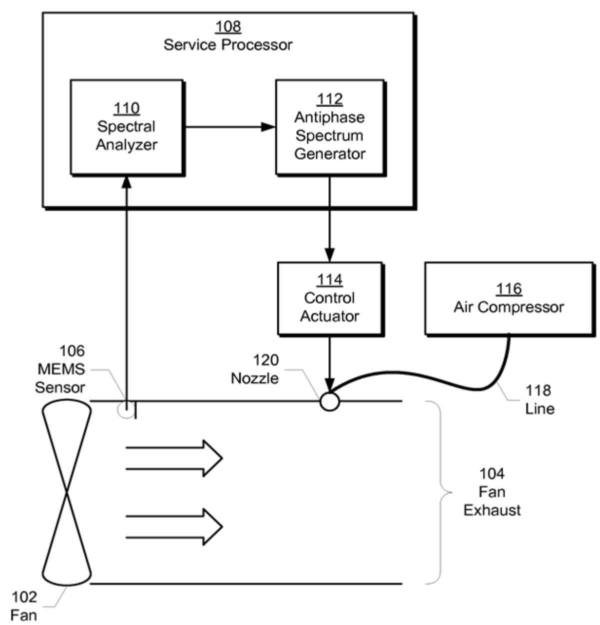


Figure 2.6: Procedure for Fan Noise Cancellation

There are also many industrial applications of ANC currently. Current industrial applications of active noise control technology are focused mainly around the control of plane wave sound propagation in air handling ducts, gas turbine exhausts or diesel engine exhausts, as well as active ear muffs. Perhaps the most important application that has been successfully commercialized is the reduction of tonal noise in propeller driven aircraft using active engine mounts and vibration actuators mounted on the fuselage rings. Communication trouble between aircrafts and ATC towers have caused some of the deadliest accidents in human history, and thus reducing noise levels in those cases is critical. The microphones are placed in the following way to measure engine noise directly with minimal outside interference:

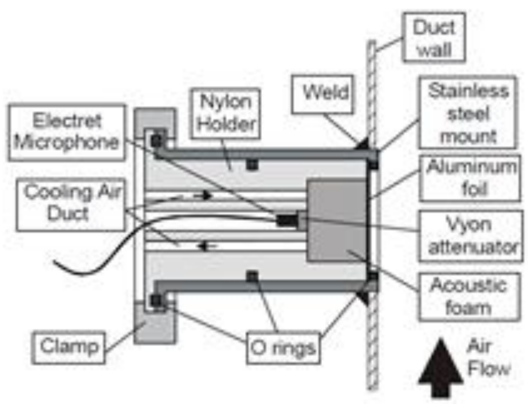


Figure 2.7: ANC for Engine Noise

This will allow us to have a clear reference signal to cancel this noise. Using this, we can also add a recording from the cockpit to perform adaptive noise cancellation: With the two audio inputs, it is possible to learn which part of the audio is noise and then cancel only that part.

Chapter 3: Previous work

Our design is built to improve and develop a noise cancellation project previously done by our colleges Adel Fayad (A1211184) and Samer Kabbara (A1411301). Their circuit, displayed below, was built on NI Multisim where the objective was to cancel out constant low frequency ambient noise.

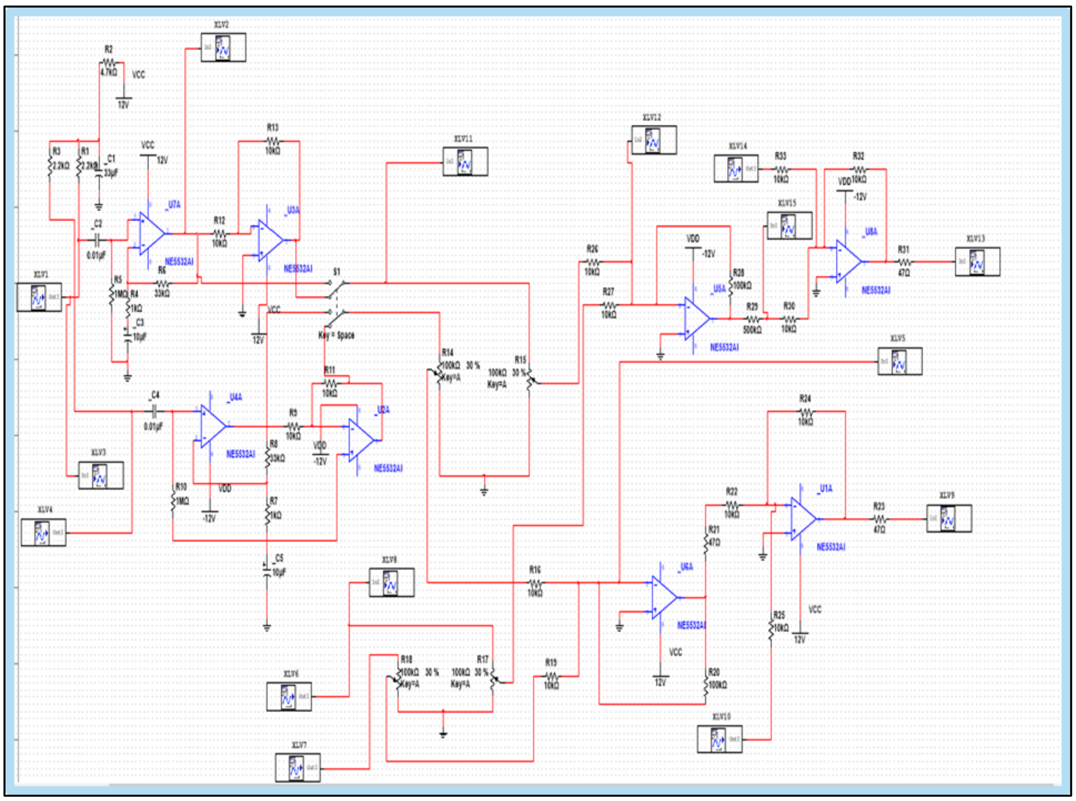


Figure 3.1: Multisim Circuit

Basically, this circuit is divided into two parts. The upper half circuit and the lower half circuit which is the mirror of the upper one since one is for the left audio feed and one for the right audio feed. After analyzing and simulating the circuit the results were as follows: The circuit is divided into four parts. The first part is responsible for amplifying the noise signal, The second part is to phase shift the noise signal by 180 degrees, The third part is to attenuate the anti-noise to have an amplitude equal to that of the original noise, and the last part is responsible for summing up the music and the anti-noise then feeding the summed signal into the headphone.

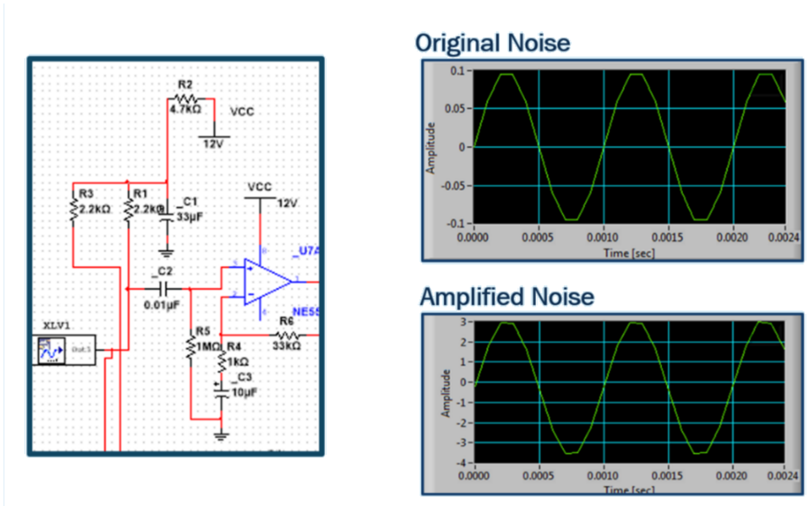


Figure 3.2: Amplified Part

The figure above is the first op amp which is U7A. This is a non-inverting pre-amplifier which is responsible for amplifying the noise signal that is generated by the signal generator XLV1. This procedure is crucial sine the characteristics of this unfavorable noise is of low frequency and low amplitude which makes it difficult for the circuit to deal with.

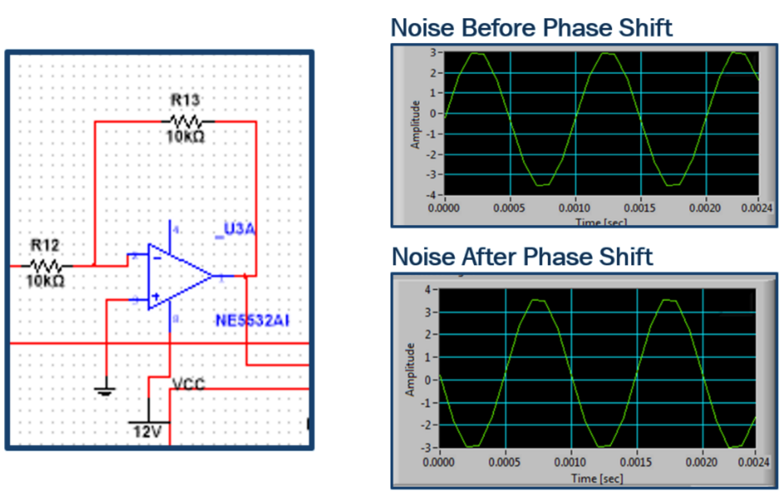


Figure 3.3: Phase Shifted Part

This second part of the circuit which is the inverting amplifier U3A is responsible for phase shifting the incoming amplified noise by 180 degrees. This is done by changing the polarity of the signals voltage while maintaining a gain of 1 to avoid amplitude change. Now that the noise is amplified and inverted, the signal is fed into the third part of the signal below.

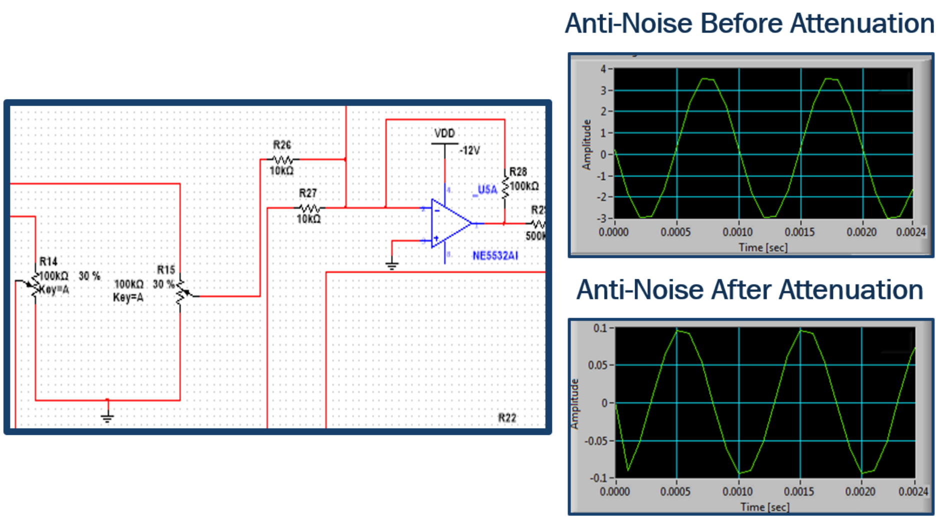


Figure 3.4: Attenuated Part

This part of the circuit is responsible for attenuating and time shifting the anti-noise. This process is done so that the amplitude of the anti-noise is equal to that of the original noise which will lead to a proper noise cancellation while also delaying the anti-noise since electronic signals are much faster than sounds. Therefore, delaying the anti-noise is necessary so that both signals arrive the ear at the same time. The final part of the circuit is the summing part as seen in the figure below.

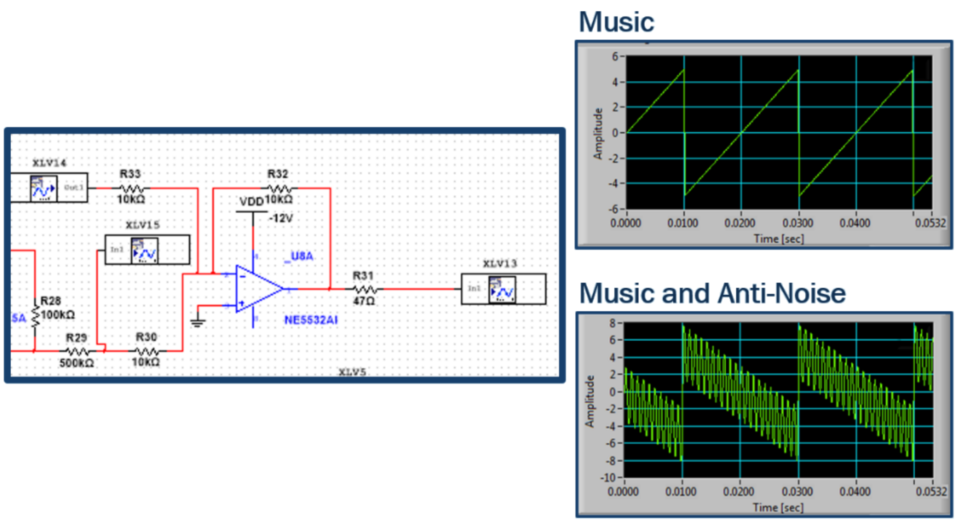


Figure 3.5: Summing Part

This last op-amp which is the summing amplifier is responsible for the summation of the anti-noise and music that is generated from the signal generator XLV14. After summing both signals it is then fed into the headphones to achieve the results as seen in the figure above. After implementing this circuit, the user can listen to music without ambient noise interference. But the limitation of this project is that if the noise is of variable frequency the circuit will not attenuate the noise properly. This result was tested using National's Instruments Virtual Bench provided by the University of Balamand's Control Lab.

As seen in the figure below, after feeding the circuit with a noise file from a laptop the noise was not properly attenuated. This shown by the slight difference between the noise and anti-noise signals, displayed in the figure below.

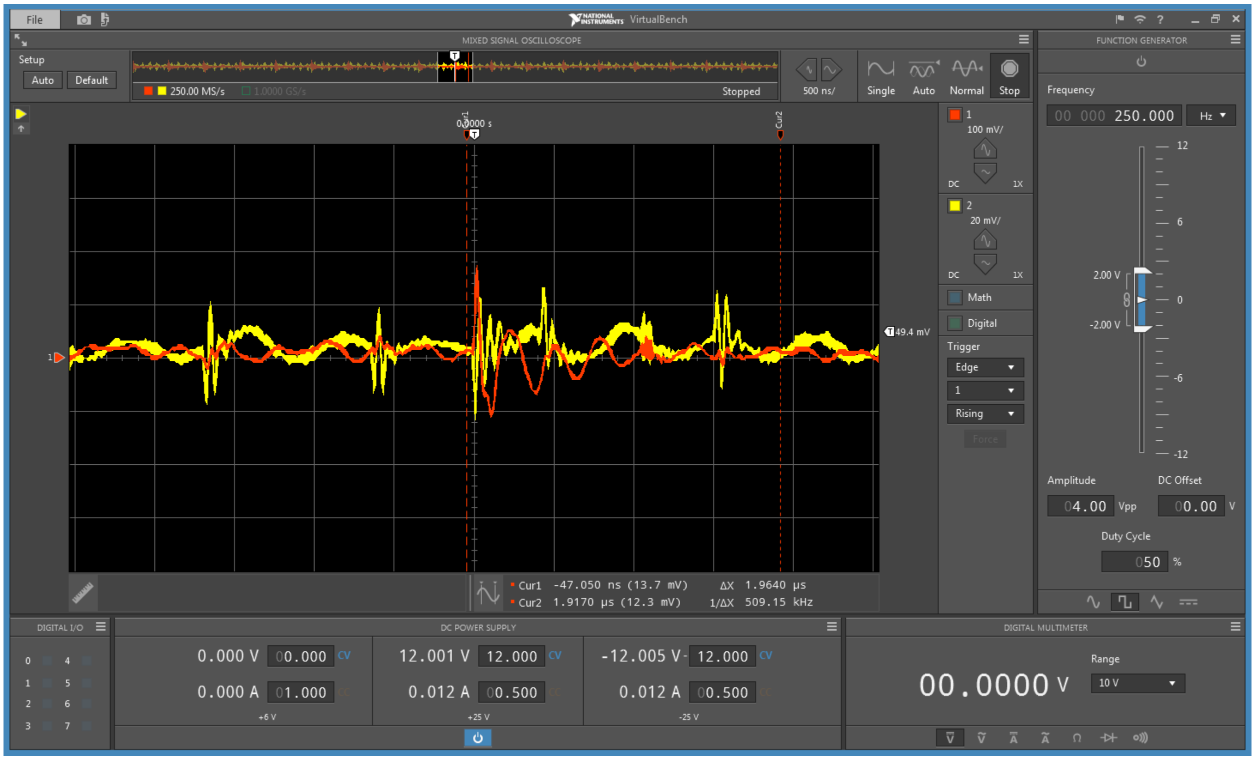


Figure 3.6: Noise (Red) and Anti-Noise (Yellow)

Therefore, our project's aim is to tackle variable frequency noise cancellation through the utilization of adaptive algorithms implemented through a software platform.

Chapter 4: Proposed Algorithms

4.1 LMS

The Least Means Squared algorithm is the basis of most active noise control systems available today. It is a type of adaptive filter based on stochastic gradient descent, first invented in 1960 by Stanford University professor Bernard Widrow with his first PhD student Ted Hoff. Least Mean Squares algorithm based filters do not attempt to automatically perform a task but rather, they are a type of self-learning filter that will adaptively change itself until it can accurately model the type of filter required for a specific application. Thus they are perfect for the types of applications where traditional filters are too inflexible or inadequate, such as our own objective of cancelling high or variable frequency noise, which as our colleagues showed in the previous work is beyond the capabilities of normal analog filters. The signal is picked up at a reference microphone x(n) and sent through an adaptive filter w(z) such that noise at the error microphone e(n) is minimized. Thus, it can be seen that as e(n) → 0, w(z) → P(z). The adaptive filter algorithm will be terminated when the column weight vector iterates up to the length of the filter and the final output of the algorithm itself. The components of the algorithm are as follows:

- w(k) is the column weight vector of the filter at the k^{th} time.
- It is used in the algorithm to update the subsequent column weight vector and can be represented by the following equation vector:

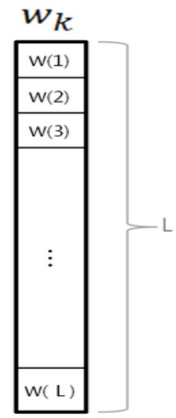


Figure 4.1: Column Weight Vector

- The error e(k) at the kth time is defined as the difference between the noise corrupted signal and the weighted noise signal

$$e(k) = y_1(k) - w^T(k)y_2(k)$$

The adaptive algorithm is represented by the update of the column vector after each iteration, as given by the following equation: $w(k+1) = w(k) + \mu e(k)$

The use of the Least Means Squared Algorithm does impose complications:

- Use of LMS in practical active noise cancellation applications is complicated by that the anti-noise created by the speaker must travel from the cancellation speaker to the error microphone, and this transition from the digital domain to the analog domain and back. This causes frequency and phase distortions to the signal which are known as the secondary path S(Z).
- The secondary path includes any signal components between the output of the adaptive filter and the input of the error signal to the LMS algorithm

To counteract the distortion introduced by S(Z), an adaptive filter Ŝ(Z) is placed between the reference microphone and the LMS algorithm, allowing for the algorithm to converge.

The convergence times are much better for FxLMS with the variable step size algorithm and for NLMS with the normalized input values. Furthermore, the xLMS algorithm converges to an absolute minimum at a faster rate than the LMS algorithm.

The following diagram illustrates the LMS algorithm explained above:

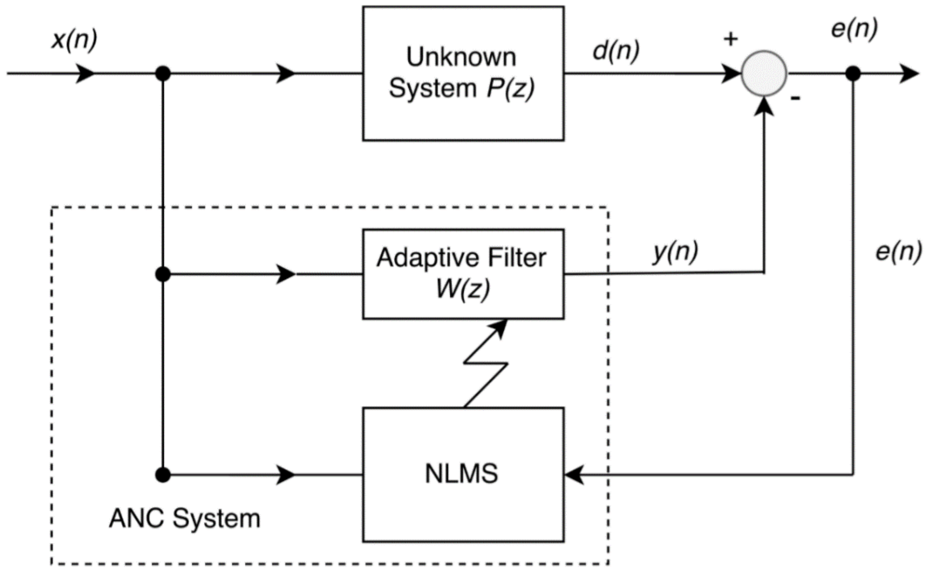


Figure 4.2: LMS Algorithm Filter Diagram

4.2 FNLMS

To improve upon the LMS algorithm and help it overcome its limitations so that it can be more useful for active noise cancellation, several other similar algorithms were proposed. One of them is the aforementioned NLMS which fixes the problems with the learning rate of LMS. In pure LMS, the algorithm is extremely sensitive to the scaling level of its input (x(n)). This makes choosing a learning rate into a very challenging endeavor indeed. It is almost impossible to find a large enough value that guarantees convergence anyway. Thus very small values must be used, which can slow convergence to a crawl. In Normalized Least Mean Squares (NLMS) filters, everything said above about the LMS filter holds true except that the power of the input is normalized (every input value is divided by the largest input value, thus generating a range of values between 0 and 1). With this learning rate, it is trivial to prove that with no interference (in the case where v(n) = 0), the optimal learning rate is simply μ = 1. Thus the learning rate in this case is independent of the real factors x(n) (the input) and h(n) (the impulse response). That remains true even in the more general case where interference v(n) is not equal to 0. In this case the optimal learning rate is:

$$\mu_{opt} = \frac{E\left[\left|y(n) - \hat{y}(n)\right|^2\right]}{E\left[\left|e(n)\right|^2\right]}$$

4.3 FxLMS

Though NLMS is indeed superior to LMS, it is not perfect. In fact NLMS still faces the same issue as LMS in not being able to converge at all (or converging much more slowly) when the secondary path is really complex, as it is not designed to cope with it. For this reason in our project we have chosen to use the FxLMS algorithm which looks as follows:

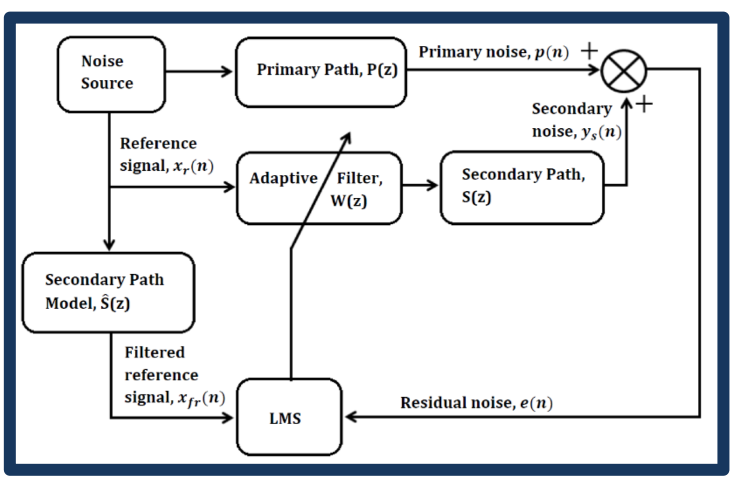


Figure 4.3: FxLMS Algorithm Filter Diagram

As can be seen in the figure, it is similar to LMS except that the Secondary Path Model is now embedded within the filter itself, allowing it to make up for the distortions introduced by it.

In practical ANC applications, the use of the LMS algorithm is complicated by the fact that the anti-noise created by the algorithm has to travel from the cancelation speaker to the error microphone, thus transitioning from the digital domain to the analog domain and back again. This introduces distortions in the frequency and phase of the signal which are known as the secondary path. The secondary path includes any signal components between the adaptive filter output and the input of the error signal to the LMS algorithm, including the reconstruction filter, the D/A converter, the amplifier, the preamplifier, the microphone, the loudspeaker, the A/D converter and the anti-aliasing filter. As shown in the block diagram above, in order to counteract the distortion that is due to the secondary path S(Z), the opposite filter S'(z) is placed between the LMS algorithm and the reference microphone. This will finally ensure that the algorithm will converge regardless of complications in the secondary path. However the system must first be tested offline before we start implementing ANC, so that we may obtain the impulse response of S(Z). There is more than one way to determine S(Z) itself but the simplest is to just go with running the system with simple white noise output. We obtain the inverse impulse response by transforming the input S(Z) into the frequency domain, inverting it there before bringing it back to the time domain again.

4.4 FuLMS

Finally, another powerful algorithm that we studied is the FuLMS algorithm. The FuLMS based filter addresses in this way the practical problem faced in real world implementation of Active Noise Cancellation; the problem of the cancellation speaker causing feedback to the

the reference microphone. It does so by adding a recursive adaptive Infinite Impulse Response filter called B(z) into the overall signal chain. The purpose of this filter is to minimize the error based on a single sample delayed instance of the function y′(n) as seen in Figure 6. The FuLMS filter has recursively updating parameters where A(z) is the main Finite Impulse Response adaptive ANC filter, B(z) is an Infinite Impulse Response for the purpose of removing feedback and $y'(n-1) = s'(n) * y(n-1)$ is a one sample delayed version of the cancellation signal filtered through the inverse of the secondary path signal filter.

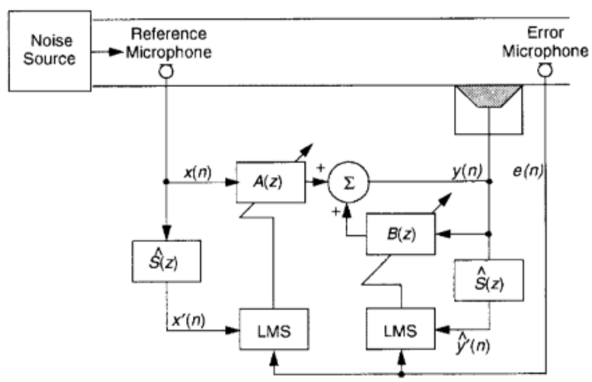
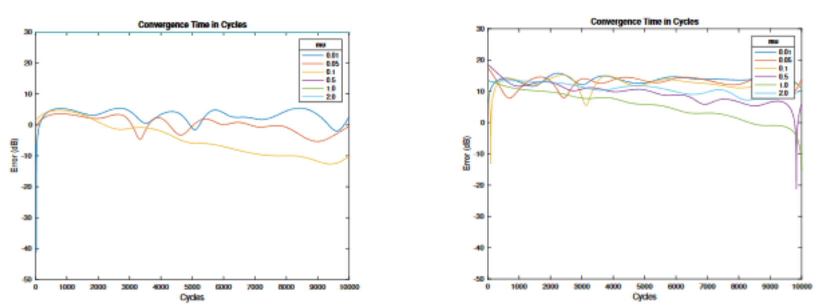


Figure 4.4: Block Diagram of an ANC System Using the FuLMS Algorithm



(a) FuLMS (b) FuNLMS

Figure 4.5: Convergence Times for FuLMS and FuNLMS Algorithms

These components are updated through the following equations:

$$y(n) = \mathbf{a}^T(n)\mathbf{x}(n) + \mathbf{b}^T(n)\mathbf{y}(n-1)$$

$$\mathbf{a}(n+1) = \mathbf{a}(n) + \mu\mathbf{x}'(n)e(n)$$

$$\mathbf{b}(n+1) = \mathbf{b}(n) + \mu\hat{\mathbf{y}}'(n-1)e(n)$$

However, the FuLMS algorithm is still not perfect. One of its drawbacks is that it cannot be mathematically proven to converge. This is because it is using non-quadratic IIR filters to minimize the error, and these filters may converge to a local minimum instead of the global minimum. Furthermore the Infinite Impulse Response filters themselves are not always stable, which could cause problems.

However, there exists a variant upon the FuLMS algorithm which is known as SHARF. This variant can be proven to be incredibly stable. The modification this version introduces is a low-pass filter that is used to smooth the error that will be fed to the LMS algorithm that is updating B(z).

In fact, researches have even added 80% sound from the cancelling speaker to the reference microphone to create exceptional feedback to test this version under. Even still, the algorithm was shown to converge, as can be seen in the figure above.

A further variant of FuLMS is FuNLMS which is just taking the Normalized input method applied to LMS and applying it to FuLMS instead. The convergence graphs for constant and variable step sizes can however be seen to be different for FuLMS than for LMS itself, the method discussed above. The difference is that the variable step version actually converges more slowly than the constant step version. This stems from the presence of two adaptive filters in FuLMS which need to have the same learning rate. It is speculated that choosing the learning rate independently for the IIR filter might fix this problem. Convergence is also said to vary depending on the severity of feedback that has been added to the reference microphone.

Chapter 5: Design and Simulation

5.1 LMS MATLAB Code and Simulation

The LMS algorithm is used to implement Adaptive Noise Cancellation rather than Active Noise Cancellation. This means that it does not cancel the entire incoming sound, but rather tries to filter it, removing the noise and keeping a message signal. We implemented Adaptive Noise Cancellation on MATLAB in 2 ways, and observed how doing it with LMS improves the results:

```
clear, clc;
close all;
pkg load audio;
[f,fs] = audioread('NoisySpeech.wav');

prig = audioplayer(f,fs);
prig.play;

N = size(f,1); % Determine total number of samples in audio file
%figure;
%subplot(2,1,1);
%stem(1:N, f(:,1));
%title('Left Channel');
%subplot(2,1,2);
%stem(1:N, f(:,2));
%title('Right Channel');

df = fs / N;
w = (-(N/2):(N/2)-1)*df;
y = fft(f(:,1), N) / N; % For normalizing, but not needed for our analysis
y2 = fftshift(y);
%figure;
%plot(w,abs(y2));

%% Design a bandpass filter that filters out between 700 to 12000 Hz
pkg load signal;
n = 7;
beginFreq = 700 / (fs/2);
endFreq = 12000 / (fs/2);
W = [beginFreq, endFreq];
[b,a] = butter(n, W, 'stop');

%% Filter the signal
fOut = filter(b, a, f);

%% Construct audioplayer object and play
p = audioplayer(fOut, fs);
filename='DenoisedSpeech5.wav';
audiowrite(filename,fOut*1.2,fs);
```

Figure 5.1: Simple MATLAB Code to Implement Adaptive Noise Cancellation

This is the more basic way, not using LMS. Going through it section by section:

Lines 1-4:

We clear and clean the workspace. We load the audio package of MATLAB because we will need its functions to manipulate audio files. Then we read in the NoisySpeech file, storing it into F, and its sample rate in Fs.

Lines 5-6:

Plays the sound file to demonstrate what it was before noise cancellation

Line 9:

Determines the number of samples in the audio file, this will be used in equations later

Lines 10-16 and 22-23:

Draws the files before and after noise cancellation. This takes time so it was removed for this training example, as playing the files was enough to determine whether the noise cancellation was good enough.

Lines 18-21:

Moving the extracted sound file from time domain to frequency domain so that it can more easily be manipulated

Lines 26-34:

Through experimentation, the frequencies of the noise harmonics were determined. This part then removes them from the overall signal using a bandstop filter

Lines 37-39:

Plays the cleaned-up audio file and saves a copy of it as DenoisedSpeech so that it may be replayed later or used in an application

This basic method had a certain rate of success and was certainly easy to implement, but it suffered from a number of problems. The LMS algorithm usually expects two inputs: One that would be the Noisy Speech and another one that would be the Noise Reference. As that was not available here, the frequencies of the noise had to be manually added. While this allows for cancelling noise with several different frequencies, it is impractical if we do not know what kind of noise to expect, and even more impractical if the frequencies of the noise and human speech match.

```
clc
close all
clear all

N=input('length of sequence N = ');
t=[0:N-1];
w0=0.001;  phi=0.1;
d=sin(2*pi*[1:N]*w0+phi);
x=d+randn(1,N)*0.5;
w=zeros(1,N);
mu=input('mu = ');
for i=1:N
   e(i) = d(i) - w(i)' * x(i);
   w(i+1) = w(i) + mu * e(i) * x(i);
end
for i=1:N
yd(i) = sum(w(i)' * x(i));
end
subplot(221),plot(t,d),ylabel('Desired Signal'),
subplot(222),plot(t,x),ylabel('Input Signal+Noise'),
subplot(223),plot(t,e),ylabel('Error'),
subplot(224),plot(t,yd),ylabel('Adaptive Desired output');
```

Figure 5.2: MATLAB Implementation of the LMS Algorithm

This is an implementation of the LMS algorithm. It allows the user to specify the length of sequence N and the learning rate mu, however that is simply for demonstration purposes. The same N and mu can be used for all kinds of different noises. This MATLAB code was not developed further, for we decided to resort to LabVIEW to design and construct our active noise cancellation circuit. The reason behind that was the diverse signal processing library available on LabVIEW which allowed us to develop a more complex algorithm, the FxLMS algorithm, to perform more efficient active noise control. In addition, LabView equipped us with detailed in-simulation power, something which allowed us to delve into the precise details of our design. However, MATLAB is a possible avenue for future work which should not take too much effort. For now this code works to perform adaptive noise cancelation on sine/cosine wave inputs as shown below:

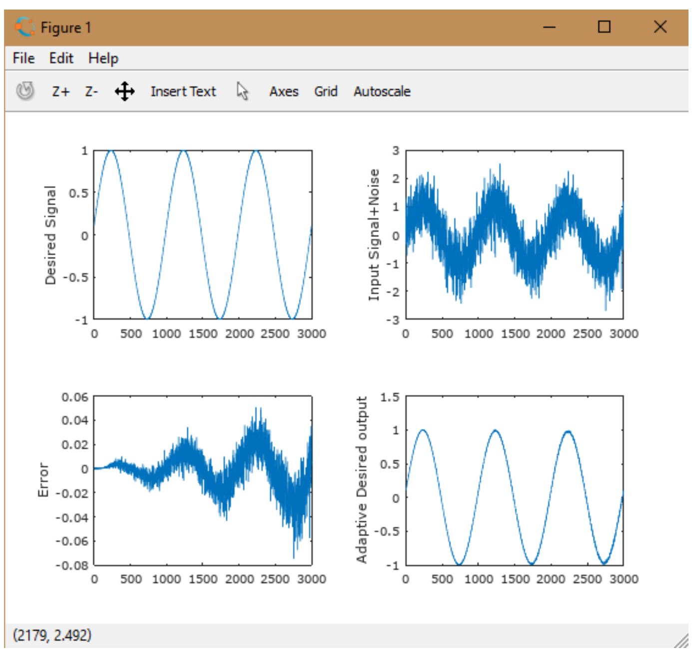


Figure 5.3: Outputs of the LMS Algorithm MATLAB Simulation

5.2 FxLMS LabView Design and Simulation

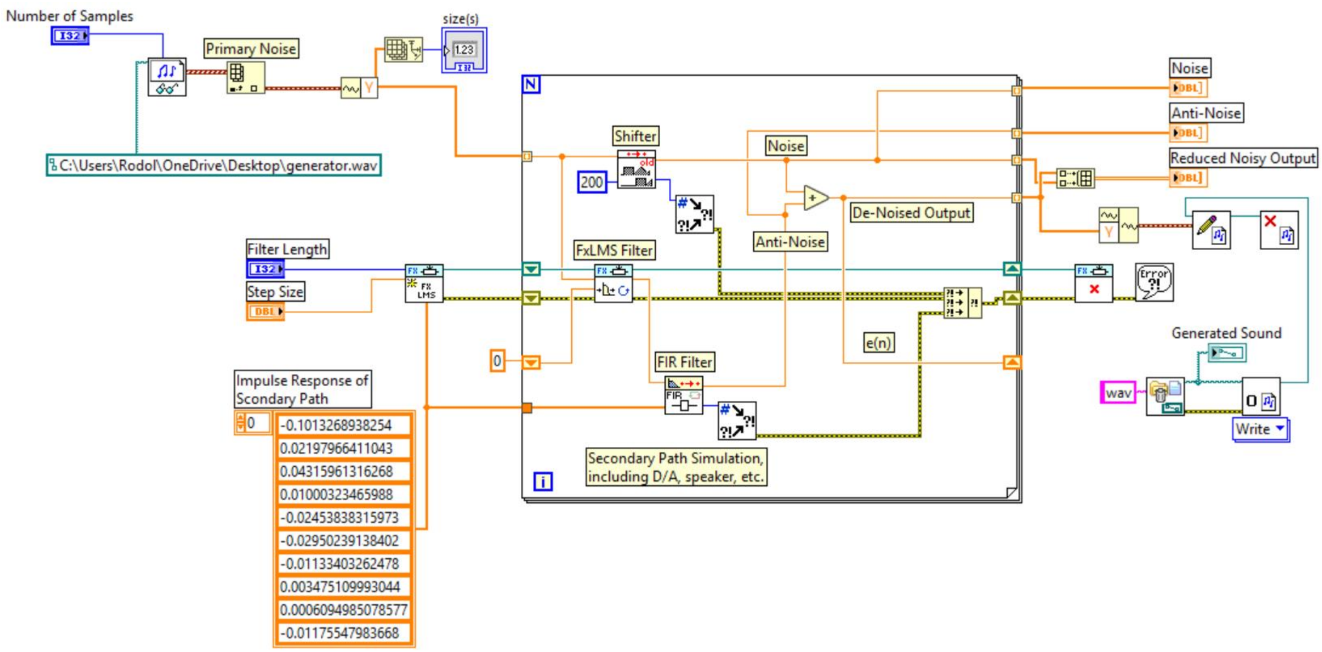


Figure 5.4: Active Noise Cancellation LabView Circuit

The above circuit was constructed to perform active noise control on a noise .wav file injected into the system input. In order to achieve the aforementioned goal, the circuit performs several operations with the main ones being the generation of the parameters for the xLMS filter, generation of the anti-noise signal, and synchronization and addition of the anti-noise signal and noise signal to produce the denoised output.

To start off, the waveform injected into the circuit – by means of a .wav file – is passed through the "Get Waveform Components" function block. This block extracts the data values of the waveform components, concatenating them into an array that can be analyzed and manipulated by the circuit. The data array produced is then fed into the system, which runs iterations until the preset filter length is reached, iteratively reducing the noise through repeated implementation of the FxLMS algorithm.

The production of the anti-noise signal starts with the “AFT Create FIR Filtered-X LMS” block which, as the name suggests, creates an adaptive finite impulse response (FIR) filter with the FxLMS algorithm. The block initializes the parameters based on the specified filter length and step size, passing these parameters to define the specifications of the following FxLMS filter block.

The FxLMS filter block, which receives the aforementioned adaptive filter specification, also takes as input the primary noise as well as an initial error value of zero. The error e(n) at time n is then iteratively updated with the result of the superposition of the noise and anti-noise signal. The FxLMS filter block is responsible for the phase shift of the noise signal, which in other words is the production of the anti-noise signal to be used in the noise control process.

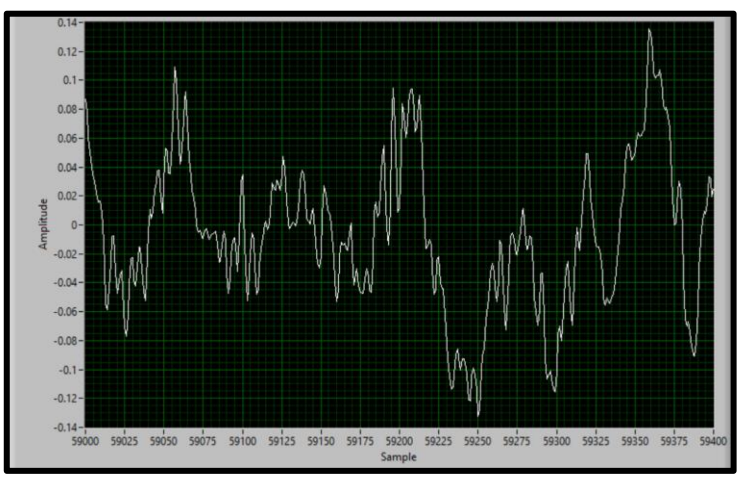


Figure 5.5: Initial Noise (Shifted by 160)

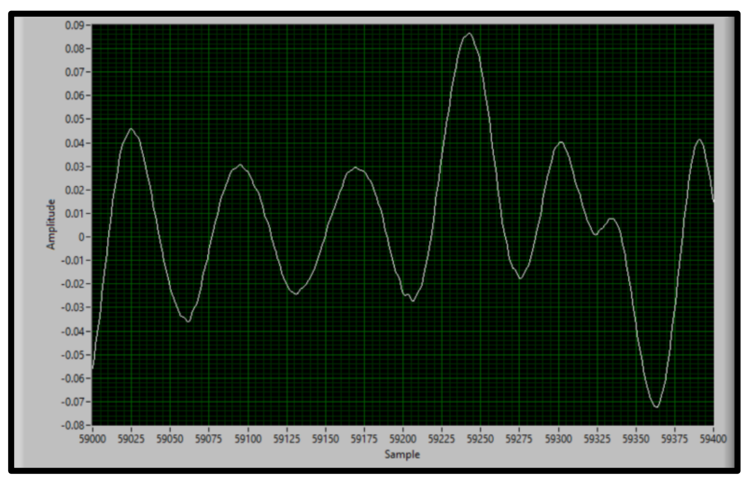


Figure 5.6: FxLMS Filter Output Signal

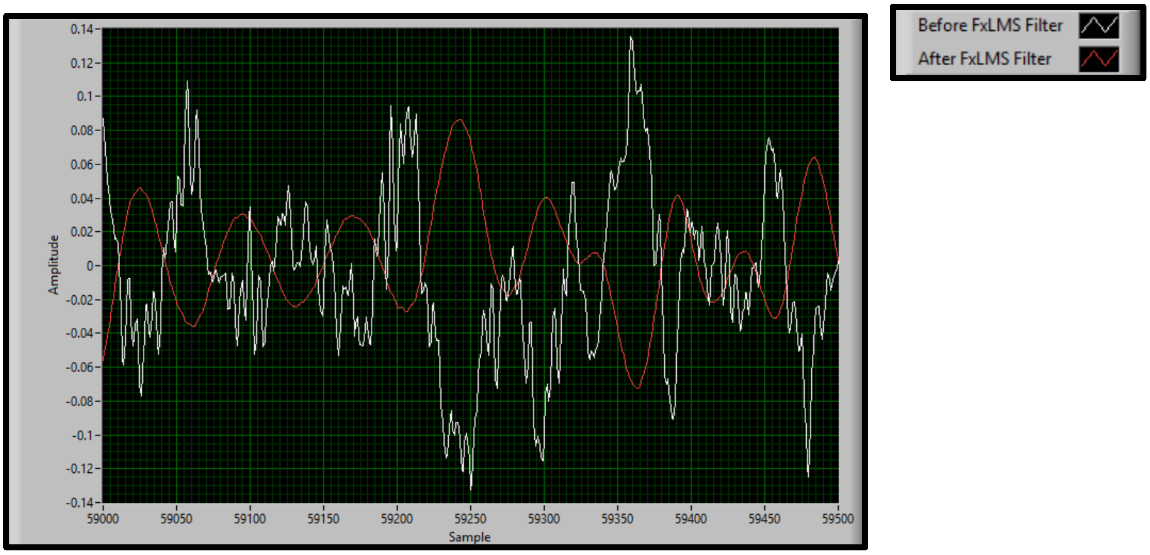


Figure 5.7: Display of Both Signals

The above figures summarize the role of the FxLMS filter block: The initial noise signal fed into the filter block is inverted, producing an anti-noise signal of opposite phase and approximately similar amplitude. However, due to the action of the filter, the output anti-noise signal suffers from a delay of approximately 160 samples. Therefore, for the sake of display and comprehension, the initial noise signal in figure 4 was shifted 160 samples and displayed in-phase with the anti-noise signal to properly show the action and effect of the FxLMS filter.

A FIR low-pass filter, whose forward coefficients are specified by the impulse response of the noise signal's secondary path, then filters the FxLMS filter block output, producing the final anti-noise signal responsible for the active noise control.

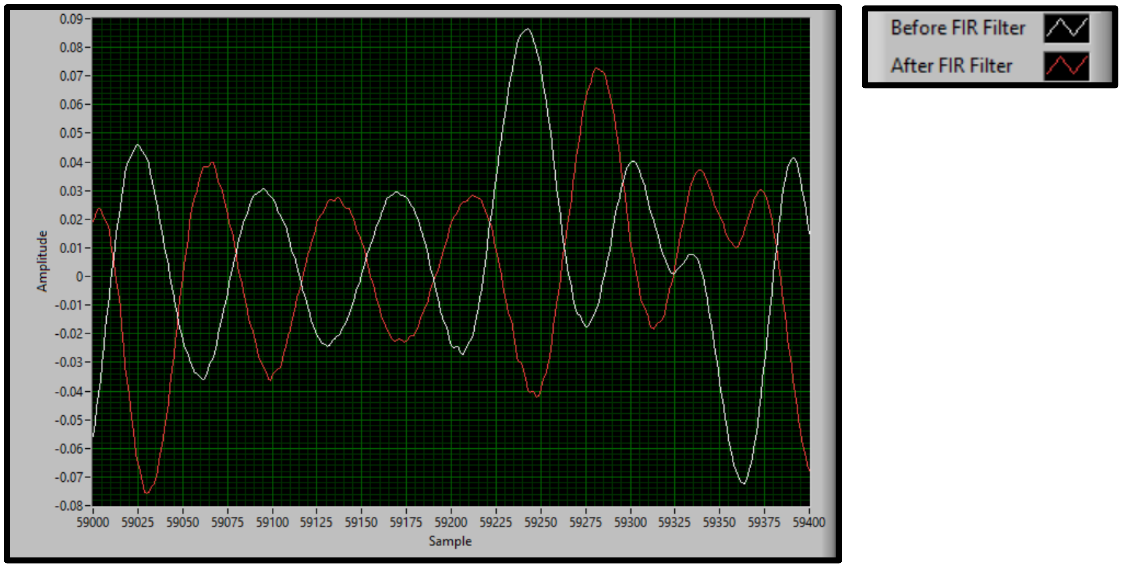


Figure 5.8: Anti-Noise Signal Before and After FIR Filter

In addition, similarly to the previous FxLMS filter, the FIR filter also causes the output anti-noise signal to suffer from further delay, as seen in figure 5.8. The phase shift, whose value is approximately 40 samples, will bring the total delay value of the final anti-noise signal to approximately 200 samples from the initial noise signal. As a result, in order to synchronize the anti-noise signal with the initial primary noise signal and achieve proper noise cancellation, the primary noise signal is passed through a point-by-point shifter. The shifter, whose shift value is 200, in turn outputs a shifted noise signal that is in phase with the produced anti-noise, thus making the successful superposition of these signals possible. A zoomed in portion of the noise and produced anti-noise signals is displayed in Figure 5.9, seen below.

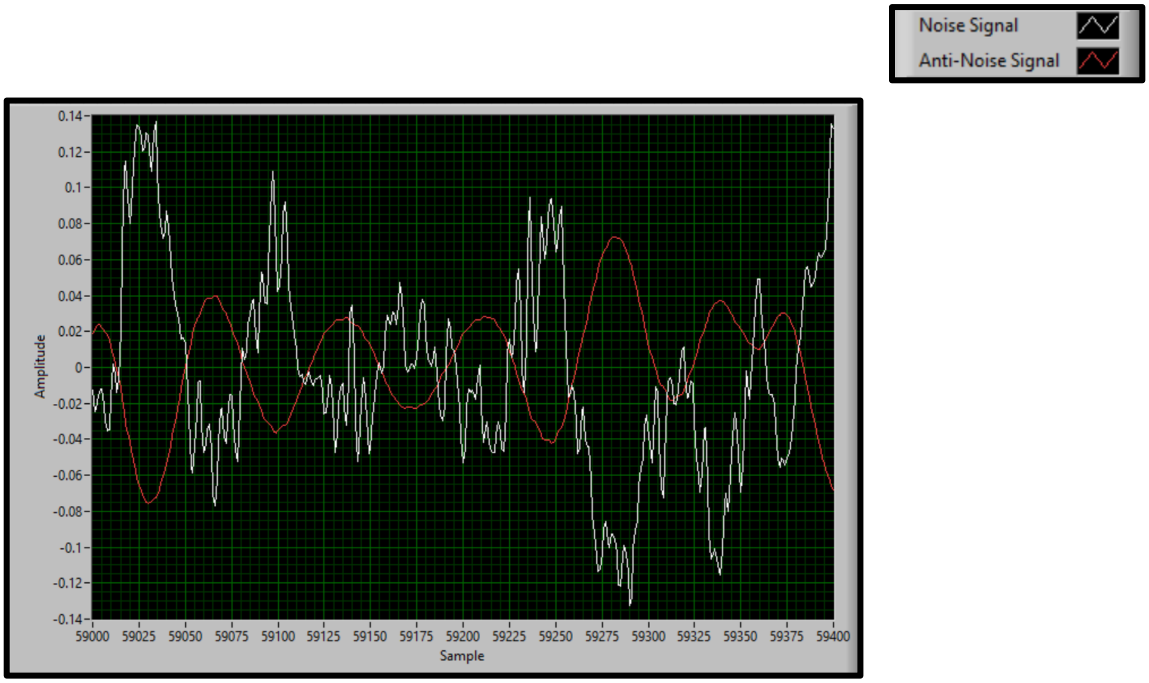


Figure 5.9: In-Phase Noise and Anti-Noise Signals

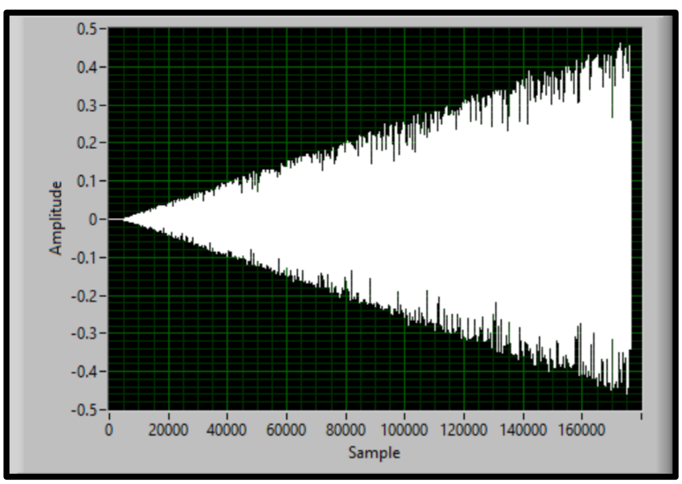


Figure 5.10: Initial Noise Signal

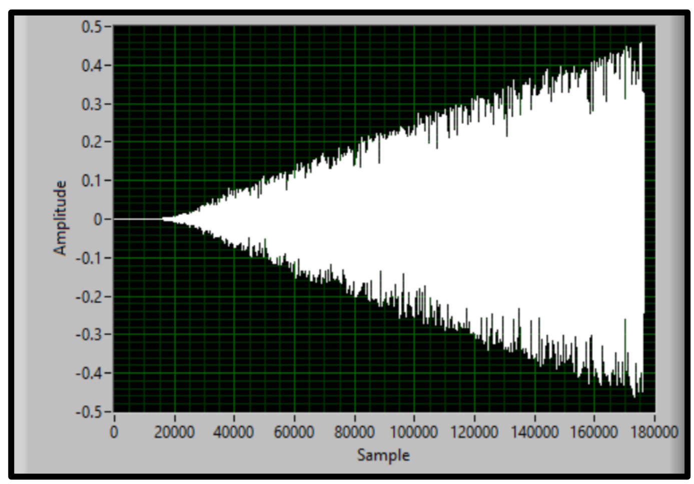


Figure 5.11: Produced Anti-Noise Signal

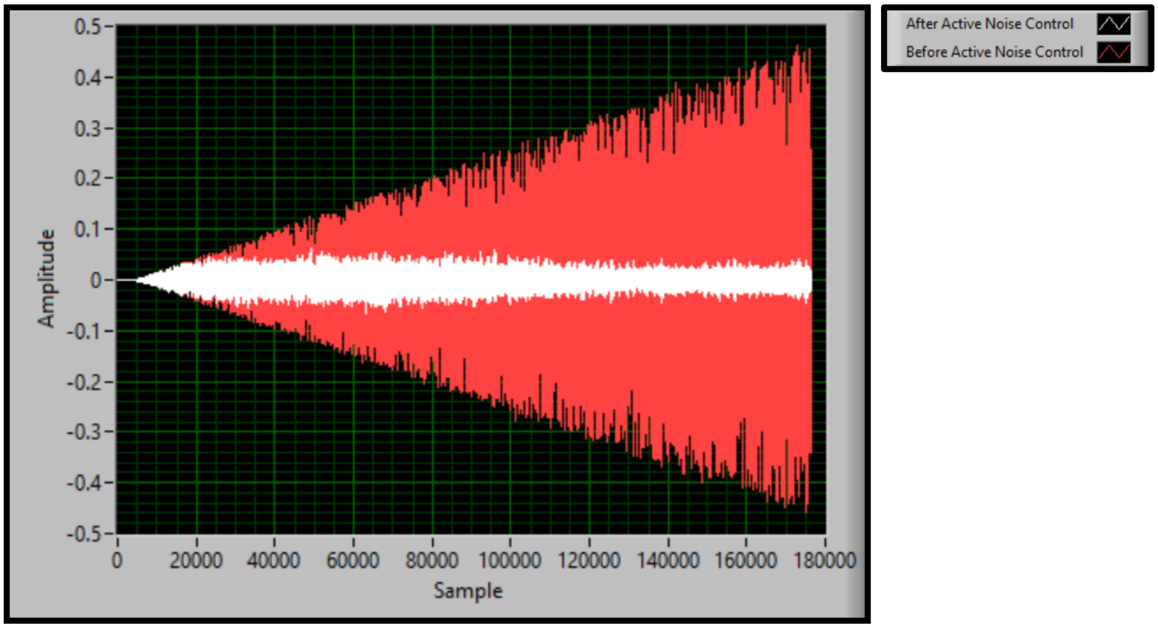


Figure 5.12: Initial Input vs Denoised Output

The result of the superposition of the in-phase noise and anti-noise signals is displayed in Figure 5.12. Figure 5.12 shows the notable difference in amplitude that the circuit has caused in the output noise signal, especially with the increase in number of samples, thus affirming that the constructed circuit performed as expected and yielded proper results.

In order to further verify the proper function and effectiveness of the designed filter circuit, further tests on noises of different sources, amplitudes and frequencies were performed. Firstly, a sound file containing the launch sound of an airplane was used. Keeping the filter parameters exactly the same, the below .wav file was fed into the active noise cancellation system. As shown by figure 5.13 below, the noise file is of randomly and inconsistently varying amplitude and frequency, thus making it a theoretically harder noise to cancel due to its varying properties.

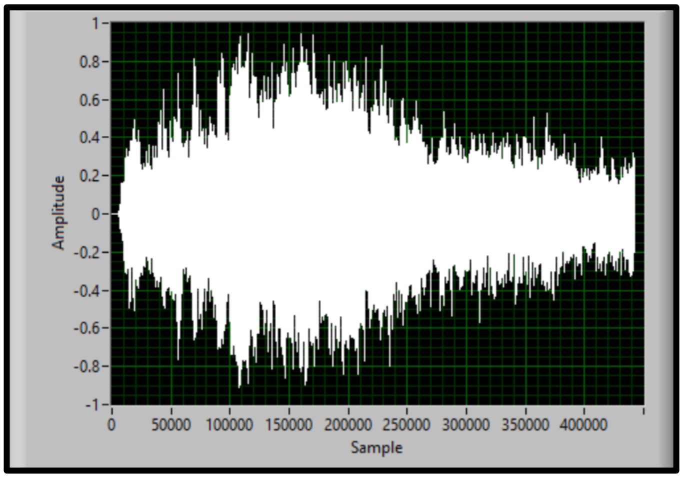


Figure 5.13: Initial Airplane Noise Signal

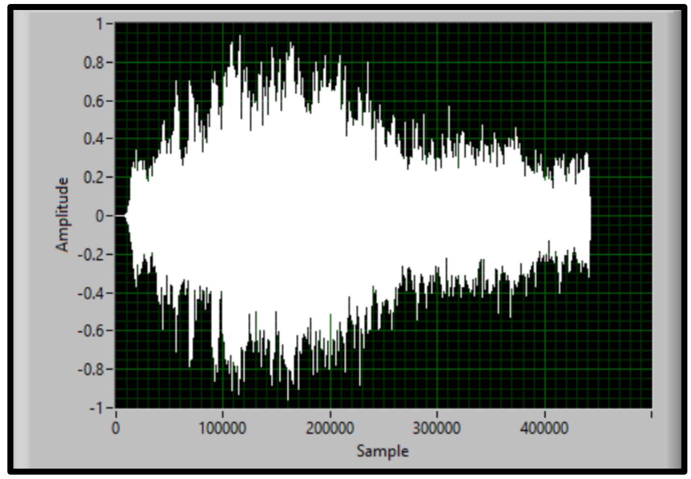


Figure 5.14: Produced Anti-Noise Signal

Upon receiving the .wav file, the system performs the same steps as in the previous example: It extracts the sound file's waveform components, concatenates them into an array and feeds it to the circuit to produce the corresponding anti-noise (figure 5.14). The produced anti-noise is then added to the noise signal, which was shifted 200 samples to achieve synchronization, producing the de-noised output signal displayed below.

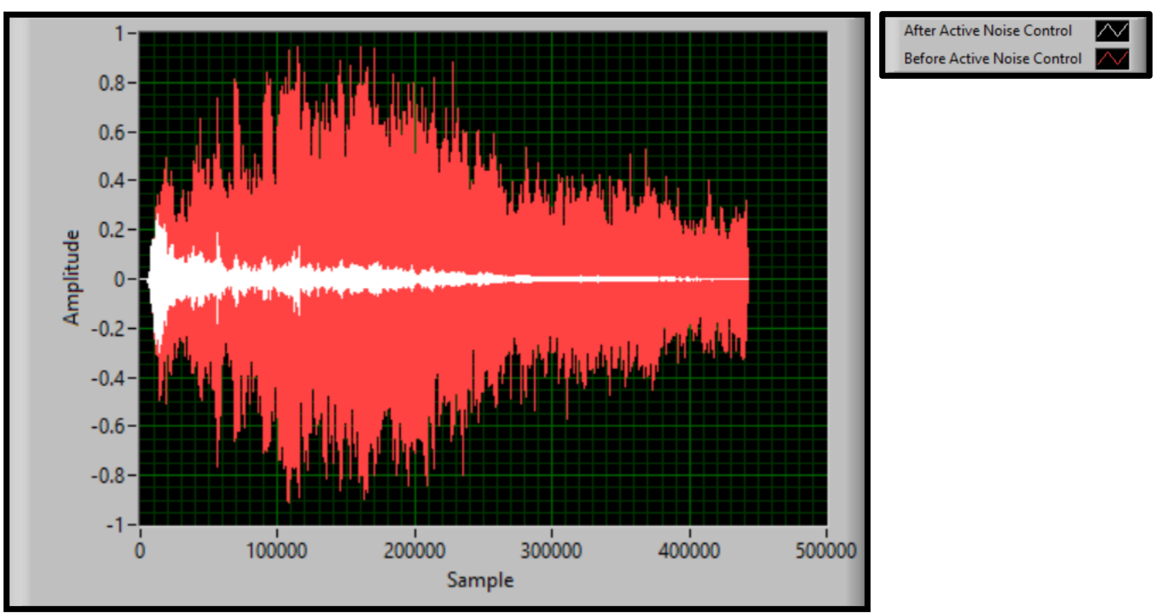
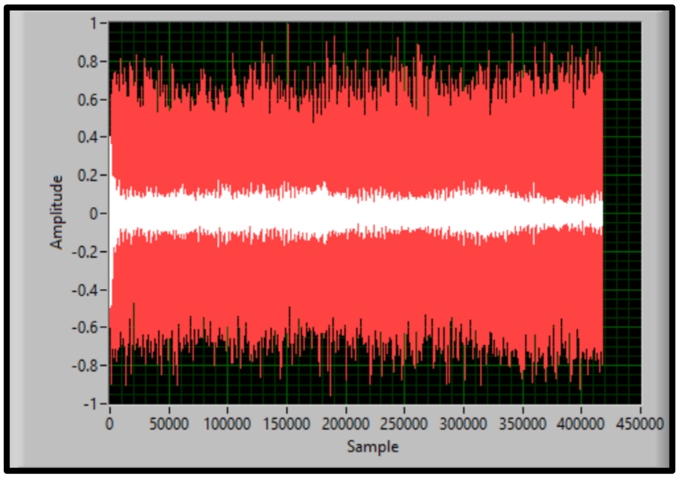


Figure 5.15: Initial Input vs Denoised Output

In addition to airplane noise, the noise cancellation circuit was tested with two additional audio files, the first one being the sound of a loud diesel generator (figure 5.16), and the second one being an audio test file of intensely varying amplitude and frequency (figure 5.17) .



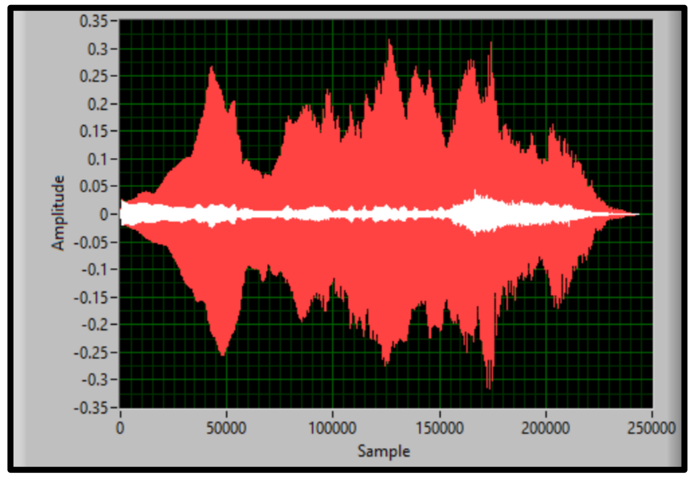
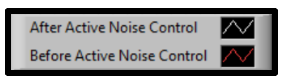


Figure 5.16: Diesel Generator Initial Input vs Denoised Output

Figure 5.17: Test File Initial Input vs Denoised Output



5.3 Results

As apparent in the above figures, the circuit performed effective and drastic active noise control on multiple noise sources. The initial noise signals, displayed in red, were attenuated to an amplitude lower than 15% of the initial value, displayed in white. To further verify the effectiveness of the constructed active noise control circuit, each audio file's sound intensity was measured, using a sound meter smartphone app, and compared with its corresponding denoised version. The results are displayed in the tables below:

	Generator 1	**Airplane**	**Generator 2**	**Test File**
Before Active Noise Control	72 dB	75 dB	76.7 dB	69.8 dB
After Active Noise Control	49.6 dB	50.5 dB	47.4 dB	38.3 dB

Table 1: Table Comparing Sound Intensity Before and After Active Noise Control

	Generator 1	Airplane	Generator 2	Test File	Average Attenuation
Attenuation Value	22.4 dB	24.5 dB	29.3 dB	31.5 dB	26.925 dB

Table 2: Table Showing the Attenuation Value Achieved in Each Simulation

Though the methods of measuring noise power may be somewhat inaccurate, the values recorded, paired with the obtained graphical results, give an approximation about the effectiveness of the ANC circuit. As shown by the above tables, the constructed ANC circuit performed effective noise control upon simulation. Throughout the series of test simulations performed, the circuit was able to achieve an average attenuation of 26.925 dB, a significant value considering the variability of the sources, amplitudes and frequencies of the noise files fed into the circuit.

Chapter 6: Future Work

There are many ways by which future students can build upon and improve this project. Firstly, the LabVIEW circuit is a great target for hardware implementation. LabVIEW itself provides cRIO hardware that supports its circuits. Thus, with the help of a couple of microphones for noise input and output, and an appropriately constructed sound station, this project could be easily moved from software to real life hardware implementation.

Secondly, this project could be implemented to achieve large scale active noise control. This would require more work and be a more ambitious project, but it might be possible to use the algorithms and implementations here to cancel, for example, all the noise coming from a generator. This would require future students to work out challenges such as how to channel the noise into one direction, and how to properly place the speakers and microphones to be able to cancel it without doubling its value at other points through interference. It would also require a large number of speakers and a profound knowledge in stochastics and optimization. However, the results would be worth the investments for any groups that might be willing to go into this direction and build upon this project to solve real life problems.

Chapter 7: Conclusion

This project allowed us to accumulate a profound knowledge of the history, methods and different applications of Active Noise Cancellation technology. Throughout this project, several adaptive algorithms were studied and analyzed, paving the way towards the design of a circuit that, according to simulated results, can perform effective active noise control on noise of variable frequency and amplitude.

The circuit was designed and simulated using LabView, a program that we gained profound experience in and became adept at using. The obtained results affirmed the effectiveness and applicability of the designed circuit on noises of variable types and frequencies. This opens the door towards the possibility of the ANC circuit being implemented to cancel noise both on a small scale (headphones), as well as large scale, considering that proper measures are taken, and precise calculations made.

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