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DEVELOPMENT OF ALGORITHM FOR AN ACOUSTIC SURVEILLANCE SYSTEM IN UAVs

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ABSTRACT

The main objective of this project is to develop an algorithm which is used for the surveillance system in Unmanned Mini Aerial Vehicles. Primarily the surveillance systems are based on the visual methods and are limited for its vicinity and range coverage. In contrast to this problem, the proposed system includes microphones (acoustic sensors) which are used to record the sound signals from longer ranges. Then the recorded signals are suitably processed by several processing stages for the accurate prediction of the object which includes localization and detection algorithms. Since the microphones record both the source and the target sound signals, it is necessary to possibly eliminate the source sound from the recorded signals so that leaving only the target sound signal. For this processing the adaptive filters which uses Least Mean Square algorithm (LMS) in the MATLAB environment are used. Adaptive noise cancellation with LMS algorithm is one of the most popular algorithms to solve many real time problems. Its popularity comes from its ability to perform well for both static and dynamic noise disturbances, easy to implement and effective to use.

Keywords: Surveillance, Unmanned Aerial Vehicles, Microphones, Adaptive LMS filter.

I INTRODUCTION

An unmanned aerial vehicle commonly known as a drone is an aircraft without a human pilot on board. Today, UAVs are offering various services, including intelligence gathering for tactical missions and maritime surveillance missions. UAVs are performing these missions with dedicated payloads like acoustic microphones. The sensors permit monitoring of approach ground or air vehicles and impulsive events (small arms fire, mortars, artillery, and explosions) from all directions, day or night, in dust or fog and under camouflage. They can detect operating vehicles or other sound sources, determine their location, and send detection data to the UAV operator to map the battlefield more rapidly and with more confidence than narrow field-of-view imaging sensors allow. This acoustic sensor solution is effective for small to medium-sized unmanned aircraft. The technology is also valuable for larger unmanned and manned aircraft when flying at low altitude and lower speed, where collisions are most likely.

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II ADAPTIVE NOISE CANCELLATION

An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. Because of the complexity of the optimization algorithms, most adaptive filters are digital filters. Adaptive filters are required for some applications because some parameters of the desired processing operation are not known in advance. The adaptive filter uses feedback in the form of an error signal to refine its transfer function to match the changing parameters.

2.1 Block Diagram

The block diagram, shown in the following figure, serves as a foundation for particular adaptive filter realizations, such as Least Mean Squares (LMS) and Recursive Least Squares (RLS). The idea behind the block diagram is that a variable filter extracts an estimate of the desired signal.

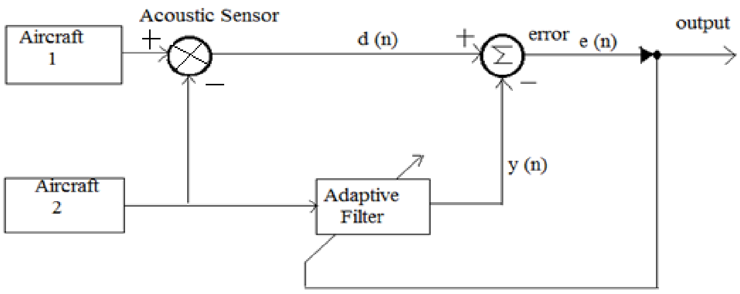

Fig 1 Adaptive Noise Canceller

Consider the microphone is present in the aircraft 2.The acoustic sensor (microphone) records the sounds from both the sources. This recorded signal is considered to be the input signal d (n) for the noise canceller as shown in the above figure. So to detect the presence of any acoustic sources around the aircraft structures 2, it is needed to cancel out its background noise from the microphone so that leaving only the required signal.

III ALGORITHM

For these purposes, there were several techniques to implement, and one which is most popular was adaptive filter techniques. The adaptive algorithm is nothing but continuously adjusting its filter weights throughout its iteration period for gradually reducing the error. LMS is famous for its robustness and its popularity comes from its ability to perform well for both static and dynamic noise disturbances, easy to implement and effective to use. To implement this adaptive algorithm it is necessary to determine the filter characteristics and performance issues such as the filter length, iteration time period, adequacy and step size. The performance characteristics are explained briefly and some statistic reports shown that FIR adaptive filter which uses LMS algorithm was used to solve noise cancellation processes in many real time problems. The basic operations involve filtering process, which produces an output signal in response to a given input signal. An adaptation

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process which aims to adjust the filter parameters to the environment. Often, the (average) square value of the error signal is used as the optimization criterion. The assumptions to be made out for understanding the processes are

a) The input signal is the sum of a desired signal d (n) and interfering noise v(n)

$$X(n) = d(n) + v(n) \qquad 3.1$$

b) The variable filter has a Finite Impulse Response (FIR) structure. For such structures the impulse response is equal to the filter coefficients. The coefficients for a filter of order p are defined as

$$w_n = [w_n(0),\ w_n(1), \dots \dots w_n(p)]^T \qquad 3.2$$

c) The error signal is the difference between the desired and the estimated signal

$$e(n) = d(n) - \hat{d}(n) \qquad 3.3$$

d) The variable filter estimates the desired signal by convolving the input signal with the impulse response. In vector notation this is expressed as

$$\hat{d}(n) = w(n) * x(n) \qquad 3.4$$

Where

$$X(n) = x[x(n), x(n-1), \dots \dots \dots x(n-p)]^T \ {}^{\wedge}T$$ is

an input signal vector. Moreover, the variable filter updates the filter coefficients at every time instant

$$w_{n+1} = w_n + \Delta w_n \qquad 3.5$$

Where Δw_n is a correction factor for the filter coefficients.

The adaptive algorithm generates this correction factor based on the input and error signals

3.1 LMS Algorithm

The LMS is one of the simplest algorithms used in the adaptive structures due to the fact that it uses the error signal to calculate the filter coefficients. The output y (n) of FIR filter structure can be obtain from Equation

$$y(n) = \sum_{m=0}^{N-1} w(m)\, x(n-m) \qquad 3.3.1$$

Where *n* is no. of iteration

The error signal is calculated by Equation

$$e\ (n)=d\ (n)-y\ (n) \qquad 3.3.2$$

The filter weights are updated from the error signal e (n) and input signal x (n) as in Equation

$$w\ (n+1)=w\ (n)+\mu\ e\ (n)\ x\ (n) \qquad 3.3.3$$

Where: w (n) is the current weight value vector, w (n+1) is the next weight value vector, x (n) is the input signal vector, e (n) is the filter error vector and μ is the convergence factor which determine the filter convergence speed and overall behavior. Most popular adaptation algorithm is LMS. It defines the cost function as mean-squared error based on the method of steepest descent move towards the minimum on the error surface estimated for every iteration.

$$\begin{bmatrix} update\ value \\ of\ tap\ weight \\ vector \end{bmatrix} = \begin{bmatrix} oldvalue \\ of\ tap\ weight \\ vector \end{bmatrix} + \begin{bmatrix} learning \\ rate \\ parameter \end{bmatrix} \begin{bmatrix} tap \\ input \\ vector \end{bmatrix} \begin{bmatrix} error \\ signal \end{bmatrix} \qquad 3.1.4$$

The stability of LMS algorithm convergent in the mean square if and only if the step-size parameter satisfies

$$0<\mu < \frac{2}{l_{max}} \qquad 3.1.5$$

Here λ_{max} is the largest eigenvalue of the correlation matrix of the input data.

More practical test for stability is

$$0<\mu < \frac{2}{input\ signal\ power} \qquad 3.1.6$$

Larger values for step size increases adaptation rate (faster adaptation) increases residual mean-squared error.

3.2 Performance Issues

To evaluate the basic criteria for performance to provide qualitative guidance as to how to choose filter length (L) and step size (μ) to identify the stationary systems.

3.3 Choice of Filter Length

We have seen that as the filter length L is increased, the speed of convergence of the LMS adaptive filter decreases, and the misadjustment in steady-state increases. Therefore, the filter length should be chosen as short as possible but long enough to adequately model the unknown system, as too short a filter model leads to poor modeling performance. In general, there exists an optimal length L for a given μ that exactly balances the penalty for a finite length filter model with the increase in misadjustment caused by a longer filter length, although the calculation of such a model order requires more information than is typically available in practice.

3.4.2 Choice of Step Size

We have seen that the speed of convergence increases as the step size is increased, up to values that are roughly within a factor of 1/2 of the step size stability limits. Thus, if fast convergence is desired, one should choose a large step size according to the limits. However, we also observe that the misadjustment increases as the step size is increased. Therefore, if highly accurate estimates of the filter coefficients are desired, a small step size should be chosen. This classical tradeoff in convergence speed vs. the level of error in steady state dominates the issue of step size selection in many estimation schemes.

If the user knows that the relationship between x (n) and d (n) is linear and time-invariant, then one possible solution to the above tradeoff is to choose a large step size initially to obtain fast convergence, and then switch to a smaller step size to obtain a more accurate estimate of near convergence. The point to switch to a smaller step size is roughly when the excess MSE becomes a small fraction (approximately 1=10th) of the minimum MSE of the filter.

However, we can make several qualitative statements relating the speed of convergence to both the step size and the filter length.

a) The speed of convergence increases as the value of the step size is increased, up to step sizes.

b) The speed of convergence decreases as the length of the filter is increased.

c) The maximum possible speed of convergence is limited by the largest step size that can be chosen for stability for moderately correlated input signals.

d) The speed of convergence depends on the desired level of accuracy that is to be obtained by the adaptive filter.

IV RESULTS

The LMs adaptive filter designed yield the following results. The amplitude spectrum (samples in time versus Amplitude) and Frequency versus Amplitude were plotted. In addition to this Spectrogram plot for the reference signal, onboard signal and the filtered output signal were compared for better understanding.

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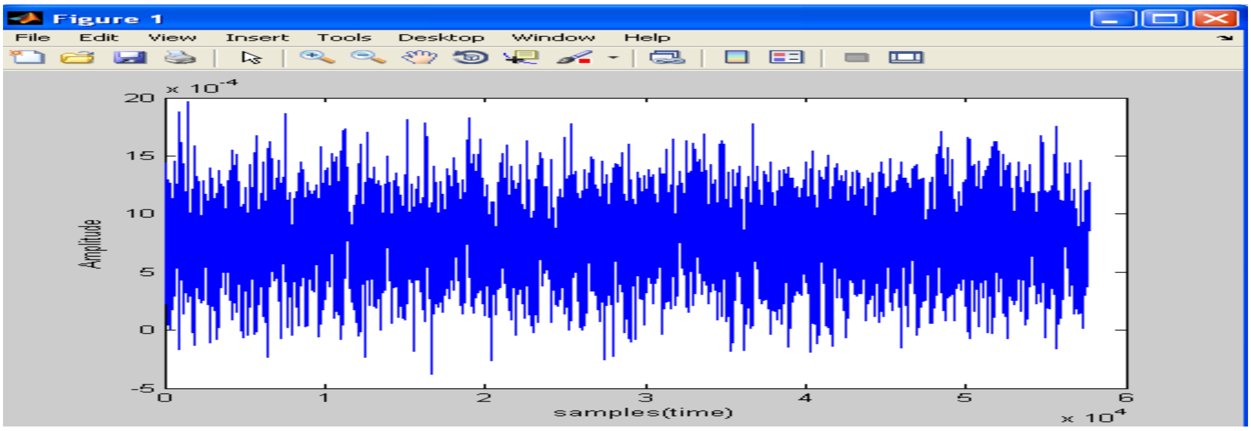

Figure 2.Reference Signal

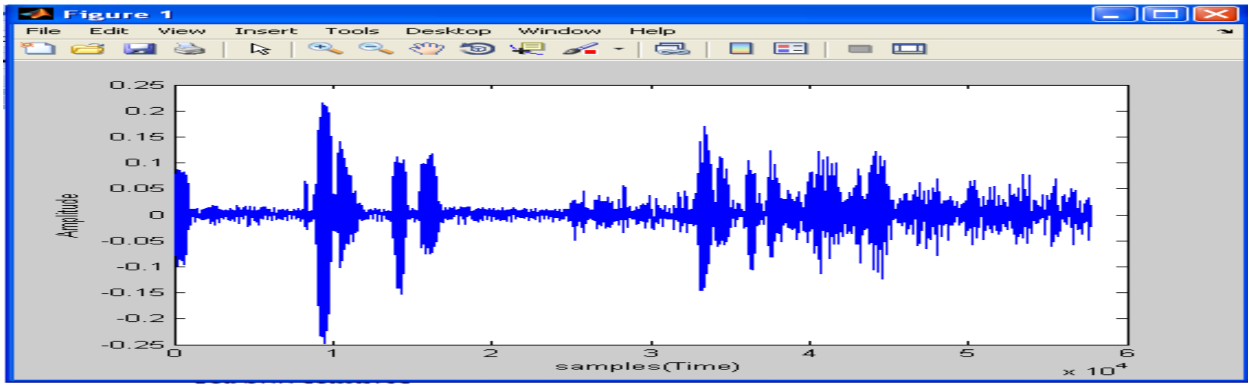

Figure 3.Onboard signal

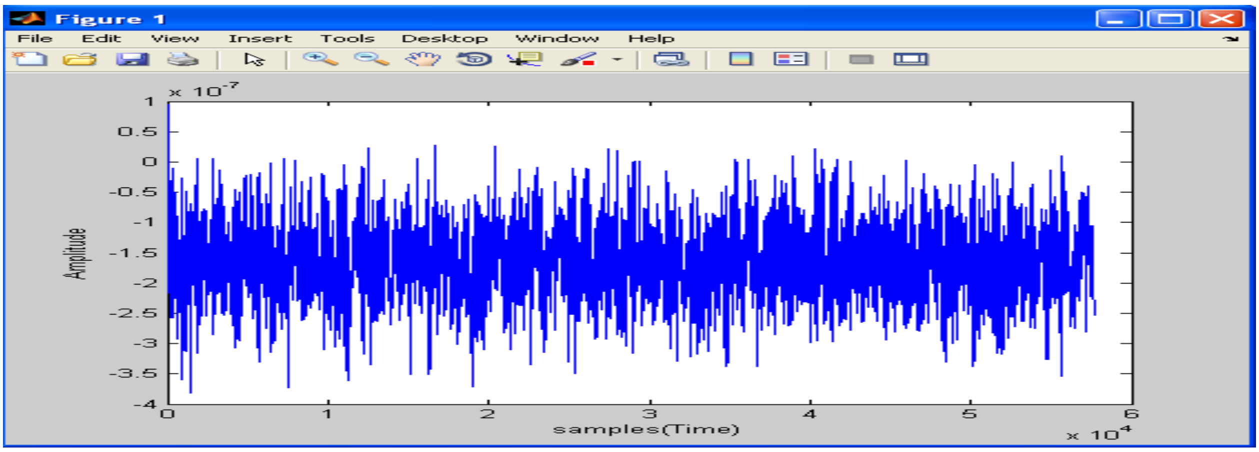

Figure 4.Filtered output signal

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4.1 Spectrogram Comparison

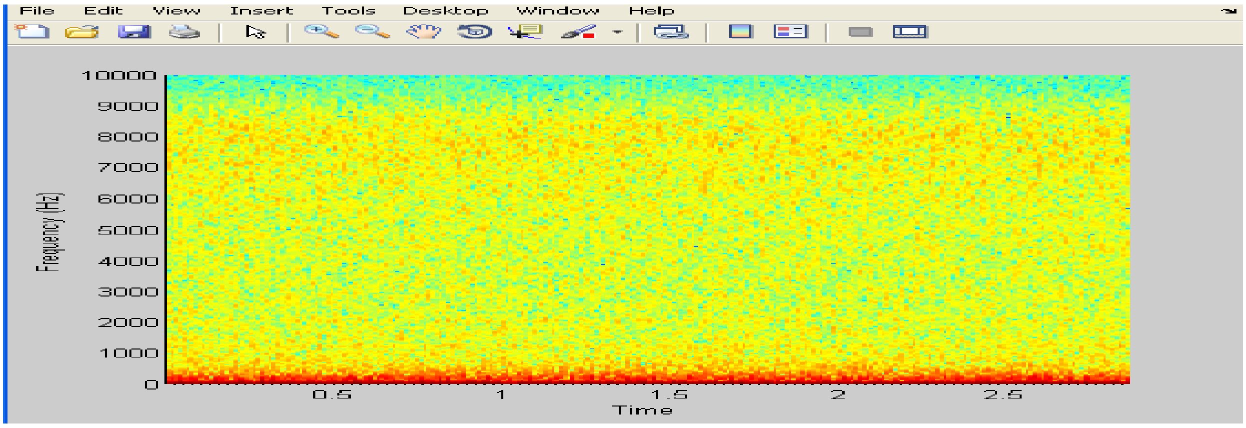

Figure 5.Reference Signal

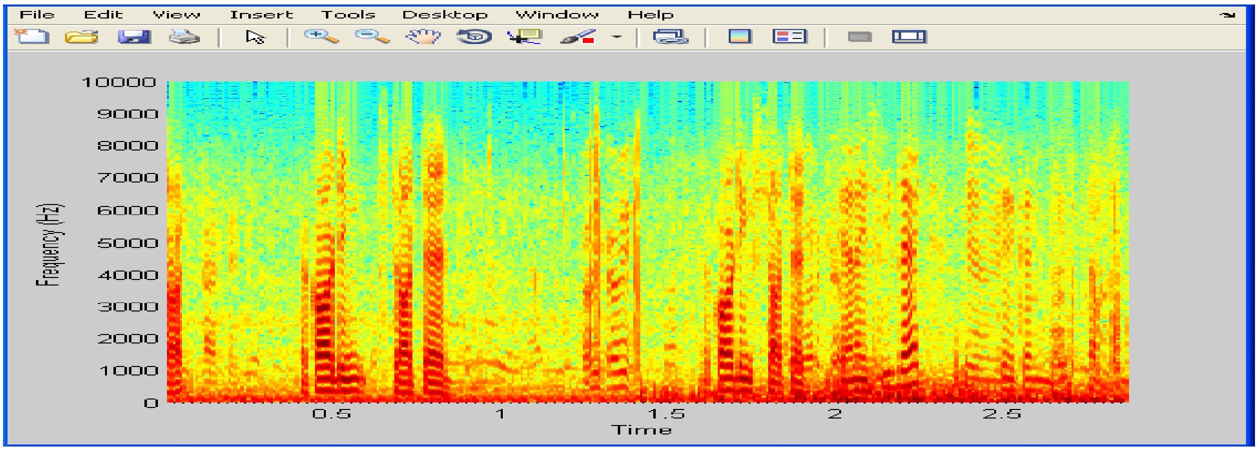

Figure 6.Onboard Signal

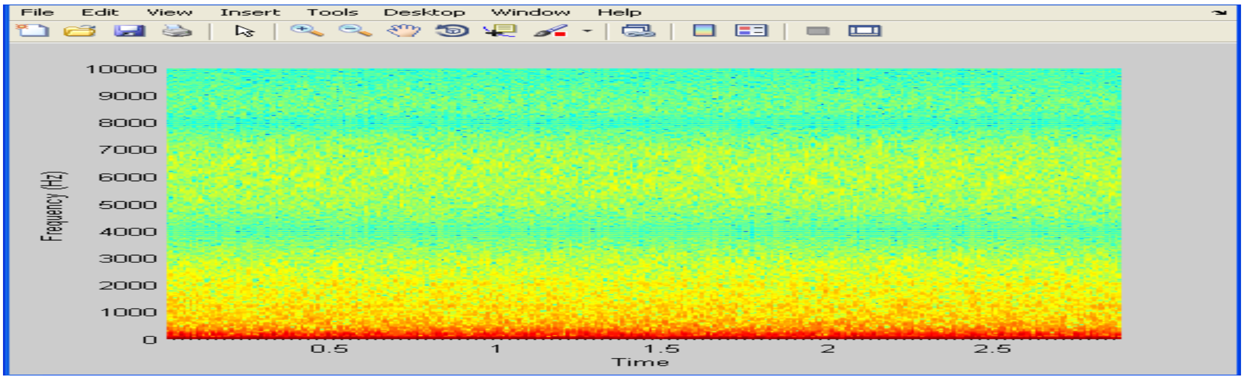

Figure 7.Filtered output signal

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4.2 Plot in dbm values

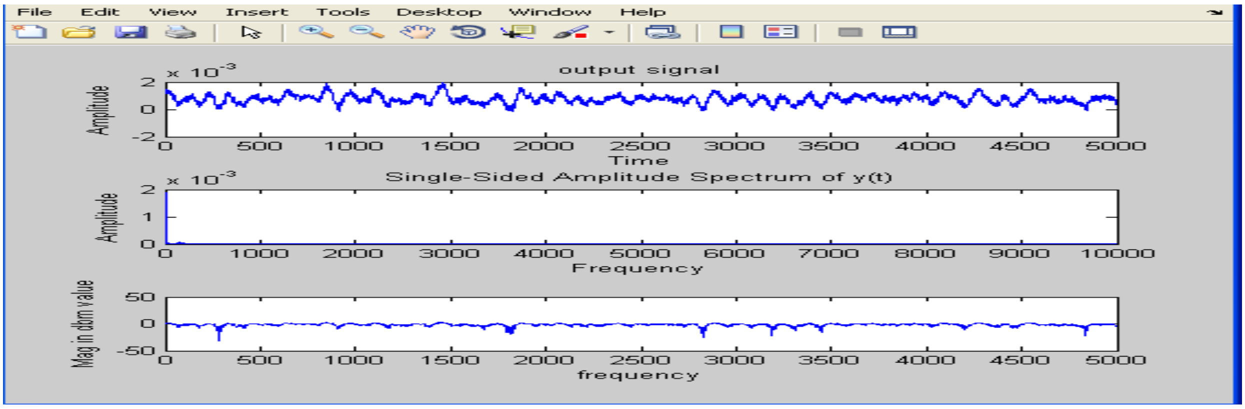

Figure 8.Reference Signal

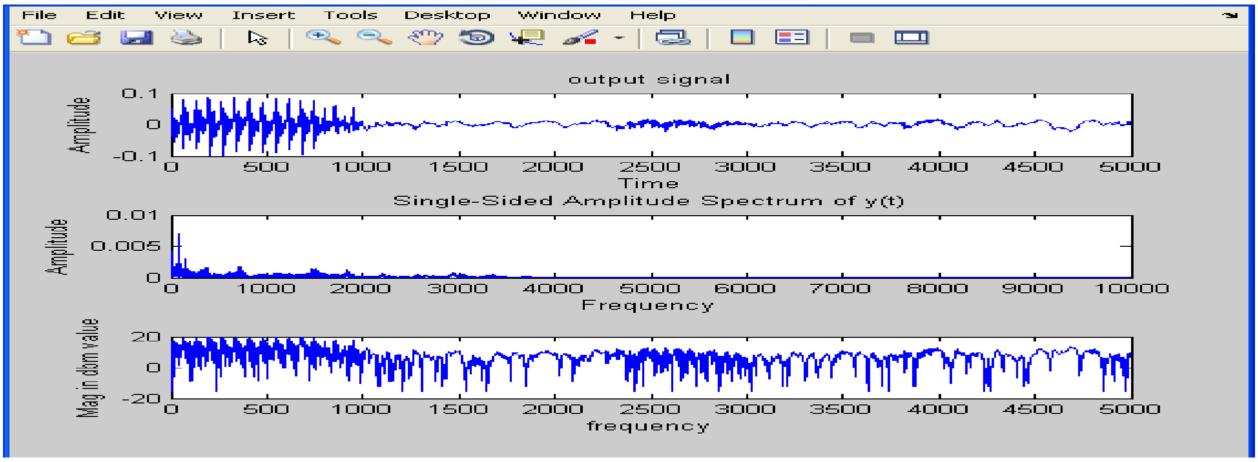

Figure 9.Onboard Signal

These plots show clearly that the Filtered signal and the reference signal somehow have some amplitude differences (pressure values) but having same frequencies.

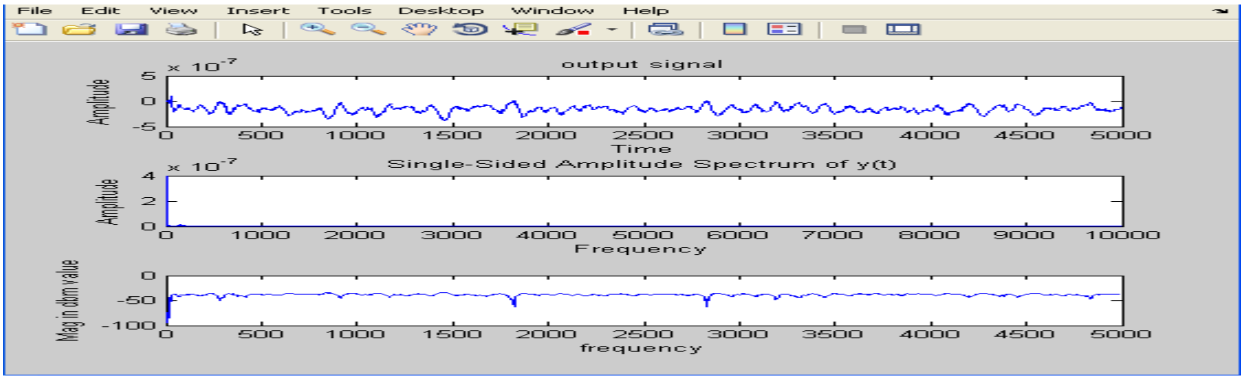

Figure 10.Filtered Output Signal

V CONCLUSION

There has been increasing interest in the military, security and law enforcement communities to collect acoustic data from airborne platforms and particularly from unmanned aerial vehicles (UAVs). So the surveillance system based on the acoustic data has the ability to be deployed quickly, remotely and easily cover larger areas. This method faces two difficulties namely the engine and the wind noise. The acoustic sensors record both the host sound (engine noise) as well as the sounds from nearby objects. So the first process is to remove the background noise to know the exact characteristics of nearby objects. Next to this process, the object must be localized to estimate its position. The proposed method uses adaptive filter with LMS algorithm for noise removal and it results shown that it successfully removed the background noise signal.

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