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Adaptive Noise Cancellor In Automotive Systems

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Abstract— The problem of controlling the noise level has become the focus of a tremendous amount of research over the years. In last few years various adaptive algorithms are developed for noise cancellation. This Paper involves the study of the principles of Adaptive Noise Cancellation (ANC) and its Applications. Adaptive Noise Cancellation is an alternative technique of estimating signals corrupted by additive noise or interference. Its advantage lies in that, with no prior estimates of signal or noise, levels of noise rejection are attainable that would be difficult or impossible to achieve by other signal processing methods of removing noise. Its cost, inevitably, is that it needs two inputs - a primary input containing the corrupted signal and a reference input containing noise correlated in some unknown way with the primary noise. The reference input is adaptively filtered and subtracted from the primary input to obtain the signal estimate. Adaptive filtering before subtraction allows the treatment of inputs that are deterministic or stochastic, stationary or time-variable. The effect of uncorrelated noises in primary and reference inputs, and presence of signal components in the reference input on the ANC performance is investigated. It is shown that in the absence of uncorrelated noises and when the reference is free of signal, noise in the primary input can be essentially eliminated without signal distortion. A configuration of the adaptive noise canceller that does not require a reference input and is very useful many applications is also presented.

Keywords—Adaptive Noise Cancellation, ANC, Adaptive filtering, Interference, Signal Distortion, Primary Input, Reference Input.

I. INTRODUCTION

In the process of transmission of information from the source to receiver side, noise from the surroundings automatically gets added to the signal. This acoustic noise [6] picked up by microphone is undesirable, as it reduces the perceived quality or intelligibility of the audio signal. The problem of effective removal or reduction of noise is an active area of research [7]. The usage of adaptive filters is one of the most popular proposed solutions to reduce the signal corruption caused by predictable and unpredictable noise.

Adaptive Noise Cancellation is an alternative technique of estimating signals corrupted by additive noise or interference. The usual method of estimating a signal corrupted by additive noise is to pass it through a filter that tends to suppress the noise while leaving the signal relatively unchanged i.e. direct filtering.

Figure 1.1

Adaptive Noise Cancellation has applications in various fields like automotive, adaptive self-tuning filter, antenna sidelobe interference canceling, cancellation of noise in speech signals, etc. Adaptive filtering before subtraction allows the treatment of inputs that are deterministic or stochastic, stationary or time-variable.

Noise Cancellation is a variation of optimal filtering that involves producing an estimate of the noise by filtering the reference input and then subtracting this noise estimate from the primary input containing both signal and noise.

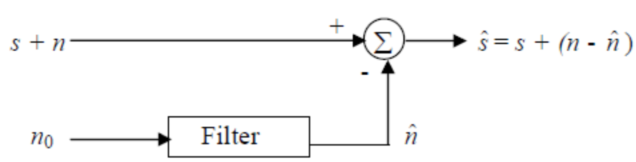

Figure 1.2

It makes use of an auxiliary or reference input which contains a correlated estimate of the noise to be cancelled. The reference can be obtained by placing one or more sensors in the noise field where the signal is absent or its strength is weak enough.

Subtracting noise from a received signal involves the risk of distorting the signal and if done improperly, it may lead to an increase in the noise level. This requires that the noise estimate n ˆ should be an exact replica of n. If it were possible to know the relationship between n and n ˆ , or the characteristics of the channels transmitting noise from the noise source to the primary and reference inputs are known, it would be possible to make n ˆ a close estimate of n by designing a fixed filter. However, since the characteristics of the transmission paths are not known and are unpredictable, filtering and subtraction are controlled by an adaptive process. Hence an adaptive filter is used that is capable of adjusting its impulse response to minimize an error signal, which is dependent on the filter output. The adjustment of the filter weights, and hence the impulse response, is governed by an adaptive algorithm. With adaptive control, noise reduction can be accomplished with little risk of distorting the signal

II. RELATED WORK

2.1 Adaptive Noise Cancellation – Algorithms

The error signal to be used depends on the application. The criteria to be used may be the minimization of the mean square error, the temporal average of the least squares error etc. To understand the concept of adaptive noise cancellation, the use of minimum mean-square error criterion is used. The steady-state performance of adaptive filters based on the mse criterion closely approximates that of fixed Wiener filters. Hence, Wiener filter theory provides a convenient method of mathematically analyzing statistical noise canceling problems.[3]

The basic adaptive algorithms which widely used for performing weight updation of an adaptive filter are: the LMS (Least Mean Square), NLMS (Normalized Least Mean Square) and the RLS (Recursive Least Square) algorithm [10]. Among all adaptive algorithms LMS has probably become the most popular for its robustness, good tracking capabilities and simplicity in stationary environment. RLS is best for non-stationary environment with high convergence speed but at the cost of higher complexity. Therefore a tradeoff is required in convergence speed and computational complexity, NLMS provides the right solution.[5]

Adaptive techniques use algorithms, which enable the adaptive filter to adjust its parameters to produce an output that matches the output of an unknown system. This algorithm employs an individual convergence factor that is updated for each adaptive filter coefficient at every iteration.

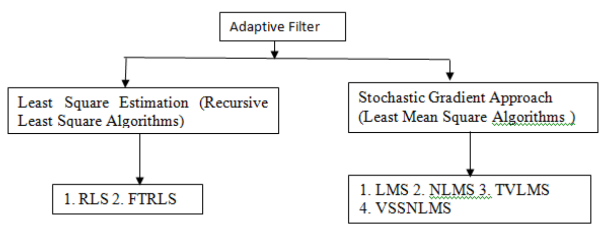

Fig 2.1: Hierarchy of Adaptive Filter

2.2 LMS Algorithm

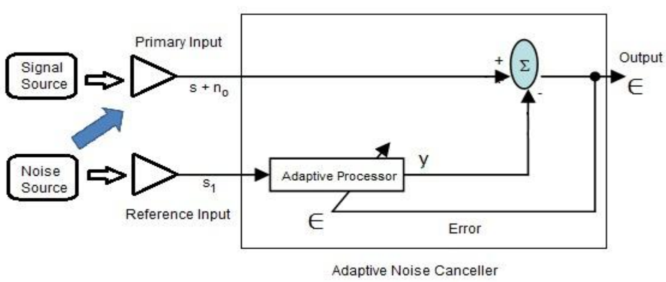

Fig. 2.2 Adaptive Noise Canceller

As shown in the figure, an Adaptive Noise Canceller (ANC) has two inputs – primary and reference. The primary input receives a signal s from the signal source that is corrupted by the presence of noise n uncorrelated with the signal. The reference input receives a noise n0 uncorrelated with the signal but correlated in some way with the noise n. The noise no passes through a filter to produce an output n ˆ that is a close estimate of primary input noise.

This noise estimate is subtracted from the corrupted signal to produce an estimate of the signal at $\hat{s}$, the ANC system output.

In noise canceling systems a practical objective is to produce a system output $\hat{s} = s + n - \hat{n}$ that is a best fit in the least squares sense to the signal s. This objective is accomplished by feeding the system output back to the adaptive filter and adjusting the filter through an LMS adaptive algorithm to minimize total system output power. In other words the system output serves as the error signal for the adaptive process.

Assume that s, n0, n1 and y are statistically stationary and have zero means. The signal s is uncorrelated with n0 and n1, and n1 is correlated with n0.

$\hat{s} = s + n - \hat{n} \Rightarrow \hat{s}^2 = s^2 + (n - \hat{n})^2 + 2s(n - \hat{n})$

Taking expectation of both sides and realizing that s is uncorrelated with n0 and $\hat{n}$,

$E[\hat{s}^2] = E[s^2] + E[(n - \hat{n})^2] + 2E[s(n - \hat{n})] = E[s^2] + E[(n - \hat{n})^2]$

The signal power $E[s^2]$ will be unaffected as the filter is adjusted to minimize $E[\hat{s}^2]$. $\Rightarrow \min E[\hat{s}^2] = E[s^2] + \min E[(n - \hat{n})^2]$

Thus, when the filter is adjusted to minimize the output noise power $E[\hat{s}^2]$, the output noise power $E[(n - \hat{n})^2]$ is also minimized. Since the signal in the output remains constant, therefore minimizing the total output power maximizes the output signal-tonoise ratio.

Since, $(\hat{s} - s) = (n - \hat{n})$ [11]

This is equivalent to causing the output $\hat{s}$ to be a best least squares estimate of the signal s.

NLMS Algorithm

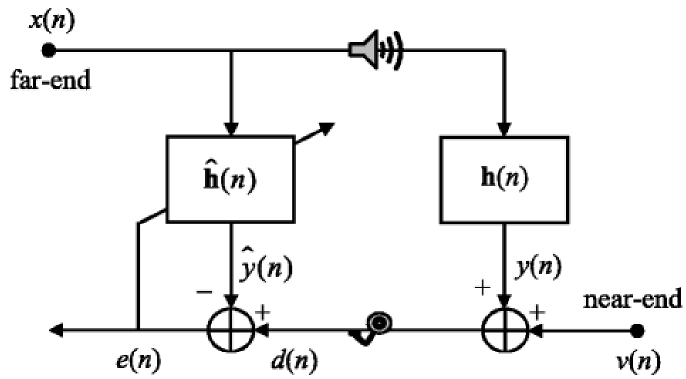

Figure 2.3

The far-end (or loudspeaker) signal, $x(n)$, goes through the echo path, $\mathbf{h}(n)$, providing the echo signal, $y(n)$, where n is the time index. This signal is added to the near-end signal, $v(n)$ (which can contain both the background noise and the near-end speech), resulting the microphone signal, $d(n)$. The adaptive filter, defined by the vector $\hat{h}(n)h\hat{}(n)$, aims to produce at its output an estimate of the echo, $\hat{y}(n)y\hat{}(n)$, while the error signal, $e(n)$, should contain an estimate of the near-end signal. [12]

Summarizing, the main goal of this application is to model an unknown system using an adaptive filter, both driven by the same zero-mean input signal, $x(n)$. These two systems are assumed to be finite impulse response (FIR) filters of length L, defined by the real-valued vectors:

$$\boxed{\hat{h}(n)=\hat{h}(n-1)+\alpha x(n)e(n)/(x^T(n)x(n)+\delta)}$$

$h(n)=[h_0(n)h_1(n)\cdots h_{L-1}(n)]^T$,

$\hat{h}(n)=[\hat{h}_0(n)\hat{h}_1(n)\cdots\hat{h}_{L-1}(n)]^T$,

where superscript T denotes transposition. The desired (or microphone) signal for the adaptive filter is

$d(n)=x^T(n)h(n)+v(n)=y(n)+v(n)$,

where $x(n)=[x(n)x(n-1)\cdots x(n-L+1)]^T$

is a real-valued vector containing the L most recent time samples of the input signal, $x(n)$, and $v(n)$ (i.e., the near-end signal) plays the role of the system noise (assumed to be quasi-stationary, zero mean, and independent of $x(n)$) that corrupts the output of the unknown system.

Using the previous notation, we may define the a priori and a posteriori error signals as

$e(n)=d(n)-x^T(n)\hat{h}(n-1)=x^T(n)[h(n)-\hat{h}(n-1)]+v(n)$, $\varepsilon(n)=d(n)-x^T(n)\hat{h}(n)=x^T(n)[h(n)-\hat{h}(n)]+v(n)$,

where the vectors $\hat{h}(n-1)h\hat{}(n-1)$ and $\hat{h}(n)h\hat{}(n)$ contain the adaptive filter coefficients at time $n-1$ and n, respectively. The update equation for NLMS-type algorithms is

$\hat{h}(n)=\hat{h}(n-1)+\mu(n)x(n)e(n), h\hat{}(n)=h\hat{}(n-1)+\mu(n)x(n)e(n)$

where $\mu(n)$ is a positive factor known as the step-size, which governs the stability, the convergence rate, and the misadjustment of the algorithm. A reasonable way to derive $\mu(n)$, taking into account the stability conditions, is to cancel the a posteriori error signal . Replacing (4) in (3) with the requirement $\varepsilon(n)=0$, it results that
ε(n)=e(n)[1−μ(n)xT(n)x(n)]=0

(5)and assuming that $e(n)\neq0$, we find μ(n)=1/xT(n)x(n).
(6)We should note that the above procedure makes sense in the absence of noise[i.e., $v(n)=0$],where the condition $\varepsilon(n)=0$ implies that xT(n)[h(n)−hˆ(n)]=0. Finding the parameter $\mu(n)$ in the presence of noise will introduce noise in hˆ(n)h^(n), since the condition $\varepsilon(n)=0$ leads to xT(n)[h(n)−hˆ(n)]=−v(n)≠0. In fact, we would like to have xT(n)[h(n)−hˆ(n)]=0, which implies that $\varepsilon(n)=v(n)$.
In practice, a positive constant α (with $0<\alpha<2$), known as the normalized step-size, multiplies (6) to achieve a proper compromise between the convergence rate and the misadjustment; also, a positive constant δ, known as the regularization parameter, is added to the denominator of (6) in order to make the adaptive filter work well in the presence of noise. Consequently, the well-known update equation of the NLMS algorithm becomes

2.3 RLS Algorithm
The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. The RLS algorithms are known for their excellent performance when working in time varying environments but at the cost of an increased computational complexity and some stability problems. In this algorithm the filter tap weight vector is updated using Eq.
w(n) = wT(n-1) + k(n) en-1(n) ..….. (1)
k(n) = u(n) / (λ+XT (n) u(n)) ……. (2)
u(n) = wλ-1(n-1) X(n) .... (3)
Eq. (2) and (3) are intermediate gain vector used to compute tap weights.
Where λ is a small positive constant very close to, but smaller than 1. The filter output is calculated using the filter tap weights of above iteration and the current input vector as in Eq. (4).
yn-1(n) = wT(n-1) X(n) ……. (4)
en-1(n) = d(n) – yn-1(n) ……. (5) [1]
In the RLS Algorithm, the estimate of previous samples of output signal, error signal and filter weight is required that leads to higher memory requirements. [13]

III. EVALUATION

3.1 Comparison of above adaptive algorithms
In table1 performance analysis of all three algorithms is presented in term of MSE, percentage noise reduction, computational complexity and stability [14]. It is clear from the table1, the computational complexity and stability problems increases in an algorithm as we try to reduce the mean squared error. NLMS is the favourable choice for most of the industries due less computational complexity and fair amount of noise reduction.

Table1. Performance comparison of various adaptive algorithms

S.N	Algorithm	Mean Squared Error (MSE)	% Noise Reduction	Complexity (No. of multiplications per iteration)	Stability
1.	LMS	2.5×10^{-2}	91.62%	2N+1	Highly Stable
2.	NLMS	2.1×10^{-2}	93.85%	5N+1	Stable
3.	RLS	1.7×10^{-2}	98.78%	$4N^2$	less Stable

Different Adaptive algorithms were analyzed and compared. These results shows that the LMS algorithm has slow convergence but simple to implement and gives good results if step size is chosen correctly and is suitable for stationary environment. For a lower filter order (<15) the LMS proved to have the lowest MSE then the NLMS and RLS, but as we increase the filter order (>15) the results showed the opposite, so we need to take this in consideration when selecting the algorithm for a specific application.
When input signal is non-stationary in nature, the RLS algorithm proved to have the highest convergence speed, less MSE, and highest percentage of noise reduction but at the cost of large computational complexity and memory requirement.

The NLMS algorithm changes the step-size according to the energy of input signals hence it is suitable for both stationary as well as non-stationary environment and its performance lies between LMS and RLS. Hence it provides a trade-off in convergence speed and computational complexity. [5]

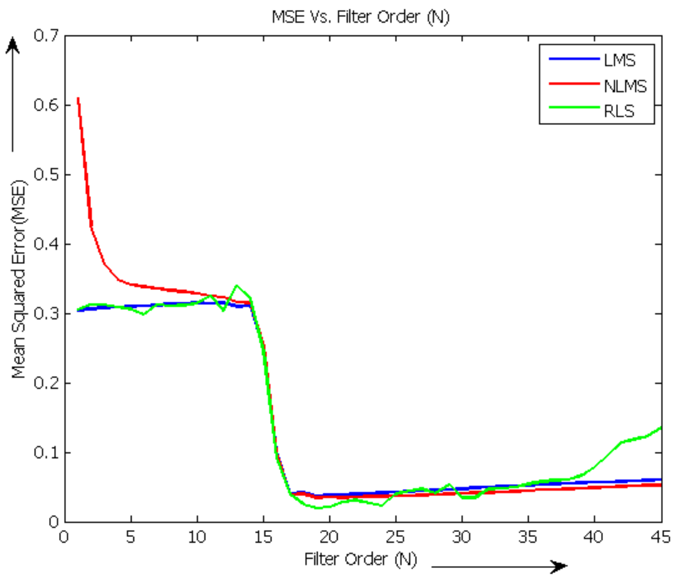

Figure 3.1

3.2 Applications in Automotive Systems

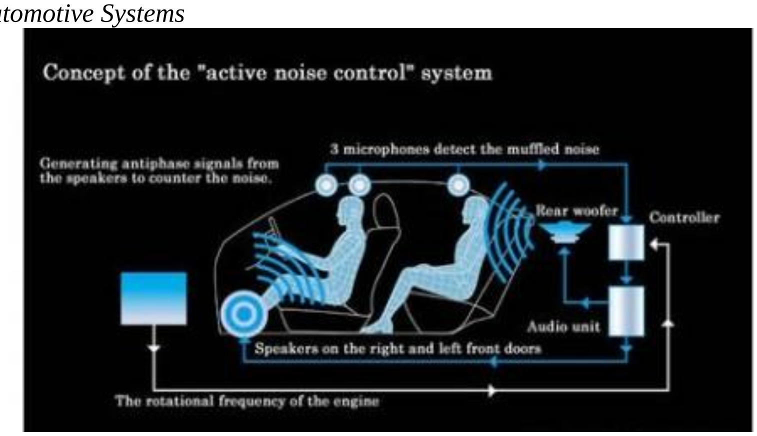

Figure 3.2

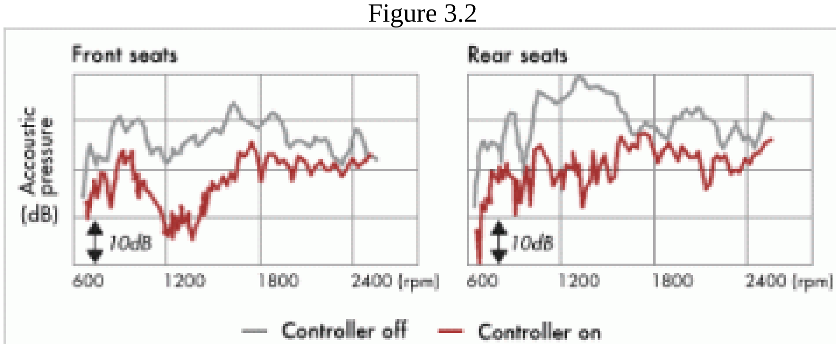

Figure 3.3

Automotive applications :
Reduce low frequency noise that is difficult to attenuate using passive approaches
Road Noise, Power train noise (Frequency/Engine Orders)

IV. RESULTS AND DISCUSSION

Simulink Model :

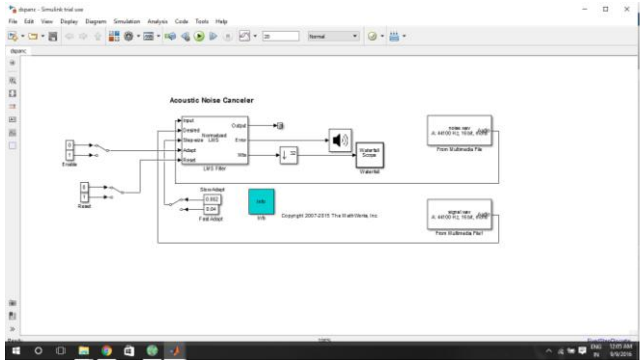

Figure 4.1

Comparisons obtained after implementation of ANC on Raspberry Pi :

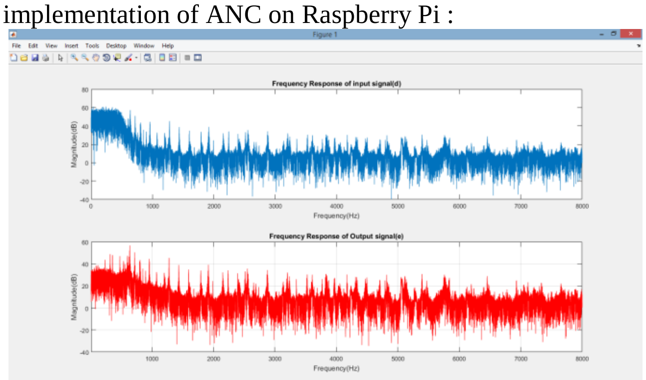

Figure 4.2

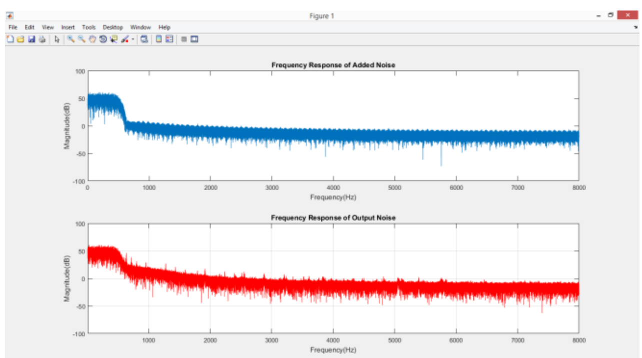

Figure 4.3

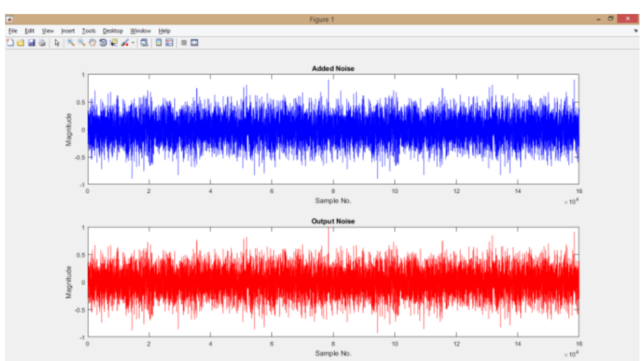

Figure 4.4

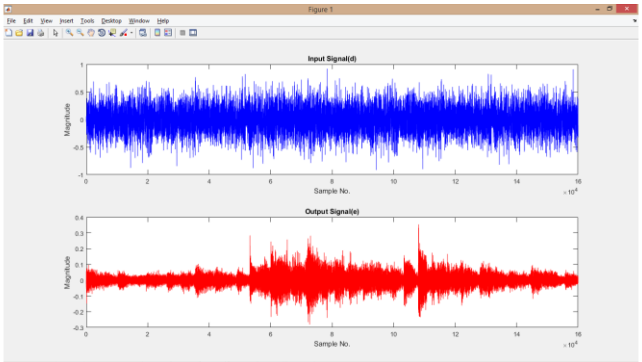

Figure 4.5

V. FUTURE SCOPE AND CONCLUSION

Adaptive Noise Cancellation is an alternative way of canceling noise present in a corrupted signal. The principal advantages of the method are its adaptive capability, its low output noise, and its low signal distortion. The adaptive capability allows the processing of inputs whose properties are unknown and in some cases non-stationary. Output noise and signal distortion are generally lower than can be achieved with conventional optimal filter configurations.

The Paper includes simulation results that verify the advantages of adaptive noise cancellation. In each instance canceling was accomplished with little signal distortion even though the frequencies of the signal and interference overlapped. Thus it establishes the usefulness of adaptive noise cancellation techniques.

The elimination of the noise from a signal to get a noise free signal with the help of the Simulink model is successfully implemented, thus comparing various audio sample simulations. Also the algorithm was implemented on Raspberry pi controller through Python code thus comparing input and output FFT waveforms. The output was successfully heard through the speaker interfaced with raspberry pi controller. Futher, implementing it with real time signals using microphone on real time application in automobiles is supposed to be executed.

VI. REFERENCES

[1] Marvin S. Ambur, “Adaptive Noise Cancelling for speech signals”, Acoustics, speech and signal processing, vol.5, 5 Oct. 1978
[2] B. Widrow, et al., “Adaptive Noise Cancelling: Principles and Applications”, Proc. IEEE, vol. 63, pp.1692-1716, Dec. 1975.
[3] Active noise control primer – Scott D. Snyder.
[4] Active control of noise and vibration (volume 1&2)
[5] Raj Kumar Thenua et al., “Simulation and Performance analysis of Adaptive Filter in Noise Cancellation”, Vol. 2(9), 2010, 4373-4378
[6] J. Benesty, et. al. , “Adaptive Filtering Algorithms for Stereophonic Acoustic Echo Cancellation”, International Conference on Acoustics, Speech, and Signal Processing, 1995, vol.5, Page(s): 3099 – 3102.
[7] Bernard Widrow, et. al. “Adaptive Noise Cancelling: Principles and Applications”, Proceedings of the IEEE, 1975, Vol.63 , No. 12 , Page(s): 1692 – 1716.
[8] Simon Haykin, “Adaptive Filter Theory”, Prentice Hall, 4th edition.
[9] Ying He, et. al. “The Applications and Simulation of Adaptive Filter in Noise Canceling”, 2008 International Conference on Computer Science and Software Engineering, 2008, Vol.4, Page(s): 1 – 4.
[10] Paulo S.R. Diniz, “Adaptive Filtering: Algorithms and Practical Implemetations” ,ISBN 978-0-387-31274-3, Kluwer Academic Publisher © 2008 Springer Science+Business Media, LLC, pp.77-195.
[11] Slock, D.T.M., “On the convergence behavior of the LMS and the normalized LMS algorithms”, IEEE Transactions on Signal Processing, 1993,Vol. 41, Issue 9, pp. 2811-2825.
[12] Abhishek Tandon, M. Omair Ahmad, “An efficient, low-complexity, normalized LMS algorithm for echo cancellation” The 2nd Annual IEEE Northeast Workshop on Circuits and Systems, 2004. NEWCAS 2004, Page(s): 161 – 164.
[13] Sanaullah Khan, M.Arif and T.Majeed, “Comparison of LMS, RLS and Notch Based Adaptive Algorithms for Noise Cancellation of a typical Industrial Workroom”, 8th International Multitopic Conference, 2004, Page(s): 169 – 173.
[14] Yuu-Seng Lau, Zahir M. Hussian and Richard Harris, “Performance of Adaptive Filtering Algorithms: A Comparative Study”, Australian Telecommunications, Networks and Applications Conference (ATNAC), Melbourne, 2003.
[15] Raj Kumar Thenua et. al. / International Journal of Engineering Science and Technology, Vol. 2(9), 2010