

Echo and Noise Cancellation using Hybrid Technique

Shrishti Dubey, Amit Kolhe

Abstract—Echo and Noise are the two major problems in any communication system. So far Echo and Noise problems have been dealt separately. In this paper a hybrid technique to cancel both Echo and Noise has been proposed. For Echo cancellation LMS technique has been employed while for Noise cancellation ANFIS technique and the results are compared with LMS and NLMS used alone for both the purpose. The performance evaluation has been done on the basis of MSE and PSNR.

Index Terms— Adaptive Filtering, ANFIS, Echo Cancellation, LMS, Noise Cancellation, NLMS.

I. INTRODUCTION

In many speech communication applications, e.g., audio-conference and hands-free IP telephony, the received multi-microphone speech signals are corrupted by acoustic background noise as well as by echo signals. The noise and echo significantly degrade the intelligibility of the desired signal, and restrict the performance of subsequent speech processing systems. Therefore efficient methods for joint noise reduction and echo cancellation are generally desirable. Echo is the delayed version of the original speech signal. It is mainly of two types i.e. Acoustic and Hybrid. For Echo cancellation an adaptive filter that self-adjusts the coefficients of transfer function according to an optimization algorithm is proposed. The adaptive filter uses feedback in the form of an error signal to define its transfer function to match changing parameters. The adaptive filter uses many algorithms that adjust these parameters. LMS algorithm is the most popular algorithm because of its simplicity, robustness and stability. The normalized least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses the issue in LMS of fixed step size by calculating maximum step size value. RLS is another class of adaptive filter that has higher convergence rate but comes with the cost of complexity which is a major concern while designing any system.

A novel architecture for Noise cancellation called Adaptive Neuro-Fuzzy Inference System (ANFIS), has been widely employed to represent or approximate a nonlinear system. Adaptive systems can be described by constructing a set of fuzzy if-then rules that represent local linear input-output relations of the system. In recent years, Takagi-Sugeno (T-S) fuzzy models are playing an important role in dealing

with problems concerning a wide class of nonlinear systems. Artificial Neural Network can be used as an alternative means for the knowledge about the engine. ANN is based on binary logic which can store knowledge by learning from recorded

data. It has been proven that T-S fuzzy systems with affine terms can smoothly approximate any nonlinear functions to any specified accuracy within any compact set, which provides a theoretical foundation for using T-S fuzzy model to represent complex nonlinear system approximately.

II. LITERATURE REVIEW

Adaptive algorithms are very popular in current scenario where adaptation of weights is necessary according to the requirement. Previous work include application of adaptive filters in Echo cancellation, Noise Cancellation, System Identification and Channel Equalization. LMS [1] is the most popular algorithm due to its simplicity, robustness and stability. Variants of LMS like FLMS have been developed for Echo cancellation. FLMS has faster convergence [2]. Various other algorithms like NLMS, VSSLMS, VSS-NLMS [3] have been developed to overcome slow convergence of LMS algorithms by changing the step size parameter. Fx-LMS [4] has greater average ERLE and least computational complexity but its convergence is slower than LMS making it unfit for real time application. A newly proposed average normalized leaky LMS algorithm has higher convergence than NLMS [5]. Higher convergence comes with the cost of greater complexity. The problem in selection of suitable step size of NLMS algorithm can be solved by using constant step size and constant filter length [6] in adaptive noise cancellation implementation. RLS has fastest convergence and smaller steady state error when applied for Noise cancellation [7]. But its high complexity makes it costly thus not much preferred over LMS and NLMS. A new technique called Adaptive neuro fuzzy inference system is gaining popularity for Noise Cancellation due to simplicity and fast convergence [8]. Neuro fuzzy filter shows increased performance in terms of SNR by around 5dB more than least square adaptive algorithm [9]. LMS has been used to cancel Echo and Noise together in FPGA implementation [10] but we already know LMS doesn't perform well in ANC system. Thus a new technique has to be used in place of LMS for Noise cancellation.

III. PROPOSED METHODOLOGY

The proposed technique is basically a combination of well-known filtering technique LMS and ANFIS based nonlinear

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filtering. First an audio signal is taken and a delayed version is added to get echo and after addition of echo, noise is added to the echo+original signal.

A. Noise Cancellation using ANFIS

The proposed Adaptive Neuro Fuzzy Inference System (ANFIS) based noise reduction technique is basically a nonlinear prediction of noise content in the noisy signal. For instance, let the noise content of the noisy signal $N(n)$ is n_2 , which is a random variation. This noise content can be considered as a nonlinear function of a randomly generated variation n_1 . Hence we can write,

$$n_2 = f(n_1) \quad \dots (1)$$

The noisy signal $N(n)$, in terms of original signal $x(n)$ and the noise content n_2 is then written as,

$$N(n) = x(n) + n_2 \dots (2)$$

However we don't have post priori knowledge of function f of equation (1), but this relationship can be predicted with the help of nonlinear regression. Let the predicted or estimated value of n_2 is est_n_2 then the filtered signal $Y(n)$ is given as

$$Y(n) = N(n) - est_n_2 \dots (3)$$

In the present paper, ANFIS has been utilized for the prediction or estimation of nonlinear function f given in equation (1). For the training of the proposed ANFIS structure two inputs have been used in which the first input is the delayed version of a randomly generated signal n_2 while the second input is the signal n_1 itself. The training target taken is the available noisy signal $N(n)$.

B. Artificial Neural Network

Neural networks are composed of simple elements operating in parallel. The network function is determined largely by the connections between elements. Neural network can be trained to perform a particular function by adjusting the value of the connections (weights) between elements. Artificial Neural Network has preserved three basic characteristics. Neural network learns from experience; generalize from learned responses, and abstract essential pattern from inputs. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems. ANNs are mathematical modeling tools which are particularly useful for predicting and forecasting in complex settings. The ANN accomplishes this through a large number of highly interconnected processing elements (neurons), working in unison to solve specific problems. Each neuron is connected to some of its neighbors with varying coefficients or weights which represent the relative influence of the different neuron inputs on other neurons.

C. Basic concepts in fuzzy logic

There are two basic concepts in fuzzy logic. They are linguistic variable and fuzzy if-then rule or fuzzy rule. There are two basic concepts in fuzzy logic. They are:

- 1) *Linguistic variable*: It is a variable whose values are words rather than numbers. Its use is closer to the tolerance for imprecision and thereby lowers the cost of solution. It encapsulates the properties of approximate or imprecise concepts in a systematic and computationally useful way. It also reduces the apparent complexity of describing a system.
- 2) *Fuzzy IF- THEN rule*: IF -THEN rule statements are used to formulate the conditional statements that comprise fuzzy logic. A single IF - THEN rule assumes the form

If x is A then y is B

where A and B are linguistic values defined by fuzzy sets on the ranges (universe of discourse) X and Y , respectively. The IF part of the rule " x is A " is called the antecedent or premise, while the THEN part of the rule " y is B " is called the consequent or conclusion.

D. Fuzzy inference systems

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned an input value to its appropriate membership value.

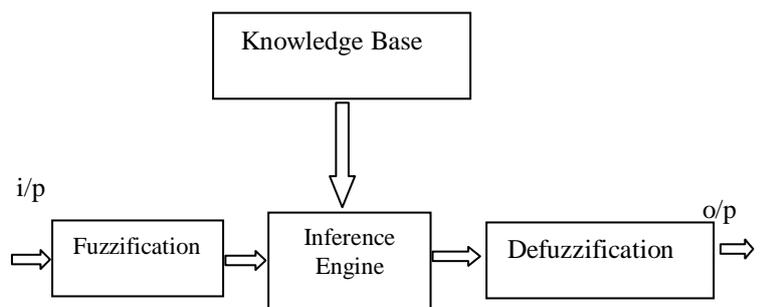


Fig 2. Framework of fuzzy logic system

There are two types of FIS:

1. Mamdani-type,
2. Sugeno-type.

Both can be implemented in fuzzy logic toolbox. These two types differ in the way output's are determined. Mamdani-type inference expects the output membership functions to be fuzzy sets. It needs defuzzification. A first order Sugeno fuzzy model has a crisp output, the overall output is obtained via weighted average, thus avoiding the time consuming process of defuzzification required in a Mamdani model.

E. Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System, first introduced by Jang, is a universal approximator and as such is able to approximate any real continuous function on a compact set to any degree of accuracy. Thus, in estimating parameters where the given data are such that the system associates measurable system variables with an internal system parameter, functional mapping can be constructed by ANFIS to approximate the process of estimation of the internal system parameter. ANFIS is a neuro-fuzzy system that combines the learning capabilities of neural networks, with the functionality of fuzzy inference systems. An adaptive network is a feed-forward multilayer Artificial Neural Network (ANN) with; partially or completely, adaptive nodes in which the outputs are

predicated on the parameters of the adaptive nodes and the adjustment of parameters due to error term is specified by the learning rules:

ANFIS Architecture: Assume that the fuzzy inference system under consideration has two inputs x and y and one output z . For a first-order Takagi-Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

- Rule 1: If x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$;
- Rule 2: If x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$;

And

$$f = \frac{w_1f_1 + w_2f_2}{w_1 + w_2} \dots (4)$$

$$f = w_1f_1 + w_2f_2 \dots (5)$$

The equivalent ANFIS architecture is as shown in Fig.3, using a Sugeno fuzzy model where nodes of the same layer have similar functions.

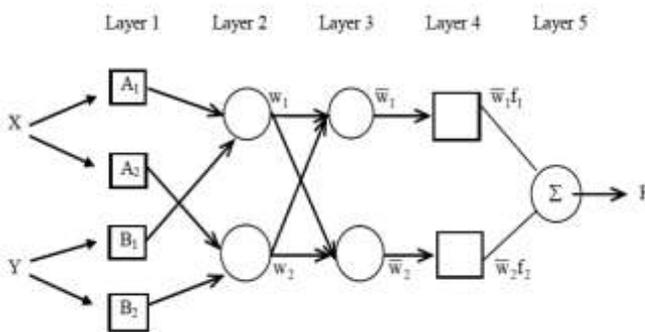


Fig 3. Basic ANFIS structure.

Layer 1: Calculate Membership value for premise parameter: All the nodes in this layer are adaptive nodes; is the degree of the membership of the input to the fuzzy membership function (MF) represented by the node,

Output $O_{1,i}$ for node $i=1,2$

$$O_{1,i} = \mu_{A_i}(x) \dots (6)$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3, 4 \dots (7)$$

where x (or y) is the input to node i and A_i (or B_{i-2}) is a linguistic label (such as "small" or "large") associated with this node. In other words, $O_{1,i}$ is the membership grade of a fuzzy set A (A_1, A_2, B_1 or B_2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A .

Layer 2: Every node in this layer is a fixed node labeled Π , whose output is the product of all the incoming signals:

$$O_{2,i} = \omega_i = \mu(x) \mu_{B_i}(y), \quad i = 1, 2. \dots (8)$$

Each node output represents the firing strength of a rule. In general, any other T-norm operators that perform fuzzy AND can be used as the node function in this layer.

Layer 3: Every node in this layer is a fixed node labeled N . The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2. \dots (9)$$

For convenience, outputs of this layer are called normalized firing strengths.

Layer 4: Every node i in this layer is an adaptive node with a node function:

$$O_{4,i} = \bar{\omega}_i f_i = \bar{\omega}_i (p_i x + q_i y + r_i) \dots (10)$$

where $\bar{\omega}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled, which computes the overall output as the summation of all incoming signals:

$$\text{overall output} = O_{5,1} = \sum_i \bar{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \dots (11)$$

Thus we have an adaptive network that is functionally equivalent to a Sugeno fuzzy model.

F. Echo cancellation using LMS technique

Adaptive algorithm

It starts its computation from prescribed initial condition and use information contained in the input data in order to estimate the weights of the filter. As the parameters of adaptive filters are updated from one iteration to next, it means that the parameters of the filter become information reliant and this provides that the adaptive filter in reality is a non-linear system. A system is said to be non-linear if it does not obey the principle of superposition otherwise system is linear. Adaptive filters have extensive applications. They are used for adaptive noise and echo cancellation system identification, channel equalization, adaptive inverse system configuration and adaptive linear prediction.

General block diagram of the adaptive filters:

Here w represents the coefficients of the FIR filter tap weight vector, $x(n)$ is the input vector sample, $d(n)$ is a delay of one sample, $y(n)$ is the adaptive filter output, $d(n)$ is the desired echoed signal and $e(n)$ is the estimation of the error signal at time n . The aim of an adaptive filter is to calculate the difference between the desired signal and the adaptive filter output, $e(n)$. The error signal is fed back into the adaptive filter and its coefficients are changed algorithmically in order to minimize a function of this difference, which is known as the cost function.

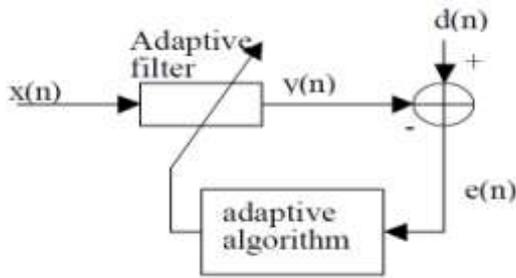


Fig 4. Block diagram of Adaptive Filter

a. LMS Algorithm

LMS is most simplest and widely used adaptive filter. LMS can be express as setof step. Initially we set the filter weights to be zero:

$$w(n) = 0$$

Then for the convergence of the error algorithm updates its byexecuting following steps for no of iterations:

1. Output of the adaptive filter is given by

$$y(n) = w^T(n)x(n) \quad .(12)$$

2. Depending upon estimate of error can be given as

$$e(n) = d(n) - y(n) \quad ..(13)$$

3. On the bases of error estimation, input signal and step size μ . updated weight vector is given by

$$w(n+1) = w(n) \pm \mu e(n)x(n) \quad .(14)$$

Range of step size is varying between $0 \leq \mu \leq 1$.

Maindrawback of LMS algorithms is that we have to select stepsize manually. If step size is very small then system Convergence rate is very slow and if step size is close to onethen system get oscillates and never converge.Operational complexity of LMS is $O(L)$, hence LMS isconsider as suitable option in case of large order adaptivefilter.

b. Normalize Least Mean Square (NLMS) Filter

NLMS is a modification of LMS algorithm.In LMS we update weight vector by using $\mu e(n)x(n)$ term. Inthis case magnitude of $x(n)$ is directly proportional to theweight update which results in gradient noise amplification.NLMS algorithm normalize this condition by new weightupdate method as follow,

$$w(n+1) = w(n) \frac{\mu}{\varepsilon + x^T(n)x(n)} e(n)x(n) \quad (15)$$

In above equation ε is a constant which is used to avoid division by small number when value of $x^T(n)x(n)$ isvery small.Where $x^T(n)x(n)$ represents power of $x(n)$.Even though number of multiplications are increased in NLMS, Time complexity of NLMS is same as LMS i.e. $O(L)$. Stability of

NLMS is get increased but at the same timecomputational cost also increases.

IV. RESULT AND DISCUSSION

This section presents the extensive testing results obtained after echo cancelation and noise reduction from input speech signal using the proposed hybrid technique, LMS technique alone and NLMS alone. To properly analyze the efficiency, both the techniques were applied over several input speech signals. Out of several analyzed results here we are reporting the one result input speech signals. The input signal used for testing is shown in fig5. Fig6 and fig7 shows the same input after addition of echo and noise respectively.

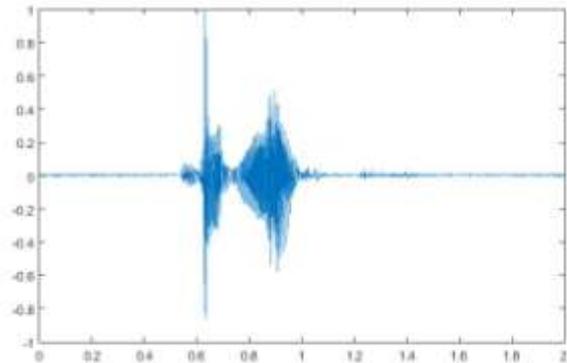


Fig 5: Original signal

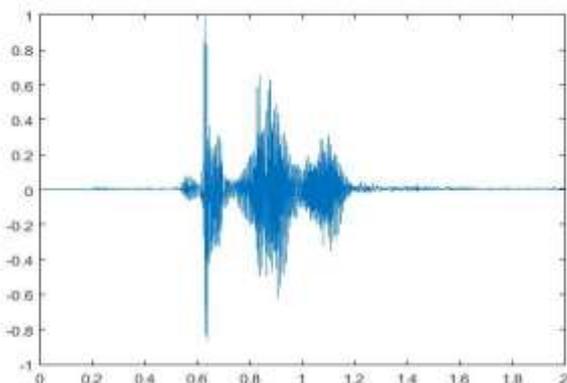


Fig 6:Signal+Echo(Delay=0.2sec and Strength=0.6)

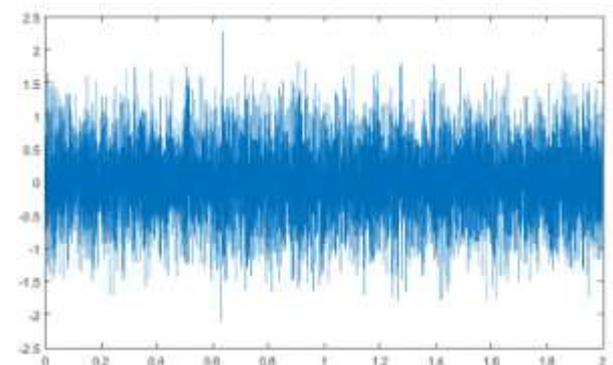


Fig 7: Signal+Echo+Noise (40% random noise)

Now the results obtained after echo cancelation and noise reduction from the signal shown in fig7, using the proposed hybrid technique is shown in fig-8 and fig-9. Whereas the resultant signal obtained after using the LMS filter and

NLMS filter alone for echo cancellation and noise reduction is shown in fig.10 and fig.11.

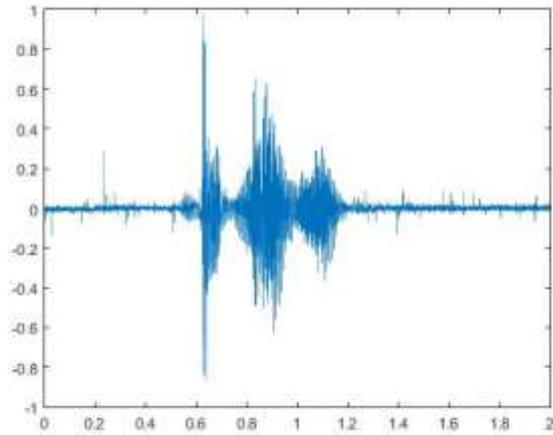


Fig 8: Noise Removed signal using ANFIS technique.

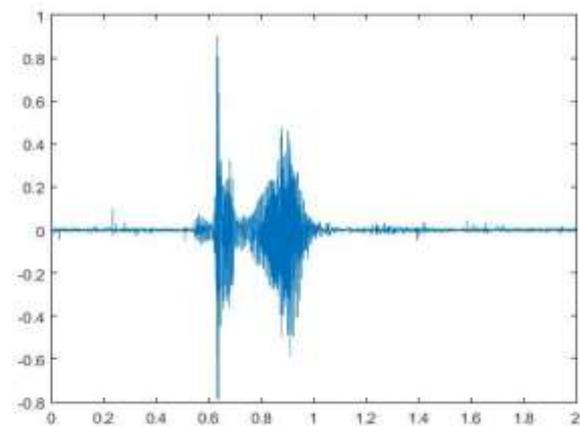


Fig 9: Echo removed using LMS technique

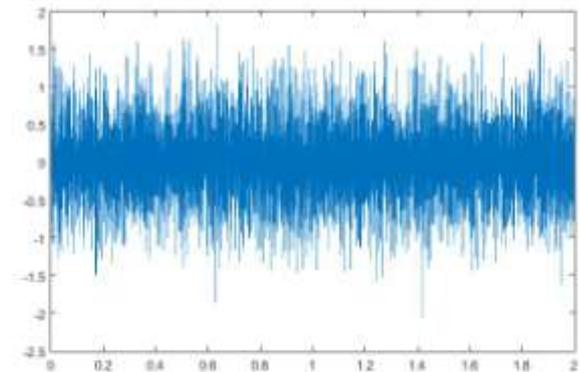


Fig10:Echo and Noise removal using LMS alone

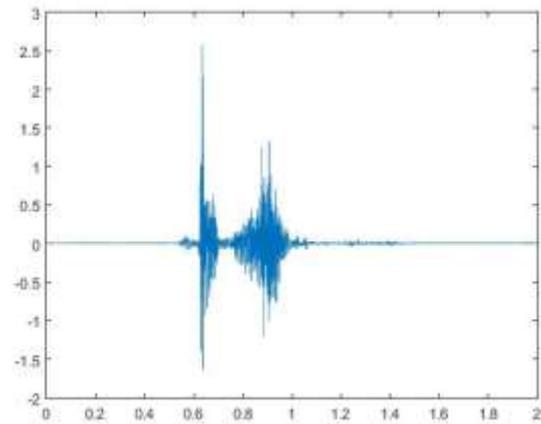


Fig 11: Echo and Noise removed using NLMS alone.

From the resultant signals obtained for the technique, it is clearly shown that the proposed hybrid technique provides very high efficiency of echo cancellation and noise reduction as compare to the conventional adaptive LMS and NLMS techniques. In addition to this the same comment is justified with the help of speech signal quality parameter obtained after echo and noise reduction using both the techniques. The PSNR and MSE values in dB obtained after testing are tabulated in table-I.

S.No.	Parameter	Proposed hybrid technique	LMS alone	NLMS alone
1	MSE	0.002	0.156	0.008
2	PSNR	75.12	56.19	68.60

Table-I: Speech Quality measured using parameters MSE and PSNR

V. CONCLUSION

Various techniques of Echo and Noise cancellation have been developed so far. Adaptive filtering techniques like LMS and NLMS are very popular due to low complexity, stability and robust nature. In this paper we present a hybrid technique for echo and noise cancellation using LMS and ANFIS technique and compared the result with two techniques i.e LMS and NLMS technique when used alone to cancel Echo and Noise. The result show that proposed technique gives better result in terms of PSNR and MSE.

REFERENCES

- [1]UpalMahbub and Shaikh Anowarul Fattah, "Gradient Based Adaptive Filter Algorithm for Single Channel Acoustic Echo Cancellation in Noise"IEEE, pp 880-883, 7th International Conference on Electrical and Computer Engineering, Dec 2012.
- [2] Sushir Kumar Dubey and Nirmal Kumar Rout, "FLMS algorithm for Acoustic Echo Cancellation and its Comparison with LMS", 1st Int'l Conf. on Recent Advances in Information Technology, RAIT-2012.
- [3] Botond Sandor Kirei, IoanaHomana, Marina Dana Topa,"Echo cancelling using adaptive algorithms", pp.317-321,september 2009.
- [4] Abhishek Deb ,Asutosh Kar and Mahesh Chandra, "A Technical Review on Adaptive Algorithms for Acoustic Echo Cancellation", International Conference on Communication and Signal Processing, April 2014.
- [5] Sahar Mobeen, IramBaig and AnumRafique, "Comparison Analysis of Multi-Channel Echo Cancellation Using Adaptive Filters", International Conference on Open Source Systems and Technologies(ICOSST), 2015

- [6] Ms. Mugdha. M. Dewasthale and Dr. R. D. Kharadkar, "Improved NLMS Algorithm with Fixed Step Size and Filter Length using Adaptive Weight Updation for Acoustic Noise Cancellation.", pp. 1-7, December, 2014.
- [7] Harjeetkaur and Rajneesh Talwar, "Performance and Convergence Analysis of LMS Algorithm", 2012 IEEE International Conference on Computational Intelligence and Computing Research Pp: 1 – 4.
- [8] Radek Martinek, Michal Kelnar, Jan Vanus, Petr Koudelka, Petr Bilik, Jiri Koziorek, and Jan Zidek, "Adaptive Noise Suppression in Voice Communication Using a Neuro-Fuzzy Inference System", 38th International Conference on Telecommunications and Signal Processing (TSP), Pp: 382 - 386, 2015.
- [9] Jay Kumar, Girish Parmar, Neeraj Gupta and Richa Kapoor, "Environmental Noise Cancellation by using Neuro Fuzzy Adaptive Filtering", Fifth International Conference on Communication Systems and Network Technologies, Pages: 1157 – 1162, 2015.
- [10] Niras C V and Yinan Kong, "LMS algorithm Implementation in FPGA for Noise Reduction and Echo Cancellation", pp: 193 – 195, 2012.