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Performance Analysis of Various Noise Cancellation Methods

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Abstract: Due to evolvement of technology immense necessity has been increased of noise reduction in signal processing. Various techniques are being used for this. In this paper an attempt has been made to compare various techniques which are being used for noise reduction and cancellation for existing results. LMS, NLMS and RLS are being compared using various parameters like convergence time, computation speed, SNR, complexity and stability.

Keywords: LMS, NLMS, RLS, Convergence time, SNR, Computation speed, complexity.

I. INTRODUCTION

Noise cancellation is a special case of optimal filtering which can be applied when some information about the reference noise signal is available. The noise cancellation technique has many applications, e.g. speech processing, echo cancellation and enhancement, antenna array processing, biomedical signal and image processing and so on [1-4]. There are numerous denoising techniques used in speech processing. Most of them include hypotheses on the original signal, as well as SNR ratio and distortion [5]. However these techniques do not cover all the explicit speech models. Each of them is associated with a particular type of distortion while maximizing noise-reduction effects.

Many methods in the literatures have been used to study the noise cancellation problems [6-14]. One of the fundamental noise cancellation methods is adaptive filtering. Adaptive filters have several applications in acoustics, controls, communications, and coding. There are many structures for adaptive filter, which range from simple to complex structure. A Digital communication system consists of a transmitter, channel and receiver connected together. Typically the channel suffers from two major kinds of impairments: Intersymbol interference and Noise. The principle of noise cancellation is to obtain an estimate of the interfering signal and subtract it from the corrupted signal. Adaptive noise cancellation, a specific type of interference cancellation, relies on the use of noise cancellation by subtracting noise from a received signal, an operation controlled in an adaptive manner for the purpose of improved signal to noise ratio [15].

II. RELATED WORK

A large amount of effort has been made for noise reduction and cancellation and to compare various techniques which are being used for the same. Many new researches have been proposed and various simulators are being used for simulation and performance analysis.

In this paper a simple neural network called Adaline as adaptive filter. Experiment was based on engine noise cancellation in cars. It shows that SNR improves after passing the noise cancellation system. In the first experiment with low engine noise improvement was 7.12 dB, and in the second experiment with high engine noise we achieved an 8.46 dB improvement. Lower improvement in the third test can be explained by wind and road noise in a driving car [20].

In this paper presents an adaptive noise cancellation algorithm based fuzzy and neural network. The major advantage of the proposed system is its ease of implementation and fast convergence. The propose algorithm is applied to noise cancelling problem of long distance communication channel. The simulation result showed that the proposed model is effectiveness [21].

This paper concentrates upon the analysis of adaptive noise canceller using Recursive Least Square (RLS), Fast Transversal Recursive Least Square (FTRLS) and Gradient Adaptive Lattice (GAL) algorithms. The performance analysis of the algorithms is done based on convergence behaviour, convergence time, correlation coefficients and signal to noise ratio. After comparing all the simulated results we observed that GAL performs the best in noise

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cancellation in terms of Correlation Coefficient, SNR and Convergence Time. RLS, FTRLS and GAL were never evaluated and compared before on their performance in noise cancellation in terms of the criteria considered here [22].

In this paper an adaptive noise canceller will be presented and some useful observations will be done over the audio signals. The adaptive noise canceller is very efficient and useful system in many applications with sound video etc [23].

It showed a cooperative performance study between the time-varying LMS (TV-LMS) and other two main adaptive approaches: The Least Mean Square (LMS) algorithm and the Recursive Least Square (RLS) algorithm. Their study disclosed the algorithm execution time, the minimum Mean Square Error (MSE) and required filter order [24].

This paper uses averaging analysis to study the mean-square performance of adaptive filters, not only in terms of stability conditions but also in terms of expressions for the mean-square error and the mean-square deviation of the filter, as well as in terms of the transient performance of the corresponding partially averaged systems [25].

This paper presented a nice trade-off between convergence properties and computational complexity and showed that the convergence property of fast affine projection (FAP) adaptive filtering algorithm is superior to that of usual LMS, NLMS, and RLS algorithm [26].

This paper investigates the performance of LMS and NLMS adaptive algorithms when implemented on Texas Instruments (TI) TMS320C6713 DSP hardware [8]-[10] and tested for two types of signals; sinusoidal tone signal and ECG signal. The obtained results from DSP kit are analyzed with the help of Digital Storage Oscilloscope (DSO) and shows considerable improvement in SNR level of a filtered signal [27].

Bernard Widrow *et.al.* developed a model for noise cancellation with the help of adaptive filter and employed for variety of practical applications like the cancelling of various forms of periodic interference in electrocardiography, the cancelling of periodic interference in speech signals, and the cancelling of broad-band interference in the side-lobes of an antenna array [28].

III. NOISE CANCELLATION METHODS

A) RLS ALGORITHM [15]

Recursive Least Squares (RLS) algorithm is capable of realizing a rate of convergence that is much faster than the LMS algorithm, because the RLS algorithm utilizes all the information contained in the input data from the start of the adaptation up to the present.

1) Standard RLS Algorithm

In the method of least squares, at any time instant n>0 the adaptive filter parameter (tap weights) are calculated so that the quantity of the cost function

$$\varsigma(n) = \sum_{k=1}^{n} \rho_n(k) e_n^2(k) \qquad (1)$$

is minimized and hence the name least squares. If k=1 is the time at which the algorithm starts, $e_n(k)$, $k = 1,2,3,\ldots n$ are the samples of error estimates that would be obtained if the filter were run from time k = 1 to n ,using the set of filter parameters that is computed at time n, and $\rho_n(k)$ is a weighting function. Actually the RLS algorithm performs the following operations:

- Filters the input signal $x(n)$ through the adaptive filter $w(n-1)$ to produce the filter output $y(n)$
- Calculates the error sample $e(n)$
- Recursively updates the gain vector $k(n)$
- Updates the adaptive filter coefficients

2) Fast Transversal RLS Algorithm

Fast transversal filter (FTF) algorithm involves the combined use of four transversal filters for forward and backward predictions, gain vector computation and joint process estimation. The main advantage of FTF algorithm is reduced computational complexity as compared to other available solutions.

B) LMS Algorithm

The Least Mean Square, or LMS, algorithm is a stochastic gradient algorithm that iterates each tap weight in the filter in the direction of the gradient of the squared amplitude of an error signal with respect to that tap weight. The

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LMS is an approximation of the steepest descent algorithm, which uses an instantaneous estimate of the gradient vector [16].

To maximize the convergence speed of the LMS algorithm, a big step size is needed, and especially when one wants to address the issue of the maximum step size for stable operation of the algorithm, a theory that is valid beyond an infinitesimally small step size range is required. All results for big step size currently available use so called independence assumption. The independence assumption specifies that the sequence of input vector is a sequence. This assumption though clearly violated since in the typical time series applications have N-1 elements in common, simplifies the analysis significantly. The discrepancy between theoretical results based on this assumption and the true algorithm behaviour was investigated [17].

The LMS algorithm [28] is a stochastic gradient-based algorithm as it utilizes the gradient vector of the filter tap weights to converge on the optimal wiener solution. With each iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the following formula:

$$w(n+1) = w(n) + 2\mu\, e(n)\, x(n) \qquad (2)$$

where, *x(n)* is the input vector of time delayed input values, *w(n)* represents the coefficients of the adaptive FIR filter tap weight vector at time *n* and μ is known as the step size. Selection of a suitable value for *μ* is imperative to the performance of the LMS algorithm, if the value is too small, the time adaptive filter takes to converge on the optimal solution will be too long; if *μ* is too large the adaptive filter becomes unstable and its output diverges. Fig.1 represents a model for Adaptive Noise Cancellation.

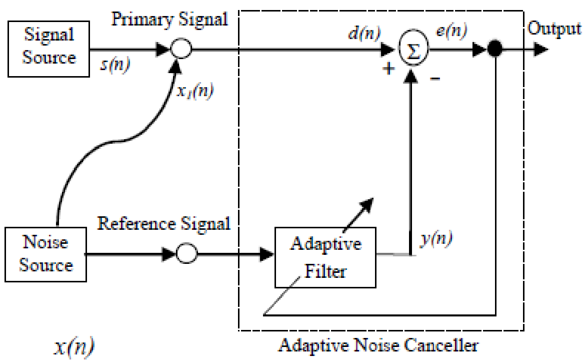

Fig.1 Adaptive Noise Cancellation [27]

C) NLMS Algorithm

The normalized LMS is based on the principle of minimal disturbance which states from one iteration to the next the weight vector of an adaptive filter should be changed in a minimal manner, subject to a constraint imposed on the updated filter's output. [18] The adaption constant for the NLMS filter is dimensionless whereas the adaption constant for the LMS filter has the dimension of inverse power. [19] `Most importantly the normalized LMS algorithm exhibits a rate of convergence that is potentially faster than that of the standard LMS algorithm for both uncorrelated and correlated input data. The main drawback of the pure LMS algorithm is that it is sensitive to the scaling of its input *x* (*n*) [18]. This makes it very hard to choose a learning rate μ that guarantees stability of the algorithm. The Normalized least mean squares filter (NLMS) is a variant of the LMS algorithm that solves this problem by normalizing with the power of the input.

In the standard LMS algorithm, when the convergence factor μ is large, the algorithm experiences a gradient noise amplification problem. In order to solve this difficulty, we can use the NLMS (Normalized Least Mean Square) algorithm. The correction applied to the weight vector w(n) at iteration n+1 is "normalized" with respect to the squared Euclidian norm of the input vector x(n) at iteration n[34][27].

We may view the NLMS algorithm as a time-varying step-size algorithm, calculating the convergence factor μ as in Eq.2

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$$\mu(n) = \frac{\alpha}{c + \|x(n)\|^2} \tag{3}$$

where α is the NLMS adaption constant, which optimize the convergence rate of the algorithm and should satisfy the condition $0<\alpha<2$, and c is the constant term for normalization, which is always less than 1. The filter weights using NLMS algorithm are updated by the Eq. (3).

$$w(n+1) = w(n) + \frac{\alpha}{c + \|x(n)\|^2} e(n)x(n) \tag{4}$$

IV. SOFT COMPUTING TECHNIQUES FOR NOISE CANCELLATIONS

Fuzzy logic was introduced by Zadeh in 1965 to represent and manipulate data and information in which there are various forms of uncertainty. Fuzzy logic is a logical system, which is an extension of multi-valued logic. It is almost synonymous with the theory of fuzzy sets, a theory that relates to classes of objects with blunt boundaries in which membership is a matter of degree [2]. ANFIS is a class of adaptive network, which are functionally equivalent to Fuzzy Inference Systems. This architecture was proposed by Jang [9] to give fuzzy systems adaptive capabilities. It uses a hybrid- learning algorithm to identify the membership function parameters of single-output, Sugeno type fuzzy inference systems (FIS). A combination of least-squares and back propagation gradient descent methods are used for training FIS membership function parameters to model a given set of input/output data. The hybrid learning algorithm which combines gradient descent and the least-squares method are briefly discussed below.

A. Artificial Neutral 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 [29].

ANNs are mathematical modelling 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 neighbours with varying coefficients or weights which represent the relative influence of the different neuron inputs on other neurons [30].

B. 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 [34] [19].

C. Fuzzy inference systems

Fuzzy inference (Fig.2) 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 [34].

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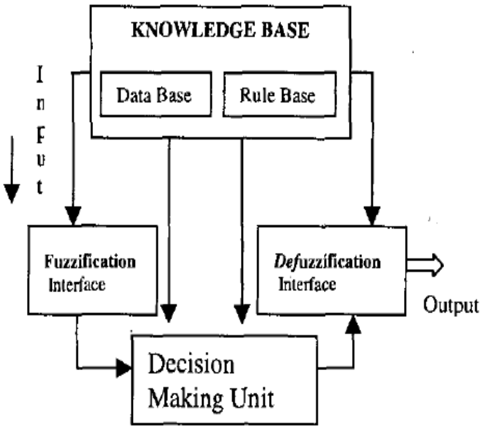

Fig.2 Functional Blocks of a Fuzzy Logic Inference System [2]

D. 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[30][31].

V. EXPERIMENTAL RESULTS

In this paper [32] LMS, NLMS and RLS algorithms are compared on the basis of mean square error, percentage noise reduction, complexity and stability. In the simulation the reference input signal x(n) is a white Gaussian noise of power two-dB generated using randn function in MATLAB, the desired signal d(n) ,obtained by adding a delayed version of x(n) into clean signal s(n), d(n) = s(n) + x1(n) as shown in Fig.3

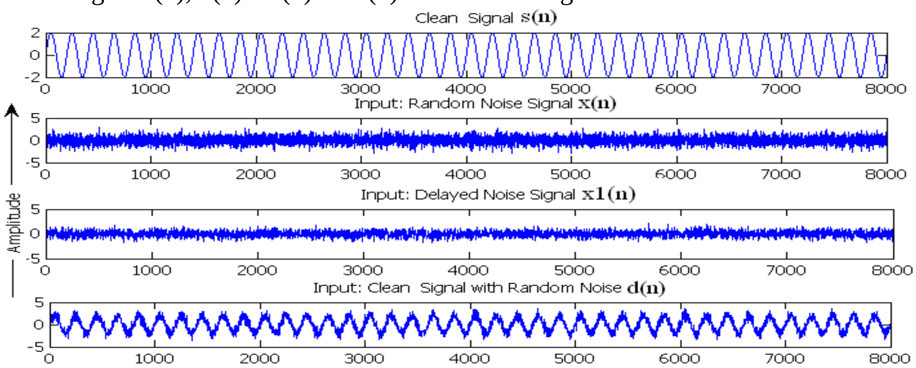

Fig.3 (a) Clean tone(sinusoid) signal s(n);(b)Noise signal x(n);(c) Delayed noise signal x1(n);(d) desired signal d(n)

The simulation of the LMS algorithm is carried out with the following specifications:
Filter order N=19, step size μ= 0.001 and iterations= 8000
The step size μ control the performance of the algorithm, if μ is too large the convergence speed is fast but filtering is not proper, if μ is too small the filter gives slow response, hence the selection of proper value of step-size for specific application is prominent to get good results.

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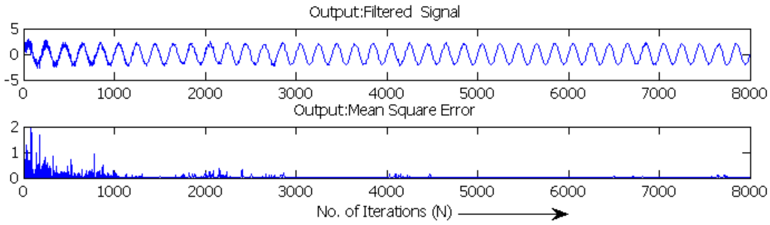


Fig.4 MATLAB simulation for LMS algorithm; N=19, step size=0.001

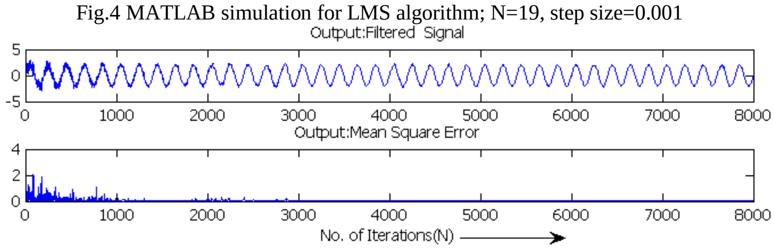


Fig.5 MATLAB simulation for NLMS algorithm; N=19, step size=0.001

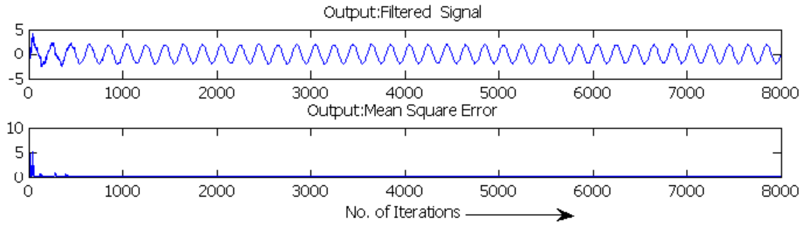


Fig.6 MATLAB simulation for RLS algorithm; N=19, lembda=1

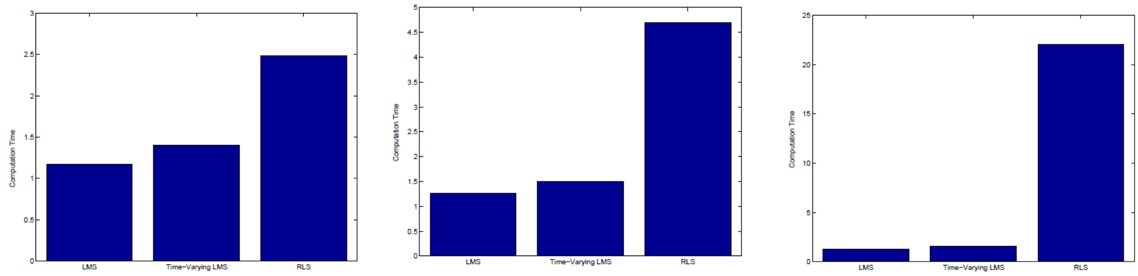
Fig.4, Fig.5 and Fig.6 shows the output results for LMS, NLMS and RLS algorithms respectively. If we investigate the filtered output of all algorithms, LMS adopt the approximate correct output in 2800 samples, NLMS adopt in 2300 samples and RLS adopt in 300 samples. This shows that RLS has fast learning rate.

In table1 performance analysis of all three algorithms is presented in term of MSE, percentage noise reduction, computational complexity and stability [24]. 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 favorable choice for most of the industries due less computational complexity and fair amount of noise reduction.

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

Table1. Performance comparison of various adaptive algorithms

In this paper[24] computation time of LMS, TV-LMS and RLS are compared. The computation time for the conventional LMS algorithm and the TVLMS algorithm is relatively similar and much less than that of the RLS algorithm. The figures below show that the RLS computation time is increasing rapidly and non-linearly with the filter order.



(a) (b) (c)

Fig.7 Computation time for different adaptive algorithms with different filter orders (a) M=10 (b) M=50 (c) M=100

In this paper [21] soft computing technique ANFIS is compared with the conventional LMS method and the following results are obtained.

	ANFIS	LMS
SNR_{input} (dB)	4	4
SNR_{output}(dB)	10.3	7.94

Table2. Comparison between ANFIS and LMS

VI. CONCLUSIONS

Going through all the experimental works, it is been concluded that the performance of a noise cancellation system depends upon the order of the filter. If the filter order is less than 15 then the performance of LMS is better than NLMS and RLS and if the filter order is greater than 15 then the performance of RLS becomes good and LMS becomes poor. Moreover RLS has a faster learning rate. The computational complexity and stability problem increases in an algorithm as we reduce the MSE. NLMS is a better choice due to its less computational complexity and fair amount of noise reduction.

Moreover we have a TV-LMS which can be used for larger filter order only as it provides an optimal MSE performance as compared to LMS and RLS with a computation time close to that of the LMS algorithm.

When these conventional algorithms are compared to the soft computing techniques particularly ANFIS, it has two advantages over LMS algorithm in low SNR environment. The first advantage is, it is more efficient to eliminate noise and second, it offers faster convergence time.

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