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COMPARATIVE ANALYSIS OF STATISTICAL ESTIMATION FOR VARIOUS ADAPTIVE ALGORITHMS IN SPEECH SIGNAL PROCESSING

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Abstract: Effective noise deportation in an acoustic environment is a very essential criteria in the field of telecommunication and signal processing since it is highly preferable to have a noiseless system. Noise problems in the environment have gained attention, as noise levels have been increasing due to the tremendous growth of technology that has led to noisy engines, heavy machinery, high speed wind buffeting and other noise sources. The problem of reducing the noise level has become the focus of a burgeoning field of research over the years. Adaptive filters came into existence to solve this hitch and it has become one of the well known and most popular approaches for the processing and analysis of speech signal. Adaptive filtering is an important basis for signal processing, in recent years has developed rapidly in various fields on a wide range of applications. This proposal focuses on the comparison of various algorithms of adaptive filters and also strives to remove the White Gaussian Noise from the original speech signal. The algorithms employed are LMS, NLMS, B- LMS, FxBLMS, RLS, and FxT-RLS. The statistical parameters using which the algorithms are analyzed and compared are Convergence speed, power spectral density, Signal to Noise ratio, stability and percentage noise removal. The performances of the various algorithms are compared by simulation using MATLAB. Based on the statistical parameters the unrivaled algorithm among all is resolved for effective noise cancellation in speech signal.

Keywords—adaptive filter, partial update, computational complexity, system identification, acoustic echo.

I. INTRODUCTION

Adaptive filters with the least-mean-square (LMS) adaptation algorithm have been extensively applied to a wide range of different fields such as communications, control, acoustics and speech processing. However, correlated input data tend to deteriorate the convergence performance of LMStype adaptive filters [1]–[3]. To increase the convergence speed of the LMS algorithm, the normalized LMS (NLMS) was introduced [2]. Also, to overcome convergence problem, Ozeki and Umeda [4] developed the basic form of an affine projection algorithm (APA) that is based on affine subspace projections. The APA is a useful family of adaptive filters whose main purpose is to increase the convergence speed of LMS-type filters, especially for correlated data [5], [6]. The computational complexity, however, has been a weak point in the implementation of APA.

With the advent of digital signal processing systems, several schemes for controlling the computational complexity of adaptive filters, by partially update of the filter coefficients, have been proposed. Early approaches were based on the intuitive notion of round robin updating of coefficient subsets (sequential partial updates) and updating all the coefficients at periodic intervals (periodic partial updates). These approached are called data-independent approaches suffer from convergence rate reduction, often proportional to the size of coefficient subsets in the case of sequential partial updates and the update frequency for periodic partial updates. More recently, data-dependent partial update techniques have been proposed with improved convergence performance. These data-dependent techniques require sorting of data leading to some complexity overheads.

In this paper, we provide a comprehensive overview of both data-independent and data-dependent approaches to partial coefficient updates; viz, periodic partial updates, sequential partial updates, stochastic partial updates ,M-max updates and selective partial updates in LMS, NLMS, and APA. Then we justify the performance of these algorithms in system identification and acoustic echo cancellation applications.

Analysis of the LMS behavior for Cyclostationary inputs studied only its convergence in the mean. The special case of apulsed variation of the input power and a linear combiner structure has recently been studied for both LMS and NLMS algorithms. An analysis of the Least Mean Fourth (LMF) algorithm behavior for non stationary inputs has been recently presented. The analytical model derived for the LMF behavior was valid only for a specific form of the input autocorrelation matrix, and cannot be easily extended to a general time-varying input statistics.

Also, as the LMF weight update equation is a function of a higher power of the estimation error, the statistical assumptions used are necessarily different from those required for the analysis of the LMS and NLMS algorithms.

Hence, the study of the behaviors of the LMS and NLMS algorithms under Cyclostationary inputs cannot be inferred from the analysis and new models must be derived. Adaptive solutions involving Cyclostationary signals have been sought for many application areas. In particular, communication, radar, and sonar systems frequently need such solutions, as several manmade signals encountered in these areas have parameters that vary periodically with time.

Thus, a statistical analysis of adaptive algorithms under Cyclostationary inputs could have a significant impact on a wide variety of problems involving Cyclostationary processes. The analysis of the adaptive filter behavior for Cyclostationary inputs is not easy because of the difficulty of modeling the input cyclostationarity in a mathematically treatable way. Thus, relatively simple models are needed from which to infer algorithm behavior for inputs with time-varying statistics.

This paper presents statistical analyses of the Least Mean Square (LMS) and the Normalized Least Mean Square (NLMS) algorithms with specific Cyclostationary input signals and an unknown system in a system identification framework. The input Cyclostationary signal is modeled by a white Gaussian random process with periodically time-varying power. These models are used to study the adaptive filter performance for input signals with sinusoidal and pulsed power variations and a transversal filter structure. The cases of fast, moderate and slow power variations are considered. Mathematical models are derived for the mean and mean-square-deviation (MSD) behavior of the adaptive weights with these input cyclostationarities. These models are derived via extension of well-known results for the LMS and NLMS algorithms to the Cyclostationary case.

These models are also applied to the non stationary channel with a random walk variation of the optimal weights. Simulation results show excellent agreement with the theoretically predicted behaviors, confirming the usefulness of the analytical model to study the adaptive filter behavior.

II. Adaptive Filter Algorithms

A. Least Mean Square Algorithm:

The LMS is an elementary algorithm used in the adaptive structures for the reason that it utilizes the error signal in order to calculate the filter coefficients. The output y(n) of FIR filter structure can be obtain from the following equation.

$$\sum_{m=0}^{N-1} w(m)x(n - m) \qquad (3).$$

B. N-LMS ALGORITHM:

The LMS algorithm suffers from gradient noise amplification when the value of convergence factor μ is out of bounds. To overcome this flaw, the NLMS (Normalized Least Mean Square) algorithm can be made use of [8]. At an iteration n+1,The correction applied to the weight vector w(n) is "normalized" with respect to the squared Euclidian norm of the input vector x(n) at iteration n.

C.Recursive Least Square Algorithm:

The RLS algorithm seeks to obtain the minimum mean squared error by obtaining the maximum estimate of the filter taps. In LMS and similar algorithms the input signal are considered stochastic. But in the case of RLS they are considered to be deterministic.RLS exhibits extremely fast convergence when compared with its counterparts. This is in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error.[2] However, this results at the cost of high computational complexity. It is based on the following considerations that if the error has

1. Zero mean
2. Statistically independent
3. Gaussian distribution

D. B-LMS Algorithm:

The complexity of weight Updation BLMS is higher when compared with LMS, as the former needs to sum up several products between data vectors and error samples. The Updation process of filter tap weights takes place after every block of data samples [9]. BLMS is more flexible with the choice of selecting the value of block length and is found to possess a configuration which is relatively simple when compared with other algorithms. Also that in real time processing it is found to have high potential towards its usage.

E. FxB-LMS:

The Updation of filter weights with FxB-LMS is done at once for each block of data samples which is nothing but an enhancement to the LMS algorithm. The filter weights are estimate from the block in order to obtain the desired signal from the input signal. Less computation is feasible with Fast BLMS in case of when the filter equals or exceeds in terms of its length [4].

F. FxT- RLS:

The Fast Transversal RLS (FxT-RLS) filter, which is identical to Recursive Least Squares (RLS) algorithm in terms of its performance, is sketched to improve the performance by furnishing the solution to filtering problem [7] Also this comes with the added advantage of reducing the computational burden which makes it an attractive solution for application employing adaptive filter. Hence the performance of RLS algorithm can be offered even for large filter order by FxT-RLSalgorithm. Hence this makes it a highly suitable solution for white noise filtering application.

III. Proposed Block Diagram

The block diagram as shown in figure 2 is explained in detail in the following section: The speech or the voice signal is taken as the input signal and gets added up with White Gaussian Noise. This results up in a noisy speech signal which is to be processed by various filtering algorithms, thereby recovering the original speech signal. The adaptive filter algorithms that implemented in this work are Least Mean Square, Normalized Least Mean Square, Block Least Mean Square, Fast Block Least Mean Square, Recursive Least Square and Fast Transversal Recursive Least Square. By using these filter algorithms the original input signal is recovered. Each algorithm varies in terms of its operation and properties. They are compared by using five statistical parameters which include: Stability, Convergence Speed, Percentage Noise Removal, Signal to Noise Ratio, Power Spectral Density. Each algorithm proves itself to be best in one or two parameters. The algorithm which maximum satisfies the parameters and proves itself to be the best in the point of hardware platform is chosen as the required adaptive filter algorithm. Later the chosen algorithm is implemented in hardware using TMS processor.

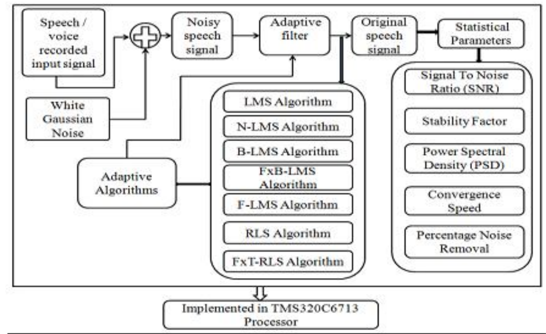

Fig.2. Block diagram of proposed model

IV. Statistical Parameters

A. Stability

A filter is said to be stable when the filter provides limited response for every limited input signal. When this requirement is not satisfied the result could be an unstable system. Certain design approaches can guarantee stability, for example by using only feed forward circuits such as an FIR filter. On the other hand, filter based on feedback circuits have other advantages and may therefore be preferred, even if this class of filters include unstable filters. In this case, the filters must be carefully designed in order to avoid instability.

1. LMS Algorithm the stability is given by

$$N = \text{length (in)}$$
$$stab\_lms = 2 * N + 1 \quad (4)$$

2. N-LMS Algorithm ,the stability is given by

$$N = \text{length (in)}$$
$$stab\_nlms = 5 * N + 1 \quad (5)$$

3. B-LMS Algorithm ,the stability is given by

$$N = \text{length (in)}$$
$$stab\_nlms = 4 * N + \log(N) \quad (6)$$

4. FxB-LMS Algorithm ,the stability is given by

$$N = \text{length (in)}$$
$$stab\_fblms = 2 * N * \log(N) \quad (7)$$

5. RLS Algorithm ,the stability is given by

$$N = \text{length (in)}$$
$$stab\_rls = 4 * N * N \quad (8)$$

6. FxT-RLS Algorithm, the stability is given by

$$N = \text{length (in)}$$
$$stab\_ftrls = (9 * N) + (13 * M) + 8 \quad (9)$$

B. Convergence Speed

The speeds of convergence of the means of the coefficient values depend on the Eigen values i and the step size. Thus, faster convergence could be obtained when the step size is increased. However, the speed of convergence could actually decrease if the step size values are greater than one. Moreover, the mean-squared behavior could limit the convergence of system, as we shall indicate shortly. The convergence Speed for various adaptive filter algorithms is computed by using the relation given below.

R = xcorr (in)
con_fac = max (sum(R))/m in (sum(R))
conver_spe ed = 1 - (u * con_fac) (10)

C. *Percentage Noise Removal*:

The percentage of noise removed can be given as the difference between approximate and exact values, as a percentage of the exact Value. One method to represent the process of removing noise is by the percentage noise removal. The Percentage Noise Removal for LMS, N-LMS, B-LMS, FxB-LMS and RLS is computed by the following relation as given below :

mm = abs(sum(wk)) (11)

The Percentage Noise Removal for FxT-RLS is computed by the following relation as given below

mm = abs((ei)) (12)

D. Power Spectral Density:

Power spectral density (PSD) refers to the amount of power per unit (density) of frequency (spectral) as a function of the frequency. The power spectral density, PSD, describes how the power (or variance) of a time series is distributed with frequency. By knowing the power spectral density and system bandwidth, the total power required can be calculated. The power spectral density (PSD) is intended for continuous spectra. The integral of the PSD over a given frequency band computes the average power in the signal over that frequency band. A one-sided PSD contains the total power of the signal in the frequency interval from DC to half of the Nyquist rate. A two-sided PSD contains the total power in the frequency interval from DC to the Nyquist rate.

E. Signal To Noise Ratio:

The signal to noise ratio is defined in terms of the ratio of signal power to the noise power. A ratio higher than 1:1 indicates more signal than noise. The noise is assumed to be white noise with zero-mean and to be uncorrelated; while the signal is considered to be band limited, representing a slowly varying spectrum in nature. The signal to noise ratio is represented in terms of decibels denoting the clarity of the signal in a circuit [10]. The greater the ratio evidenced by a larger number, the lesser the noise and the more easily it can be filtered out. The lowest number possible value of SNR is 0, which means that there is no noise present in the signal obtained. The Signal to Noise ratio for LMS, N-LMS, B-LMS, FxB-LMS and RLS is computed by the following relation as given below

snr = 10 * log10(sum(abs(fft(in)).^2)/sum (abs(fft(y k - in)).^2))
snrf = 10 * log10(sum(abs(fft(in)).^2)/sum (abs(fft(m se - in)).^2))

The Signal to Noise ratio for FxT- RLS is computed by the following relation as given below

snr = 10 * log10(sum(abs(fft(in)).^2)/sum (abs(fft(d - in)).^2))

V. Simulation Results

From the graphical figures and from MATLAB simulation the following comparison table has been framed. The table provides the necessary information about the performance of each algorithm in terms of its parametric characteristics.

Table: 1 Comparison of Various Algorithms with different statistical Parameters

S.No	Algorithms	SNR	PER	PSD	Convergence Speed	Stability
1	LMS	-4.06	2.04	449	0.99	High
2	N-LMS	-3.86	0.002	370	1.0	High
3	B-LMS	-4.05	0.06	410	0.11	High
4	FxB- LMS	-4.22	0.004	420	0.59	High
5	RLS	-4.04	0	450	1.0	High
6	FxT-RLS	-4.22	0.004	451	1.0	Very High

VI. Conclusion

Thus the simulation for parametric estimation of six algorithms employed for the adaptive filtering are carried out using MATLAB .The White Gaussian Noise which is added to the original input signal is effectively removed using adaptive filter algorithms and the unrivaled algorithm is proposed by comparing statistical parameters- Stability, Convergence Speed, Power Spectral Density, Percentage Error removal, Signal to Noise ratio. It has been proven that from the outcome the simulation results that the FxT -RLS algorithm has the upper hand over other algorithms for effectively removing white Gaussian noise since it has a convergence speed of „1‟ and PSD of „451‟. Though RLS has convergence speed of „1‟, it is very difficult to implement it in the hardware due to its high complexity. FxT-RLS has convergence speed same as that of RLS but it is not as complex as RLS. Furthermore it can be easily implemented in the hardware. Hence FxT-RLS is finally deduced as the best algorithm for the effective removal of noise from the white Gaussian noise affected input signal.

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