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Speech Enhancement using Combinational Adaptive LMS Algorithms

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Abstract

The key to successful adaptive signal processing understands the fundamental properties of adaptive algorithms like LMS. Adaptive filter is used for the cancellation of the noise component (in the Speech and acoustic signal processing)which is overlap with undesired signal in the same frequency range , but fixed LMS algorithm produces minimum convergence rate and fixed steady state error. So we presents design, implementation and performance of adaptive FIR filter, based on variations in LMS algorithm, which produces better convergence rate and minimum steady state error compare to fixed LMS, and we also obtains de noised signal at output, and also we propose to calculate SNR values of Adaptive Filter with LMS algorithms and comparison is made among the LMS algorithms.

Keywords

Adaptive Filters, Windows, Combinational LMS algorithms.

1. Adaptive Filters

Rapid Advances in the VLSI technology and digital communications/digital signal processing has brought more attention to the adaptive least squares (LS) methods [1]. Many digital signal processing applications requires linear filters and adaptive techniques in signal processing and analysis [2]. The reference and error channels of active noise control (ANC) systems may be saturated in real-world applications if the noise level exceeds the dynamic range of the electronic devices. This nonlinear saturation degrades the performance of ANC systems that use linear adaptive filters with the filtered-least-mean-square (FLMS) algorithm [3]. Adaptive filters have been included in the syllabus of undergraduate digital signal processing (DSP) courses [4].The LMS algorithm has been extensively used in many applications as a consequence of its simplicity and robustness [5].LMS based adaptive filters used in all sparse systems for noise Cancellation [6]. Adaptive algorithms are applicable to system identification and modeling, noise and interference cancelling, equalization, signal detection and prediction [7]. LMS Algorithm is widely used in a variety of applications, ranging from speech enhancement and biomedical signal processing to active control of sound and vibration[8].Adaptive Filters are widely used in numerous industrial applications Acoustics, communications, automatic control and seismology[9].Information processing in variable and noisy environments is usually accomplished by means of adaptive filters [10].Adaptive filters are successfully using in FT Analysis and in Fractional Fourier Transform[11]-[19].

2. Design of Combinational Adaptive Algorithms

In our illustrative numerical example, the adaptive filter is set to be a 100-tap FT based FIR filter to simplify numerical algebra.

2.1 Fixed LMS Algorithm

The filter adjustable coefficient wn is adjusted based on the LMS algorithm.

$$w_{n+1} = w_n + m * e(n)x(n) - - - (1)$$

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Where wn is the coefficient used currently, while w_{n+1} is the coefficient obtained from the LMS algorithm and will be used for the next coming input sample. The value of m controls the speed of the coefficient change, $e(n)$ is an error value updated each time and $x(n)$ is noised signal coefficient. The output equations of LMS algorithm leads to

$$e(n) = d(n) - y(n) - - - (2)$$

$$\text{y(n+1)}= y(n) + m * e(n)x(n) - -(3)$$

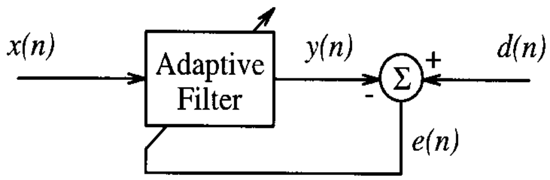

Fig 1: Block diagram of Adaptive filter

2.2 Normalized LMS Algorithm

In this algorithm the weight equations of Fixed LMS Algorithm modified as

$$w_j(n+1) = w_j(n) + \frac{\overline{\mu}}{\left\|\underline{x}(n)\right\|^2} e(n)x(n-j) — (4)$$

2.3 variable step sized LMS

Heuristics of the method: We combine the benefits of two different situations:

- The convergence time constant is small for large μ.
- The mean-square error in steady state is low for small μ.

Therefore, in the initial adaptation stages μ is kept large, and then it is monotonically reduced, such that in the final adaptation stage it is very small.
There are many receipts of cooling down an adaptation process.

- Monotonically decreasing the step size

$$\mu(n) = \frac{1}{n+c} - - - (5)$$

$\underline{w}$(n+1)=$\underline{w}$(n)+M(n)$\underline{u}$(n)e(n)----(6)

2.4 Sign algorithms

In high speed communication the time is critical, thus faster adaptation processes is needed.

$$sgn(a) = \begin{cases} 1; & a > 0 \\ 0; & a = 0 \\ -1; & a < 0 \end{cases} \text{--------(7)}$$

- **The Sign algorithm (other names: pilot LMS, or Sign Error)**

$$\underline{\omega}(n+1) = \underline{\omega}(n) + \mu\underline{\mu}(n)sgn\big(e(n)\big) - - - (8)$$

- **The Clipped LMS (or Signed Regressor)**

$$\underline{\omega}(n+1) = \underline{\omega}(n) + \mu\, sgn\left(\underline{\mu}(n)\right) e(n) — (9)$$

- **The Zero forcing LMS (or Sign Sign)**

$$\underline{\omega}(n+1) = \underline{\omega}(n) + \mu\, sgn\left(\underline{\mu}(n)\right) sgn\big(e(n)\big) - -(10)$$

The Sign algorithm can be derived as a LMS algorithm for minimizing the Mean absolute error (MAE) Criterion

$$J(\underline{\omega}) = \omega E[|e(n)|] = E\left[\left|d(n) - \underline{\omega}^T\underline{\mu}(n)\right|\right] - -(11)$$

2.5 Linear smoothing of LMS gradient estimates

We obtain simply the average of gradient components:

$$\underline{w}(n+1) = \underline{w}(n) + \frac{\mu}{N}\sum_{j=n-N+1}^{n} e(j)\underline{u}(j) - - - (12)$$

- **Momentum LMS algorithm**

When LPF is an IIR filter of first order $h(0) = 1 - \gamma$, $h(1) = \gamma h(0)$, $h(2) = \gamma 2h(0)$, . . . then,
$bi(n) = LPF(gi(n)) = \gamma bi(n-1) + (1-\gamma)gi(n)$---(13)

$$\underline{b}(n) = \gamma\underline{b}(n-1) + (1-\gamma)\underline{g}(n) - - - (14)$$

$$(n+1) - \underline{w}(n)\underline{w} = \gamma\big(\underline{w}(n) - \underline{w}(n-1)\big) + \overline{\mu}(1-\gamma)e(n)\underline{u}(n) - - - (15)$$

2.6 Nonlinear smoothing of LMS gradient estimates

If there is an impulsive interference in either $d(n)$ or $u(n)$, the performances of LMS algorithm will drastically degrade (sometimes even leading to instability).

Smoothing the noisy gradient components using a nonlinear filter provides a potential solution. The Median LMS Algorithm Computing the median of window size $N + 1$, for each component of the gradient vector, will smooth out the effect of impulsive noise. The adaptation equation can be implemented as
$W_i(n+1) = W_i(n) - \mu \cdot med\ ((e(n)u(n-i)), (e(n-1)u(n-1-i)), \ldots, (e(n-N)u(n-N-i)))$-----(16)

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3. Steps to Design Adaptive Filter

1) The Low pass filter removes the corrupting low frequency noises in signal. The order of the filter is the order of the filter is 64.

Steps to low pass filter:
The desired transfer function of filter is

$h_d(n) = \frac{sinw_c n}{\pi n}$------(17)

By multiplying the desired transfer function with windows ,we can get transfer function of FIR Low pass filter i.e

$h(n) = h_d(n) * w(n)$-------(18)

where $w(n)$ is represents Transfer function of following windows

1) Rectangle window
2) Bartlett window
3) Hanning window
4) Hamming window
5) Kaiser window

2) Now h(n) is compared with x(n) which produces e(n) .
3) The error coefficients are fed back to each LMS algorithms discussed above to update the coefficients of FrFt based LPF.
4) Steps 2 and 3 repeated up to error becomes negligible.
5) The updated coefficients of LMS Algorithm is the is the Response of desired Filter

4. Results and Implementations

The results shows responses of the Adaptive filter with LMs Algorithm and we applied a noised signal shown in Fig2 and compare the signal to noise ratio of Noised signal before and after the filtering for different combinational Adaptive algorithms

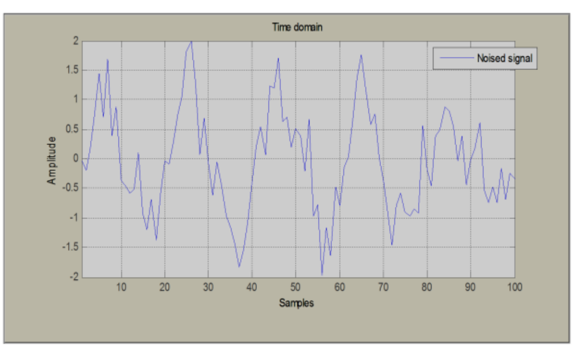

Fig 2: Noised signal

When the Noised signal of fig-2 is filtered with Adaptive Filter with Combinational LMS algorithms the whole noise was removed, producing a near clean signal of fig: 3 to fig: 5 with Rectangular window of FIR Filter and SNR, Steady state error, Convergence factor values of noised and de noised signals are calculated and shown in Table-1, Table-2 and Table-3 Respectively.

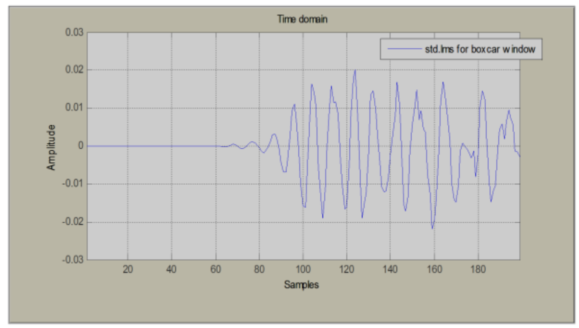

Fig 3: Response of Fixed LMS based Adaptive filter with Rectangular window

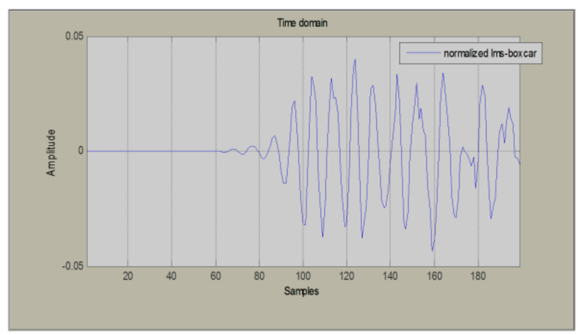

Fig 4: Response of Normalized LMS based Adaptive filter with Rectangle window

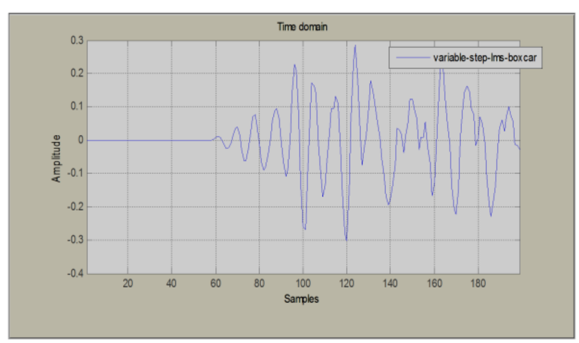

Fig 5: Response of variable step sized LMS based Adaptive filter with Rectangle window

Table1: Comparison of SNR among various LMS Algorithms

S. No	Type of LMS Algorithm	Type Of Window	Output SNR in dB
1	FIXED LMS	BOXCAR	0.0024
		BARTLETT	0.0021
		HANNING	0.0024
		HAMMING	0.0024
		KAISER	0.0023
2	NORMALIZED LMS	BOXCAR	0.0048
		BARTLETT	0.0042
		HANNING	0.0046
		HAMMING	0.0046
		KAISER	0.0044
3	VARIABLE STEP SIZED LMS	BOXCAR	0.0550
		BARTLETT	0.0527
		HANNING	0.0553
		HAMMING	0.0553
		KAISER	0.0549
4	SIGN-STEP LMS	BOXCAR	0.0359
		BARTLETT	0.0358
		HANNING	0.0362
		HAMMING	0.0362
		KAISER	0.0368
5	LINEAR SMOOTHING SIZED LMS	BOXCAR	0.0462
		BARTLETT	0.0449
		HANNING	0.0457
		HAMMING	0.0458
		KAISER	0.0465
6	NON LIEAE SMOOTHING SIZED LMS	BOXCAR	0.0024
		BARTLETT	0.0021
		HANNING	0.0024
		HAMMING	0.0024
		KAISER	0.0023

Table 2: Comparison of steady state error

S. No	Algorithm	Steady State Error
1	FIXED LMS	0.1450
2	NORMALISED LMS	0.0470
3	VARIABLE STEP SIZED	0.0062
4	SIGN STEP SIZED	0.0102
5	LINEAR SMOOTHING	0.0763
6	NON LINEAR SMOOTHING	0.0033

5. Conclusion

The Implementation of Adaptive-FIR Filter using Combinational LMS Algorithms with Different Digital windows was performed. We also applied a sample test noised signal to Adaptive filter and obtained de noised wave form at output which are shown in Fig-2 to Fig-5 for Rectangular window, and We compared SNR, steady state error and convergence factor at input and Output which are shown from Table-1.,table-2 and Table-3 Respectively. From the above discussions it is concluded that other than Fixed LMS Algorithm were given better Response in terms of SNR, steady state error and convergence factor and Enhancement of Noise signal from noised input signal.

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