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A Novel Technique for Speech Processing Using Combinational Adaptive Methods

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Abstract - This paper presents a new technic to introduce adaptive Filter with combinational Algorithm like Normalized LMS & variable stepsize LMS based on Shadow technic. Which is useful for the cancellation of the noise component mixed with Speech in the same frequency range, In this design proposed project implements an adaptive FIR filter,is based on the Shadow technic, which produces less mean square error and better convergence factor compare to LMS, here spectral characteristics of window is improved by shadow technic, finally de noised Speech is obtained at output, and also propose to calculate Signal to noise ratio values of shadow based Adaptive Filter with Normalized & variable step-sized LMS algorithm.

Keywords - *Windows, FIR, Combinational LMS Algorithm, Shadow Technique.*

1. Introduction

1.1. Adaptive filters

Adaptive filters are successfully using in removal of artifacts presenting in ECG signal [1]. For processing and analysis of speech adaptive filtering techniques plays a vital role[2].If the level of the noise exceeds the dynamic range of electronic devices, the reference and error channels of active noise control systems may be saturated in real time applications.The performance of active noise control system which uses linear adaptive filter algorithm was degraded by the non-linear saturation[3].adaptive filters have been included in the syllabus of undergraduate digital signal processing (DSP) courses[4].The LMS algorithm are widely used in many applications as an effect of its simplicity and robustness [5]. LMS based adaptive filters used in all sparse systems for noise Cancellation [6].Adaptive LMS filters are employed in the design of mechanical,electronic systems [7] LMS Algorithm is widely used in a different variety of applications, in the area of speech enhancement and biomedical signal processing to active noise control of sound and vibration[8]. Adaptive Filters are widely used in plentiful industrial applications like Accoustics, communications, automatic control and seismology[9]. Information processing in variable and different noise environments is usually collaborated by means of adaptive filters [10].Adaptive filtering is frequently employed in communications, control, and many other applications in which the statistical characteristics of the signals to be filtered are either unknown *a priori* or, in some cases, slowly time varying[11].

Adaptive filters provide excellent performence due to their essential pole-zero structure as compared with adaptive FIR filters that have an all-zero form ,in active noise control Application[12].In order to provide better stability further and further RLS Filters are introduced[13].These adaptive Filters are highly stable and effectivlyattenuates and often cancel defaults[14].An Adaptive filters are successfully used in bio-medical systems like Denoising of electro cardiogram(ECG) Waveforms[15]

Adaptive filters plays vital role in modern Digital signal processing applications in area such as telephone echocancellations,noise cancellation, equalization of communications channels, bio medical signal enhancement, active noise control, and adaptive control systems[16] and many Researchers are worked out on FIR Filters using different types of Transform techniques[17] to [20]

2. Shadow Technic

For improving the spectral charcteristics of window shadow technic is successfully used[21]. In the electronic cardiogram (ECG)and echo cancellations shadow based Adaptive filters are usd for suppression of noise signals[22-23].

3. Design of Adaptive Filter with Normalized and Variable Step Sized LMS Algorithm.

The block diagram of Adaptive filter with Fixed LMS Algorithm is shown in the figure1. Which processes the noised speech signal through it.

Where
s(n)=pure speech signal

v(n)=noise

h=Low pass FIR Filter

v1(n)=h*v(n) (low pass filter output)

d(n)=noised speech signal [s(n)+v1(n)]

y(n)=Estimated Noise signal

e(n) = d(n)-y(n) ,[Original speech signal]

3.1 Normalized LMS Algorithm

The adjustable weights are typically determined by the LMS Algorithm, the weight update equation is

$$w_j(n+1) = w_j(n) + \frac{\bar{\mu}}{\|\underline{x}(n)\|^2} e(n)x(n-j) \quad -(1)$$

Where,
$w_j(n+1)$=next weight of the filter

$w_j(n)$=current weight of the filter

e(n)=error signal

$x(n-j)$=shifted function of noise signal x(n)

3.2 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, 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

$$\mu(n) = \frac{1}{n+c} - - - (2)$$

Where c=constant
n=monotonic factor

$\underline{w}$(n+1)=$\underline{w}$(n)+M(n)$\underline{\mu}$(n)e(n)----(3)

Steps to design adaptive Filter with Normalized & variable step size LMS Algorithm

1. Create or record actual speech signal.
2. Create or record a noise signal.
3. Correlate noise by passing through a low pass filter.
4. Merge Noise signal with actual Noise signal.
5. Pass this merged signal to Adaptive filter using Normalized & variable- step sized Least mean square Algorithm.
6. Calculate error e(n)
7. Update weight equation w(n)
8. Repeat step 7 and calculate adaptive output y(n) until error is minimized.
9. Calculate input SNR and output SNR

4. Design of Adaptive Filter with Normalized & step-size LMS Algorithm based on Shadow Technic

The Figure:2 shows the block diagram of Adaptive filter with Normalized LMS Algorithm and variable step-sized Least mean square algorithm by Shadow technic In shadow filter mechanism the Low pass filter output is feedback either positively or negatively by a shadow filter of same type or different type .Here we used the shadow technic to find best combination for different values of ‘β’. Hence we can derive expression of the transfer function for the shadow concept.

With positive feedback connection is,

$$\bar{h}(n) = \frac{Low\ pass\ Filter}{1+(\beta * Low\ pass\ Filter)}$$

$$\bar{\mathrm{h}}(\mathrm{n}) = \frac{\mathrm{h}}{1+\beta*\mathrm{h})} \text{, ------------------------(4)}$$

$0 \leq \beta \leq 1$

Where

β is feedback factor

v1(n)=v(n)*$\bar{h}(n)$

d(n)=noised speech signal,[s(n)+v1(n)]

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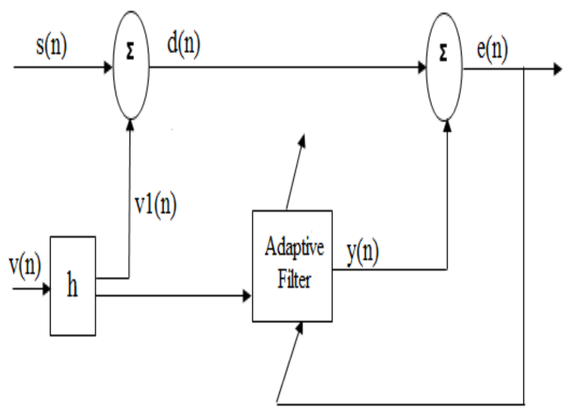

Fig1 :Block diagram of LMS Adaptive Filter

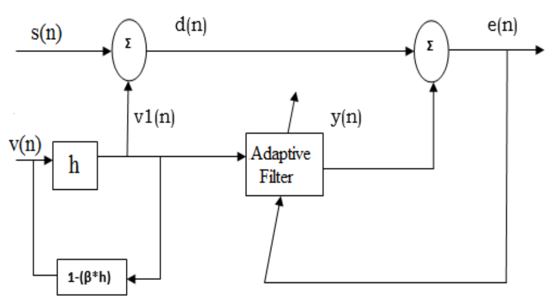

Fig2 :Block diagram of LMS Adaptive Filter with shadow factor

5. Results and Implementations

The results shows responses of the Adaptive filter with Normalized and variable stepsized least mean square Algorithm, and we applied a noise signal to Speech and compares the signal to noise ratio of Noised signal before and after the filtering for Kaiser window , which is shown in Fig3.

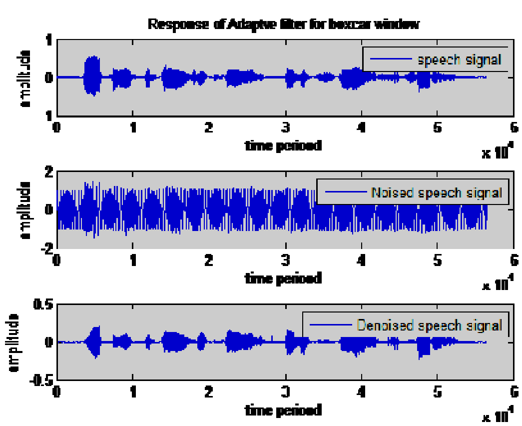

Fig3:Denoised speech with Kaiser window

When the Noised speech is filtered with Adaptive Filter with Normalized LMS algorithm the whole noise was removed, producing a near clean signal of Fig:4 to Fig:6 with different 'β' values of shadow. FIR Filter for Kaiser window. Similarly Fig:7 to Fig:9 for Variable step-sized least mean square Algorithm. SNR, mean square error are computed for adaptive filter based on without shadow and with shadow concept are shown in Table-1,Table-3 Respectively for Normalized LMS algorithm and Table-2 and table-4 for variable step-sized Least mean square algorithm.

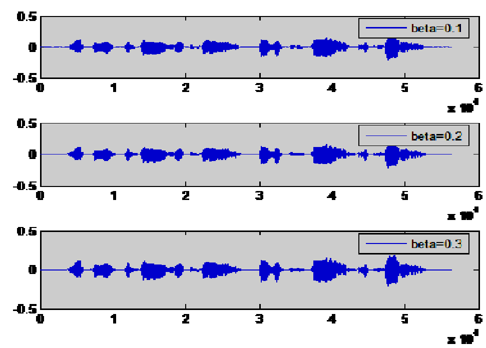

Fig 4: Denoised speech for β=0.1;0.2;0.3 For Normalized LMS

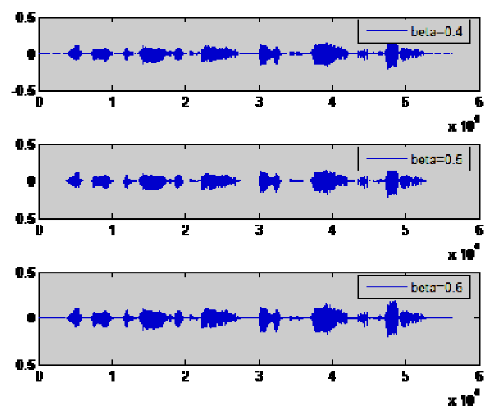

Fig 5:Denoised speech for β=0.4;0.5;0.6 for Normalized LMS

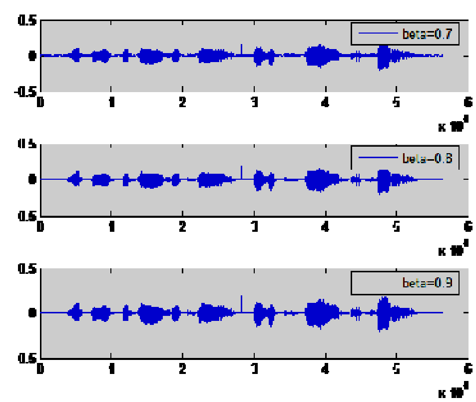

Fig 6:Denoisedspeech for β=0.7;0.8;0.9 for Normalized LMS

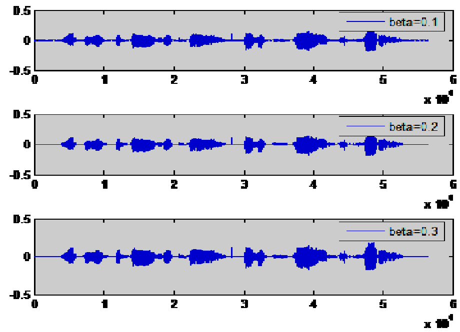

Fig-7:Denoised speech for β=0.1;0.2;0.3
for Variable step-sized Least mean square algorithm

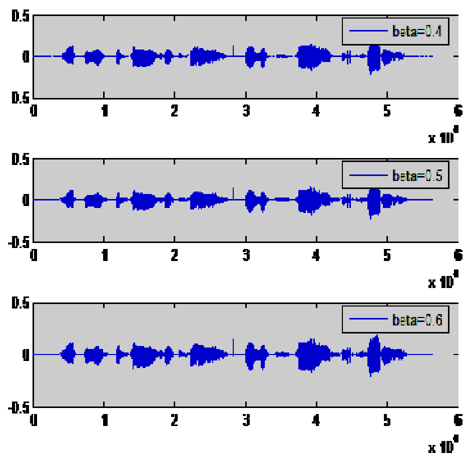

Fig-8:Denoised speech for β=0.4;0.5;0.6
for variable step sized Least mean square algorithm

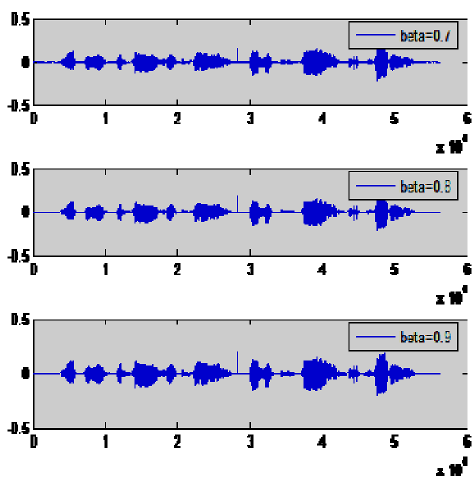

Fig-9:Denoised speech for β=0.7;0.8;0.9
for Variable step- sized Least mean square algorithm.

Table1: Comparison of SNR of before and after filtering of speech signal and MSE for Normalized LMS algorithm

S. NO	**Window**	**SNR before Filtering In db**	**SNR after filtering In db**	**mean square error**
1	Kaiser	0.0020	0.2846	1.5361 e-007

Table-2: Comparison of SNR of before and after filtering of speech signal and MSE for variable step sized Least mean square algorithm

S.NO	**Window**	**SNR before Filtering in dB**	**SNR after Filtering in dB**	**MSE (Mean Square Error)**
1	Kaiser	0.0020	0.1163	1.8098e-013

Table-3: Comparision of SNR and MSE for Kaiser window and shadow factors for Normalized LMS algorithm

S.NO	**Window**	**β**	**SNR after Filtering in dB**	**MSE (Mean Square Error)**
1		0.1	0.2223	8.6065e-008
2		0.2	0.2256	7.4309e-008
3		0.3	0.2282	6.5239e-008
\ 4	Kaiser	0.4	0.2300	5.8127e-008
5		0.5	0.2312	5.2474e-008
6		0.6	0.2318	4.7929e-008
7		0.7	0.2318	4.4241e-008
8		0.8	0.2321	4.1226e-008
9	Kaiser	0.9	0.2325	3.8750e-008
10		1.0	0.2328	3.6709e-008

Table-4: Comparison of SNR and MSE for Kaiser window and shadow factors for step-sized Least mean square algorithm

Sr. NO	Window	β	SNR after Filtering in dB	MSE (Mean Square Error)
1	Kaiser	0.1	0.1231	1.5071e-013
2		0.2	0.1295	1.2748e-013
3		0.3	0.1355	1.0936e-013
4		0.4	0.1410	9.5029e-014
5		0.5	0.1461	8.3548e-014
6		0.6	0.1505	7.4257e-014
7		0.7	0.1542	6.6674e-014
8		0.8	0.1572	6.0443e-014
9		0.9	0.1593	5.5294e-014
10		1.0	0.1605	5.1026e-014

6. Conclusion

The Implementation of Adaptive-FIR Filter using shadow concept for Kaiser window was performed. we applied a noised speech signal to Adaptive filter and obtained de noised wave form at output which is shown in Fig-3. Later We shown responses of shadow based Adaptive filter from Fig:4 to Fig:6 for different shadow factors of the Normalized LMS algorithm. Similarly Fig:7 to Fig:9 for different shadow factors of the variable ste-sized Least mean square algorithm algorithm. Finally We compared SNR, mean square error(MSE) at input and Output which are shown from Table-1.,table-3 Respectively for Normalized LMS algorithm table-2 and Table-4 for variable step-sized Least mean square algorithm. From the above discussions it is concluded that shadow based adaptive filter produces better responses in terms of SNR and MSE compared to Normalized and variable step- sized LMS algorithm.

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