

Analysis of LMS Algorithm in Wavelet Domain

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Abstract

In this paper Time Domain Least Mean Square (LMS) algorithm and Wavelet Transform Domain Least Mean Square (WDLMS) algorithm with Daubechies wavelets are used to minimize the undesired noise from speech signals. The performance of this algorithm using different Daubechies wavelets db1, db5 and db10 are evaluated in presence of car noise at different signal to noise ratio (SNR) levels. WDLMS algorithm performed better than LMS algorithm at all SNRs for Daubechies wavelets at different vanishing moments.

Keywords: Adaptive Filters, Discrete Wavelet Transform, LMS, WDLMS.

1. Introduction

The most important challenge in speech signal processing is speech enhancement by removing background noise. Several techniques have been proposed by various researchers for this purpose like spectral subtraction, adaptive noise canceling etc. The performances of these techniques depend on quality and intelligibility of the noisy speech signal to be processed. The improvement of the speech signal-to-noise ratio (SNR) is the objective of all techniques. Applications of speech enhancement techniques are mobile communications, robust speech recognition, low quality audio devices and hearing aids.

The LMS algorithm is most widely used due to its low computational complexity. The main disadvantage of LMS algorithm is its low convergence speed. If this

time domain signal is transformed into orthogonal wavelet transform domain contents and this orthogonal transformed signal is given as an input to the least mean square algorithm, then algorithm provides faster convergence speed than time domain LMS algorithm [1, 2].

2. Adaptive Noise Cancellation

Adaptive noise cancellation system [3, 4] is shown in Figure 1. The reference noise $\tilde{N}(n)$ is input to the transversal filter. The output of the transversal filter is

$y(n)$ which is convolution of reference noise $\tilde{N}(n)$ & filter tap weight $w(n)$. The noisy signal $d(n)$ which consists of an information bearing signal $s(n)$ corrupted by noise $N(n)$. The $d(n)$ & $y(n)$ are compared to give the error signal $\tilde{s}(n)$. The adaptive filter coefficients are changed iteratively according to the error signal $\tilde{s}(n)$. The filter weights are adjusted continuously to minimize the error between $d(n)$ and $y(n)$, so that the output $\tilde{s}(n)$ is a close approximation of the signal $s(n)$. Both noise signals $N(n)$ and $\tilde{N}(n)$ are uncorrelated with the signal $s(n)$ while correlated with each other. The error $\tilde{s}(n)$ gives the estimated clean signal at the output.

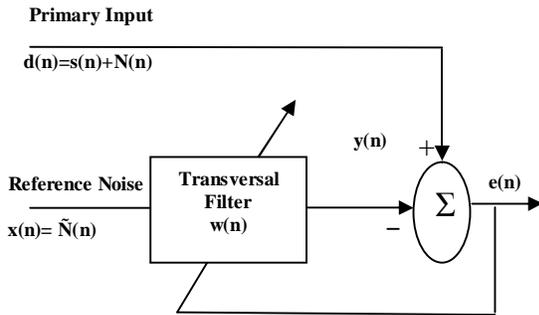


Fig. 1. Adaptive Noise Cancellation System

3. Wavelets

Wavelet analysis is different to the Fourier analysis since it provides additional freedom to the user to choose the mother wavelet [5, 6]. The Fast Fourier Transform (FFT) and the Discrete Wavelet Transform (DWT) are both linear operations. The FFT contains basis functions that are sine and cosine. The wavelet transform, contains more complicated basis functions called wavelets, mother wavelets, or analyzing wavelets. The dissimilarity between FFT and DWT transforms is that individual wavelet functions in DWT are localized in space whereas sine and cosine functions in FFT are not localized in space.

Out of many wavelet families wavelet subclasses are defined. Wavelet subclasses are distinguished by the number of coefficients and by the level of iterations. Within a family wavelet subclasses are classified by the number of vanishing moments. This is an extra set of

mathematical relationships for the coefficients that must be satisfied which is directly related to the number of coefficients. Some important members of wavelet family are Daubechies, Coiflet, Haar and Symmlet etc. The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. The most important application areas of wavelets are speech processing where they are used in de-noising, edge detection, feature extraction, speech recognition, echo cancellation etc. The Daubechies wavelet family is the first one to make it possible to handle orthogonal wavelets with compact support and arbitrary regularity. It is called as N^{th} order of the dbN wavelet. This family contains the Haar wavelet, db1, which is the simplest and the oldest wavelet. It is discontinuous, resembling a square form. Daubechies wavelets are the most popular wavelets used for speech processing.

4. Discrete Wavelet Transform (DWT)

In DWT the signal is decomposed into two sets of coefficients called approximation coefficients (denoted by c_a) and detail coefficients (denoted by c_d). These coefficients are obtained by convolving the input signal with a low-pass filter (for c_a) or a high-pass filter (for c_d) and then down sampling the convolution result by 2. The size of c_a and c_d is half of the size of the input signal. The filters are determined by the chosen wavelet. Fig. 2. shows single-level DWT decomposition.

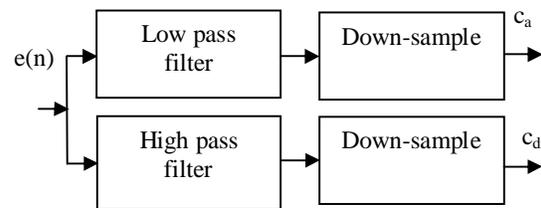


Fig. 2. Single-level DWT decomposition

5. LMS Algorithm

LMS is most widely used algorithm due to its computational simplicity. LMS adaptive filter aims to minimise a cost function equal to the expectation of the square of the difference between the desired signal $d(n)$, and the actual output of the adaptive filter $y(n)$ [1-2,7-8].

$$\xi(n) = E[e^2(n)] = E[(d(n) - y(n))^2] \quad (1)$$

The filter tap weight $w(n)$ is changed itself iteratively to trace the desired signal $d(n)$. The $x(n)$ is a known signal given to the input of FIR filter. The difference between $d(n)$ and $y(n)$ is the error signal $e(n)$ as shown in Fig. 1. The error signal $e(n)$ is then fed to the LMS algorithm to compute the updated filter coefficients $w(n+1)$ to iteratively minimize the error. The steepest descent algorithm is used in LMS algorithm. The algorithm updates the next filter tap weights using current tap weight vector and the current gradient of the cost function with respect to the filter tap weight vector $\nabla \xi(n)$ as given in equation (1).

$$w(n+1) = w(n) - \mu \nabla \xi(n) \tag{2}$$

The gradient of the cost function, $\nabla \xi(n)$, can alternatively be expressed in the following form.

$$\begin{aligned} \nabla \xi(n) &= \nabla (e^2(n)) \\ &= \frac{\partial e^2(n)}{\partial w} \\ &= -2e(n)x(n) \end{aligned} \tag{3}$$

The convergence time of the LMS algorithm depends on the step size μ . If μ is small, then it may take a long convergence time and this may defeat the purpose of using an LMS filter. However if μ is too large, the algorithm may never converge. The value of μ should be scientifically computed based on the environmental effects on $d(n)$.

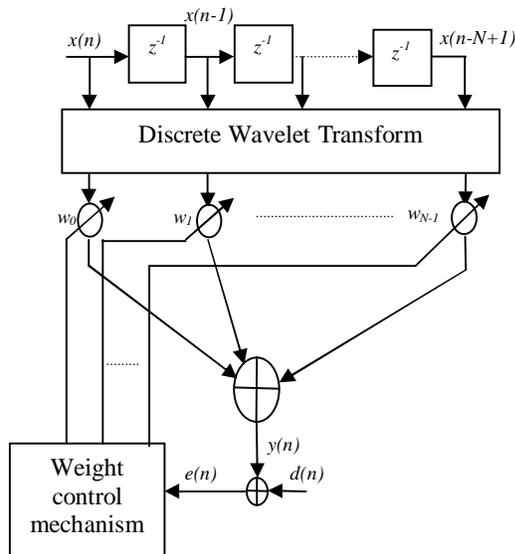


Fig. 3. A wavelet Transform Domain Adaptive Filter

6. Wavelet Transform Domain Adaptive Filters

The block diagram of Wavelet Transform Domain Adaptive Filter [9, 10] setup is shown in Fig. 3. Here input signal is first divided into corresponding sub-bands. These sub-bands represent the signal at different resolution levels. The sub-band signals are then used as inputs to an adaptive filter. Each sub-band signal is then multiplied by corresponding weights and added to give output $y(n)$. $y(n)$ is then compared with desired signal $d(n)$ and error $e(n)$ is produced. In WDLMS the weights of the adaptive filter are updated by the LMS algorithm as given in equation 4.

7. Experimental Setup and Results

For evaluating the performance of the algorithms, the first requirement is the availability of proper noisy signal. Noisy signal was prepared for Hindi digit shunya by adding car noises from NOISEX-92 database [11] to clean Hindi digit shunya signal. To generate noisy signal, car noise from this database was artificially added to clean speech at different signal-to-noise ratios (SNRs) in the range -5dB to 10dB. The noisy signal was fed into the mathematical simulation of LMS algorithm and WDLMS algorithms with Daubechies wavelets with the help of MATLAB. The filter order and step size was taken 60 and 0.01 respectively. The resulting outputs were then analyzed in order to study the behavior of these algorithms. The performance of algorithms was compared based on the improvement in SNR at various levels. It is observed from table1 that the wavelet domain LMS algorithm (WDLMS) using different wavelets db1, db5 and db10 is superior to that of time domain LMS algorithm in terms of improvement in SNR. It is also observed that this improvement in SNR is at the cost of increased computational complexity. It is also observed from Table 1 that LMS algorithm shows a maximum improvement of 7.23dB at 0dB input SNR level whereas WDLMS shows a maximum improvement of 11.80dB at -5dB input SNR level for db10 wavelet. At the same time, the time taken by time domain LMS algorithm to converge is much less than that of wavelet domain LMS algorithm. This shows that WDLMS provides improvement in SNR at the cost of increased computational complexity. Fig. 4. - Fig. 7. shows the graphical representation of improvements in SNR at -5dB, 0dB, 5dB and 10dB respectively for

signal corrupted by car noise. Fig. 8 shows the average time taken by each algorithm for all input SNR levels. It is observed from Fig. 8 that WDLMS algorithm with db10 wavelet takes maximum time compared to other algorithms at all input SNR levels.

Table 1: Performance comparison of LMS and WDLMS Algorithms for car noise

Algorithms	INPUT SNR	-5dB	0dB	5dB	10dB
LMS	Output SNR	1.8556	7.3213	11.228	13.7635
	time	1.2344	1.1875	1.2188	1.2031
WDLMS using db1	Output SNR	1.9124	7.358	11.2574	13.7864
	time	15.9063	16.0156	15.9062	16.0781
WDLMS using db5	Output SNR	5.4231	9.9137	12.9631	14.6937
	time	17.5938	17.75	17.75	17.6094
WDLMS using db10	Output SNR	6.8009	10.8563	13.5188	14.9496
	time	19.5781	19.7031	19.875	20.1563

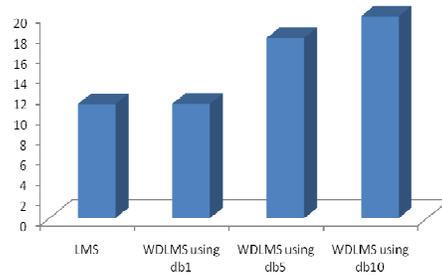


Fig. 6. Output SNR for 5dB input SNR

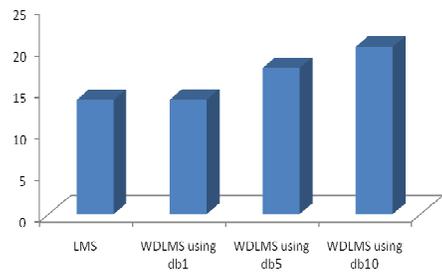


Fig. 7. Output SNR for 10dB input SNR

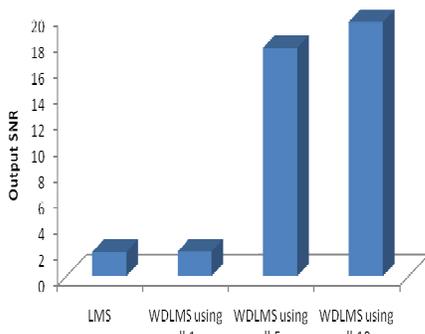


Fig. 4. Output SNR for -5dB input SNR

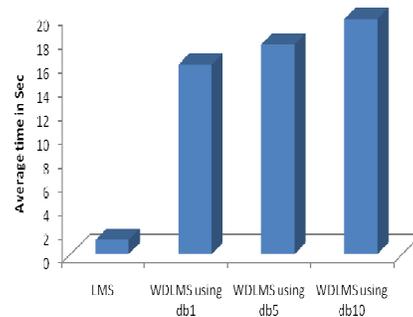


Fig. 8. Average time taken by each Algorithm in Seconds

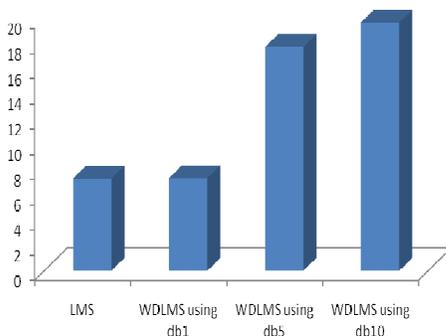


Fig. 5. Output SNR for 0dB input SNR

8. Conclusion

WDLMS algorithm with Daubechies db1, db5 and db10 wavelets was implemented to minimize the noise from speech signals. The performance of WDLMS is superior to LMS at the cost of increased computational complexity. Improvement in SNR is achieved by increasing the order or number of vanishing moments N

of Daubechies dbN wavelet since wavelets with increasing numbers of vanishing moments result in sparse representations for a signal. However, this increment is at the cost of increased computational complexity.

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