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Elimination of White Noise Using MMSE & HAAR Transform

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***Abstract*-- Noises present in communication channels are disturbing and the recovery of the original signals from the path without any noise is very difficult task. This is achieved by denoising techniques that remove noises from a digital signal. Many denoising techniques have been proposed for the removal of noises from the digital audio signals. But the effectiveness of those techniques is less. Here MMSE and Harr Wavelet Transforms are used for denoising. Output Signal to Noise Ratio (SNR) and Mean Square Error is calculated & compared using different techniques. Harr wavelet provides better result as compared to MMSE Transform. Analysis is done on noisy speech signal corrupted by white noise at 0 – 18 dB signal to noise ratio levels. Analysis is done on noisy speech signal corrupted by white guassian noise Signal to Noise Ratio levels at 0-18 db. . Output signal to noise ratio and mean square error is calculated & compared using MMSEand, HAAR wavelet. Simulation & results are performed in MATLAB 7.10.0 (R2010a).**

Keywords*- Harr wavelet, MMSE, *Signal To Noise Ratio.

I. INTRODUCTION

Wavelets have become a popular tool for speech processing, such as speech analysis, pitch detection and speech recognition. Wavelets are successful front end processors for speech recognition, this by exploiting the time resolution of the wavelet transform. For the speech recognition, the mother wavelet is based on the Hanning window. The recognition performance depends on the coverage of the frequency domain. The goal for good speech recognition is to increase the bandwidth of a wavelet without significantly affecting the time resolution.

Wavelet analysis, as opposed to Fourier analysis, provides additional freedom since the choice of atoms of the transform deduced from the analyzing wavelet is left to the user. Moreover, according to the objectives of wavelet processing, we may prefer the continuous transform to the discrete transform, if the redundancy is useful for analyzing the signal. We would make the opposite choice, if we were looking for signal compression. In the latter case we must restrict ourselves to wavelets with filters, whereas in the former case almost any zero integral function is appropriate.

Since the Haar base appeared at the beginning of the last century, since renamed the Haar wavelet, passing by Gaussian Morlet wavelets, Meyer wavelets [MEY 90] (obtained using *ad hoc* construction) and Daubechies wavelets [DAU 88] and [DAU 92] that are the most widely used, numerous wavelets regularly appear in books and are made available in specialized software applications. Construction of new wavelets was very intense in the first ten years of their young history, but recently it has become less regular and bears on increasingly specific goals, often associated with limited application contexts.

Wavelet family associated with ψ :

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad a \in \mathbb{R}^+, b \in \mathbb{R} \qquad \text{…. (1)}$$

A. Signal Decomposition

Starting with a discrete input signal vector s, the first stage of the DWT algorithm decomposes the signal into two sets of coefficients. These are the approximation coefficients cA1 (low frequency information) and the detail coefficients cD1 (high frequency information). The coefficient vectors are obtained by convolving s with the low-pass filter Lo_D for approximation and with the high-pass filter Hi_D for details. This filtering operatio is then followed by dyadic decimation or down sampling by a factor of 2. Mathematically the two-channel filtering of the discrete signal s is represented by the expressions.

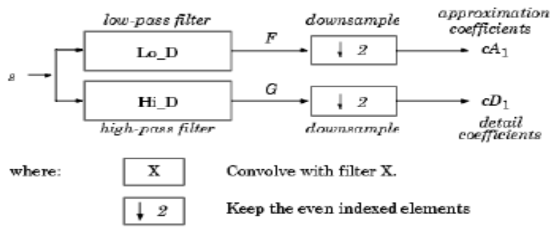

Fig.1. Filtering operation of the DWT

These equations implement a convolution plus down sampling by a factor 2 and give the forward fast wavelet transform. If the length of each filter is equal to 2N and the length of the original signal s is equal to n, then lengths of the coefficients cA1 and cD1.

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree the utilization to be a low-frequency high-frequency operation the corresponding.

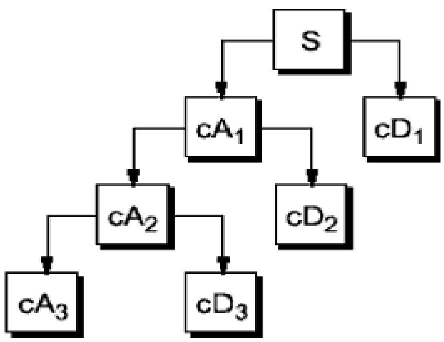

Fig.2. Decomposition of DWT coefficients

Since the analysis process is iterative, in theory it can be continued indefinitely. In reality, the decomposition can on proceed until the vector consists of a single sample. Normally, however there is little or no advantage gained in decomposing a signal beyond a certain level. The selection of the optimal decomposition level in the hierarchy depends on the nature of the signal being analyzed or some other suitable criterion, such as the low-pass filter cut-off. The original signal can be reconstructed or synthesized using the inverse discrete wavelet transform (IDWT). The synthesis starts with the approximation and detail coefficients cAj and cDj, and then reconstructs cA_{j-1} with the reconstruction filters.

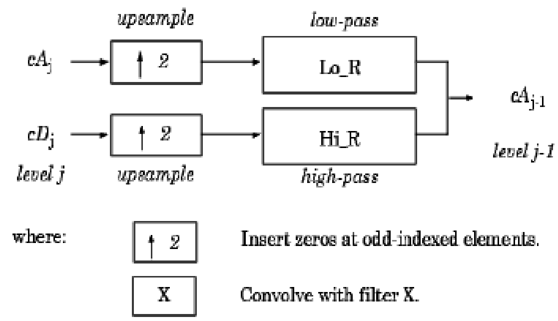

Fig 3. Wavelets reconstruction

The reconstruction filters are designed in such a way to cancel out the effects of aliasing introduce decomposition phase. The reconstruction filters (Lo_R and Hi_R) together with the low and high pass decomposition filters. For a multilevel analysis, the reconstruction process can itself be iterated producing successive approximations at and finally synthesizing the original signal.

B. Signal Denoising

It has been seen that wavelets can remove noise more effectively than the traditionally used methods wavelet transforms to denoise data is accomplished by wavelet transformation to the noisy data, thresholding the resulting coefficients which are below some value in magnitude, and then inverse transforming to obtain a smoother version of the original data.

In this work the concept of Additive White Gaussian Noise (AWGN) is used. This simply means a noise, which has a Gaussian probability density function and white power spectral density function (noise distributed over the entire frequency spectrum) and is linearly added to whatever signal being analyzed. In the simplest model we suppose that,

$$s(n) = f(n) + \sigma e(n) \quad \ldots\ldots\ldots (2)$$

Where time n is equally spaced. e(n) is a Gaussian white noise N (0,1) and the noise level σ .The de-noising objective is to suppress the noise part of the signal s and to recover f. The method is efficient for families of functions f that have only a few nonzero wavelet coefficients.

C. Denoising procedure

The general de-noising procedure involves three steps. The basic version of the procedure follows the steps described below.

- Decompose - Choose a wavelet, choose a level N. Compute the wavelet decomposition of the signal s at level N.

- Thresholding: Threshold detail coefficients - For each level from 1 to N, select a threshold and apply soft or hard thresholding method to the detail coefficients.
- Reconstruct - Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

D. Soft and Hard Thresholding

Hard Thresholding is the simplest method. Soft Thresholding has nice mathematical properties and the corresponding theoretical results are available.

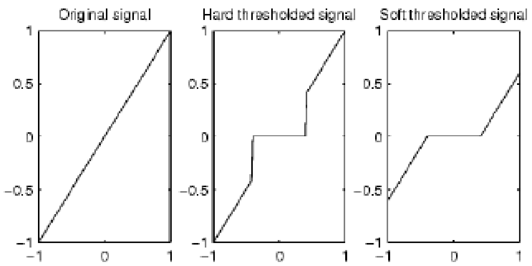

Fig.4. Signal, hard thresholding and soft thresholding

Let t denote the threshold. The hard threshold signal x is x if |x| > t, is 0 if |x| t. The soft threshold signal x is sign(x)(|x| - t) if |x| > t is 0 if |x| t. Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards 0. The hard procedure creates discontinuities at x = ±t, while the soft procedure does not.

E. Choice of wavelet

Choosing a wavelet that has compact support in both time and frequency in addition to significant number of vanishing moments is essential for an algorithm. Several criteria can be used in selecting an optimal wavelet function. The objective is to minimize reconstructed error variance and maximize signal to noise ratio (SNR).Optimum wavelets can be selected based on the energy conservation properties in the approximation part of the coefficients. Wavelets with more vanishing moments should be selected as it provides better reconstruction quality and introduce less distortion into processed speech and concentrate more signal energy in few coefficients. Computational complexity of DWT increases with the number of vanishing moments and hence for real time applications it cannot be suggested with high number of vanishing moments.

II. RESULTS AND IMPLEMENTATION OF WAVELET

The speech signals used for the work are pronounced by male and female speakers, recorded using sound recorder facility with external microphone using mono channel. Samples used are 11000. Signal is sampled at sampling frequency Fs=8000 Hz, encoded using 16 bits, and degraded by additive Gaussian white noise. Signal is corrupted by 5db, 10 db and 15 db additive noises. Thus we have the noisy signal in required SNRs. In case of additive background noise the assumptions made for developing enhancement methods are (i) speech and noise signals are uncorrelated at least over a short-time basis, (ii) noise is either stationary or slowly varying as compared to speech, and (iii) noise can be represented as zero mean random process. The degradation level of additive background noise is normally specified by the measure called Signal to Noise Ratio (SNR) and is defined as the ratio of signal energy to noise energy. For evaluating performance of the method both objective and subjective tests are conducted. In objective test, SNR of signal after denoising is computed. Other two parameters used for comparing results are time required for reconstruction of signal and mean square error between clean signal and denoised signal. Haar and Daubechies wavelets are implemented on noisy signal and effort is made to remove additive white Gaussian noise from noisy signal. Signal is decomposed to level 4 and level 5. Let s (n) is the clean speech, y (n) the noisy, s^ (n) the enhanced signal and w (n) the noise then we have:

$$y(n) = s(n) + w(n) \quad \ldots\ldots\ldots\ldots (3)$$

SNR of denoised signal can be calculated as

$$SNR_{out} = 10 \log_{10} \frac{\sum s^2(n)}{\sum (s(n) - s\hat{}(n))^2} \quad \ldots\ldots\ldots\ldots (4)$$

Minimizing mean square error (MSE) between the processed speech and the clean speech is a commonly used technique in the filtering algorithms. MSE is a valid distance measure between two speeches and it is computed directly as,

$$MSE = \frac{1}{N} \sum_{n=0}^{N-1} (\hat{s}(n) - s(n))^2 \quad \ldots\ldots (5)$$

Speech signal pronounced by male speaker is as shown in figure and respective spectrogram of '.wav' file is as shown. Results are shown for level 4 decomposition of noisy signal with Haar wavelet implementation.

III. RESULTS AND DISCUSSION

Table 1: Results for B1 (male voice -data base-1).
Wav input file for application of MMSE & Haar wavelet

SNR(db)	MMSE	HAAR Wavelet
0	0.0004541000	0.0006574700

1	0.0004151900	0.0005347800
2	0.0003787800	0.0003793200
3	0.0003494700	0.0003651600
4	0.0003238700	0.0003071300
5	0.0002997400	0.0002575900
6	0.0002793500	0.0002210500
7	0.0002638200	0.0001905700
8	0.0002479200	0.0001675600
9	0.0002377000	0.0001490700
10	0.0002270300	0.0001335700
11	0.0002197500	0.0001213700
12	0.0002136000	0.0001121900
13	0.0002085300	0.0001045300
14	0.0002045600	0.0002042100
15	0.0002044200	0.0002011400
16	0.0001098150	0.0000899320
17	0.0001016300	0.0000871806
18	0.0001943800	0.0000846880

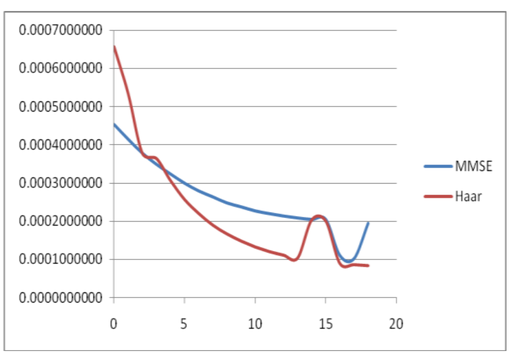

Fig.5 Graphical represantion of data base -1

Table 2: Results for B2(male voice -data base-2).
Wav input file for application of MMSE & Haar wavelet

SNR(db)	MMSE	HAAR Wavelet
0	0.0007084300	0.0001010400
1	0.0006400300	0.0008325800
2	0.0005770600	0.0007031000
3	0.0005232300	0.0005942500
4	0.0004750200	0.0004744600
5	0.0004296800	0.0004370800
6	0.0003940000	0.0003847400
7	0.0003604900	0.0003391700
8	0.0003600130	0.0003396200
9	0.0003121200	0.0002769000
10	0.0002931100	0.0002552400
11	0.0002792000	0.0002378900
12	0.0002658800	0.0002240000
13	0.0002569400	0.0002132000
14	0.0002491100	0.0002043200
15	0.0002430100	0.0001976700
16	0.0002370700	0.0001920700
17	0.0002338150	0.0001878000
18	0.0002298200	0.0001843100

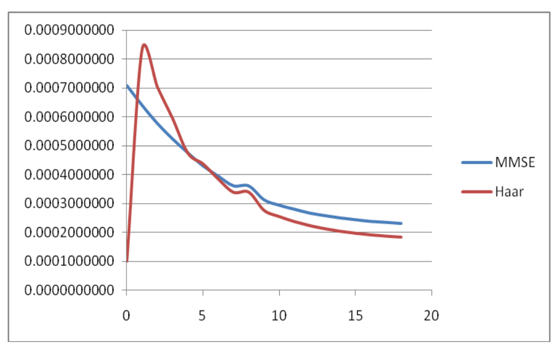

Fig.6 Graphical represantion of data base -2

Table 3: Results for B3 (male voice -data base-3). Wav input file for application of MMSE & Haar wavelet

SNR(db)	MMSE	HAAR Wavelet
0	0.0001035200	0.0001606100
1	0.0008289100	0.0001071300
2	0.0008248400	0.0001076800
3	0.0007375900	0.0008909500
4	0.0006563600	0.0007358700
5	0.0005822300	0.0006266500
6	0.0005207500	0.0005301700
7	0.0004652600	0.0004571800
8	0.0004210900	0.0003997000
9	0.0003847400	0.0003519000
10	0.0003504400	0.0003138800
11	0.0003236700	0.0002843200
12	0.0003032600	0.0002615000
13	0.0002849900	0.0002429600
14	0.0002702700	0.0002280400
15	0.0002592300	0.0002136000
16	0.0002495500	0.0002070100
17	0.0002424300	0.0001994400
18	0.0002369900	0.0001939800

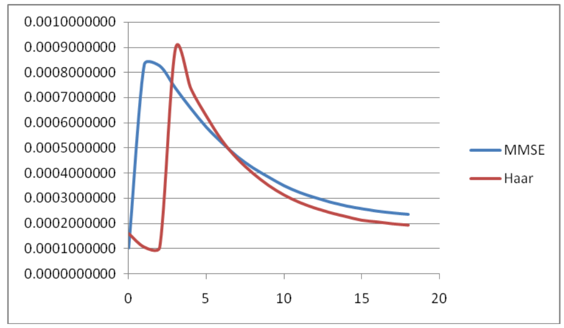

Fig.7 Graphical reprensation of data base -3

From above mention table(1,2 and 3) & graph (5,6 & 7)at 0 to 18 db SNR the computation time of MMSE is large as compare to Haar Wavelet. It shows that Haar transform is faster as compare to MMSE

IV. CONCLUSION

In the present work wavelet based speech Denoising algorithm is addressed. Wavelet Denoising is a non-parametric estimation method that has been proposed in recent years for speech enhancement applications. In this work both objective and subjective methods were used for evaluation of wavelets performance in speech Denoising confirms its superiority. Haar wavelet has comparatively good performance than some other wavelets.. Therefore From results obtained it can be concluded that Haar wavelet is suitable for speech Denoising application. As Haar is not smooth as compared to other wavelets it has limitations when applied to non stationary signal such as speech. Higher order Daubechies can be used and are found to be suitable for the work done.

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