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Wavelet Transform EDNSS LMS Adaptive Filtering for Echo & Noise Cancellation in Speech Signals

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Abstract

In this paper we have proposed wavelet transform error data normalized step size least mean square (WT-EDNSS LMS) adaptive filtering algorithm in which tap delayed reference noisy samples are projected onto a convolution filter formed by sampling and scaling the Daubechies-2 wavelet. These projections are used as inputs to the linear combiner. The weights of linear combiner can be updated by the WT- EDNSS LMS algorithm. The results obtained in our work provide better results when compared with the conventional EDNSS LMS adaptive filter algorithm for white & colored Gaussian noise cancellation in speech signals. This concept also works better when compared with the conventional EDNSS LMS algorithm to cancel echo and noise in speech signals. The main advantage of this technique is it can be used in real time signal processing applications because of its simplicity.

Keywords: Adaptive filtering, WT-EDNSS LMS, Wavelet transform.

Introduction

Adaptive filtering has been widely used in networks for noise cancellation, data communications, active noise control and image de-noising purposes. An adaptive filter can be characterized by its topology of adaptive algorithm. The adaption is a time varying process as the weights are updated from time to time to achieve the desired goal. The signals like speech, music and radio signals are non-stationary ones; hence the adaptive filtering of such signals is very much essential in order to remove noise from the above mentioned signals when they are embedded with noise and echo. In practice, by modeling the linear systems with the help of basis functions like Legendre polynomials, spline functions, prolate basis [1, 2] and wavelet basis [3] become time-varying systems. In our present paper, we have combined the wavelet and conventional EDNSS LMS technique for adaptive filtering purposes as wavelets provide better time-frequency localization. The use of wavelet transform in adaptive filtering technique is similar to that of Fourier transform (FT). The Discrete Fourier transform (DFT) based techniques [4, 5] cannot provide better results for time varying systems. In discrete wavelet analysis, signals are represented by a weighted sum of the translates and dilates of mother wavelet which are treated as basis. Multi-resolution analysis constructs the orthonormal basis for wavelets which spans around the space L^2(R) of square integrable functions [6, 7] or finite energy functions. These wavelets can be grouped by their scaling constant into disjoint subsets spanning proper and orthogonal subspaces of L^2(R). These subspaces, that corresponding to different scales are said to represent signals at different resolution levels. In this paper we have used the adaptive filter configuration which is shown in Fig.1.

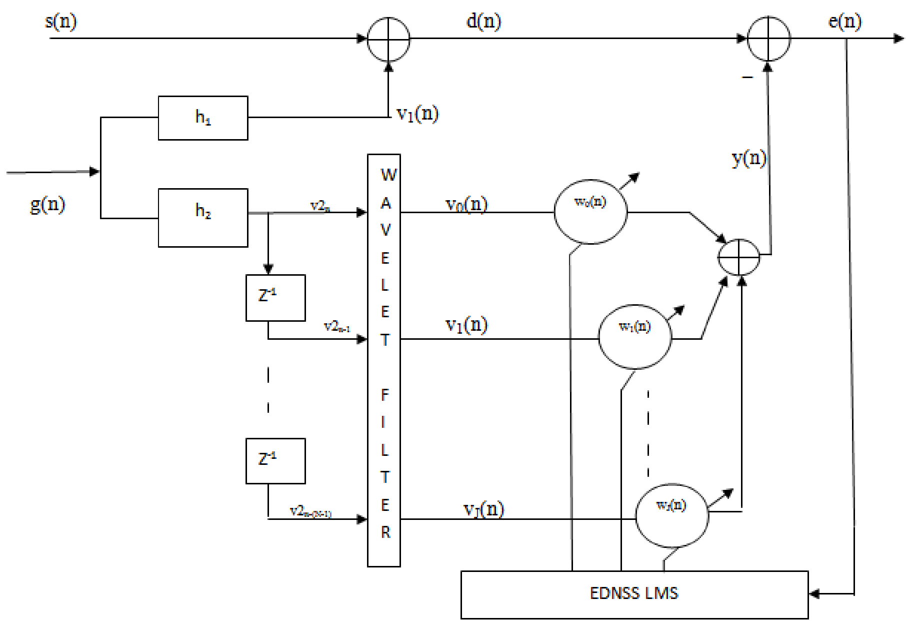

Figure 1: Wavelet Transform domain EDNSS LMS adaptive noise canceller.

The noise (v1) was generated and mixed with original speech signal and tap delayed reference noisy (v2) samples are projected onto a convolution filter formed by sampling and scaling the Daubechies-2 wavelet. These samples are used as inputs to a linear combiner. The weights of linear combiner are updated using the WT-EDNSS LMS algorithm. Wavelet domain based techniques are more complex than conventional LMS but it is widely used because of its stability and simplicity. However, the wavelet transform based algorithms provides significant improvement for colored noises in speech signals along with echo in the telecommunication networks. If we try with conventional LMS based FIR filter for echo and noise cancellation purposes, we require adaptive filters of tap length 512 or 1024 taps which provide large computational complexity at each iteration level. But this can be eliminated by taking Recursive Least Square (RLS) techniques [8], but its complexity prevents it to implement in a low cost commercial digital signal processors. Considering the above difficulties, we have implemented wavelet transform domain adaptive filtering technique for both echo and noise cancellation purposes which are generally accompanied with original speech signals during the time of tele-conferencing, mobile communication and other such situations.

This paper is organized as follows: Section 2 presents fundamental concept of wavelets and convolution filters, section 3 provide the implementation of WT-EDNSS algorithm and section 4 shows some simulation results followed by conclusion.

Wavelet Transform based Adaptive Filters

In this section we develop the wavelet transform based tapped delay line adaptive filter. Any signal in continuous time domain can be represented in terms of wavelet basis function which can be represented as:

$$x(t) = \sum_{k \in Z} c_{0k} \varphi_{0k}(t) + \sum_{j=0}^{\infty} \sum_{k \in Z} d_{jk} \psi_{jk}(t) \tag{1}$$

Here, Z represents the set of integers and j and k are the scaling and translation parameters respectively. $\{\varphi_{jk}(t) = 2^{j/2} \varphi(2^j t - k)\}_{k \in Z}$ is an orthonormal basis derived from the scaling function $\varphi(t)$ for the subspace $V_j \subset V_{j+1}$, and $\{\psi_{jk}(t) = 2^{j/2} \psi(2^j t - k)\}_{k \in Z}$ is wavelet functions constitute an orthonormal basis for the subspace $W_j = V_{j+1} - V_j$. These subspaces define a multiresolution analysis on $L^2(R)$ if the following additional properties are to be satisfied like, $\bigcap V_j = \{0\}$, $\bigcup V_j$ is dense in $L^2(R)$ and a function $s(t)$ is in V_j if and only if $s(2t)$ is in V_{j+1}. We can construct the scaling function coefficients (c_{jk}) and wavelet coefficients (d_{jk}) by using the relations which are expressed as follows:

$$c_{jk} = \int x(t) \varphi_{jk}(t) dt = \langle x(t), \varphi_{jk}(t) \rangle \tag{2}$$

$$d_{jk} = \int x(t) \psi_{jk}(t) dt = \langle x(t), \psi_{jk}(t) \rangle \tag{3}$$

The projection of the signal $x(t)$ onto the wavelet subspace W_j given by

$$x_j(t) = \sum_{k \in Z} d_{jk} \psi_{jk}(t) \tag{4}$$

The above equation can be represented in discrete time domain [9] as

$$x_j(n) = \sum_{k \in Z} d_{jk} \psi_{jk}(n) \quad j = 0,1,2........J \tag{5}$$

The approximation of signal $x_j(n)$, which is denoted as $V_j(n)$ can be represented as

$$V_j(n) = \sum_{k \in Z} a_{jk} \psi_{jk}(n) \tag{6}$$

Where,

$$a_{jk} = \sum_{n} x(n) \psi_{jk}(n) \tag{7}$$

Substituting the values of a_{jk} in $V_j(n)$ we get

$$V_j(n) = \sum_{m} x(m) \psi_{jk}(m) \psi_{jk}(n) \; = \sum_{m} x(m) r_j(m,n) \tag{8}$$

Where, $r_j(m,n) = \sum_{k \in Z} \psi_{jk}(m) \psi_{jk}(n)$. Equation (7) gives the discrete wavelet transform (DWT) and equation (8) gives a reconstruction formula based on the approximation and in terms of a generalized discrete convolution of the input signal $x(n)$ with the filter described by the sequence $r_j(m,n)$ which forms the projection of the signal at different scales. These filters are formed by using the convolution of Daubechies-2 wavelet on different projections. The wavelet we used in our WT-EDNSS adaptive filtering technique is Daubechies-2 wavelet (Fig.2).

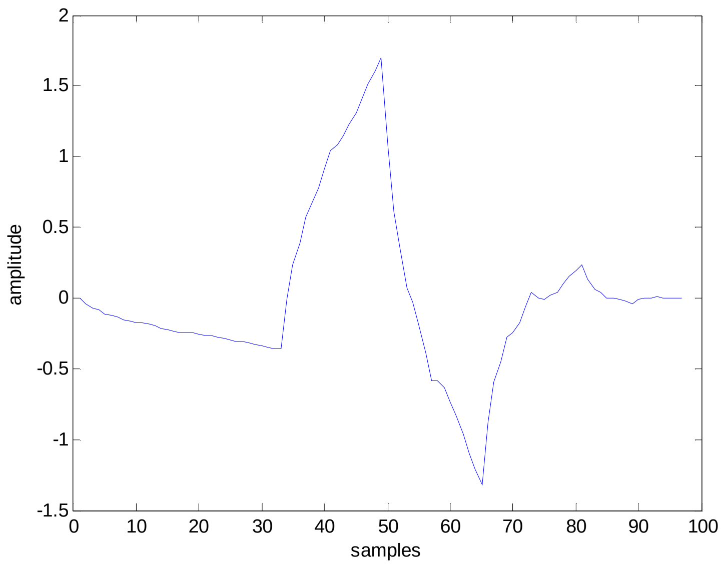

Figure 2: Daubechies 2 wavelet.

Proposed Implementation of Adaptive Filter for Echo & Noise Cancellation in Speech Signals

Equation (8) forms the essence of the transformed input to the adaptive filter. In general, the filters described above are time variant and the discrete-time approximation to projections of the signal $x(n)$ onto different scale levels j are not orthogonal. However, it can be shown that both time invariance and orthogonality can be satisfactorily approximated with sufficiently high rates of sampling, which may result in oversampling of the signal x (t)[3]. With the assumptions of time invariance and orthogonality, we can write

$$\mathbf{V}(n) = \mathbf{RX}(n). \tag{9}$$

Where,

$$\mathbf{V}(n) = [v_0(n), v_1(n), v_2(n)....v_J(n)]^T,$$

$$\mathbf{X}(n) = [x(n), x(n-1),....x(n-N+1)]^T \text{ and } \mathbf{R} = \boldsymbol{\psi}\boldsymbol{\psi}^T$$

Matrix R is plotted in the Fig3. Wavelet function $\boldsymbol{\psi}$ is formed by scaling and sampling the Daubcheis-2 Mother wavelet and 'N' is the number of scales to be analyzed.

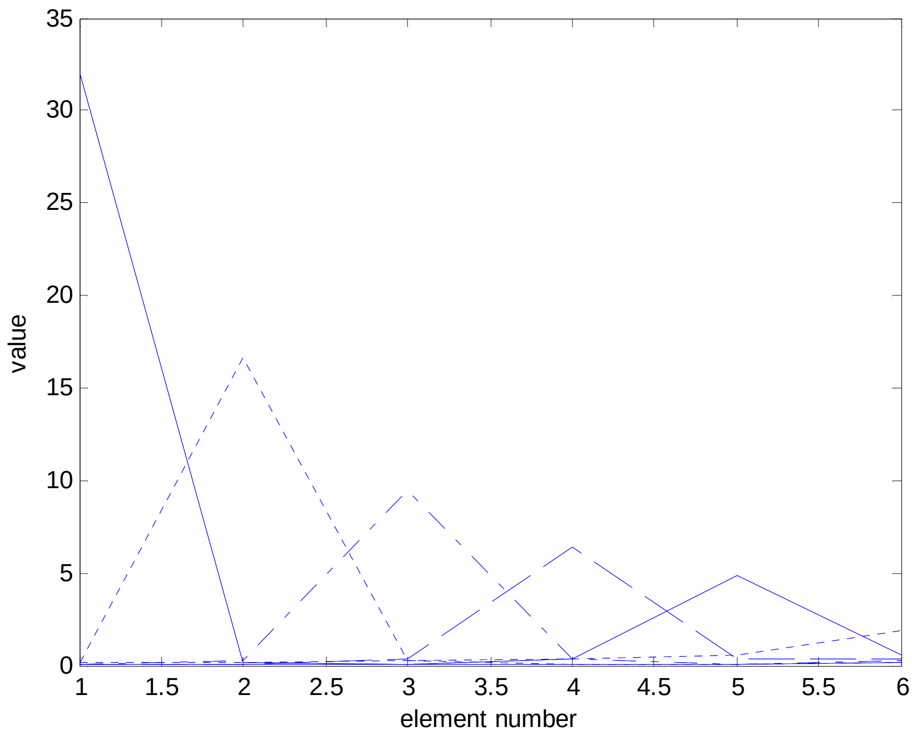

Figure 3: Row of Convolution matrix 'R'

The LMS based adaptive filter is shown in Fig.1. In this figure we decomposed reference noise v_2 using the equation (9). The output of the network model is given by

$$y(n) = \sum_{i=0}^{J} V_i(n) W_i(n)$$

Where

$$J = 0,1,2....5 \tag{10}$$

The error signal generated at the output level is expressed as: $e(n) = d(n) - y(n)$. We note that autocorrelation of the new input $R_v = E[V(n)V^T(n)]$. The weight updatation equation for conventional EDNSS LMS algorithm is defined as [10]

$$w(n+1) = w(n) + \mu \frac{e(n)V_j(n)}{\alpha \left\| e_L(n) \right\|^2 + (1-\alpha)\left\| V_j(n) \right\|^2} \tag{11}$$

Where, $\left\| e_L(n) \right\|^2 = \sum_{i=0}^{L-1} \left| e(n-i) \right|^2$, Length of the error vector $L = 20N$, N is the length of the filter and μ is the learning rate parameter which is considered as constant and it remains within the values '0' to '1' which can be given by the following expressions.

$$0 \le \mu \le \frac{2}{\lambda_{\max}} \text{ or } \frac{2}{3} trace(R_v) \tag{12}$$

Where, $\lambda_{\max}$ is the largest Eigen value of R_v and α value is considered between 0 and 1.

Simulation Results for Echo & Noise Cancellation in Speech Signals

In this section we describe two experiments carried out to compare conventional EDNSS with the wavelet transform domain EDNSS algorithm for noise cancellation and echo plus noise cancellation by considering both white and colored Gaussian noise. The simulations are carried using MATLAB 7.0.1.

Example 1: Noise Cancellation (White & Colored)

The recorded sentence "A quick brown fox jumps over the lazy dog" is taken as original speech signal. This sentence contains almost all the alphabets of the English language and it also provides nonstationay signals of variety of characteristic of waveform. White and colored Gaussian noise with SNR 7.776dB was generated and added to the original speech signal. The speech signal exists for 3.1515 seconds duration in PCM format, 11.025 kHz sampling rate and is recorded in 16 bit mono samples. Simulations are carried out for white & colored noise separately. The original speech signal, noise, noisy speech signal, de-noised speech signal for both the cases of white and colored noise are shown in Fig 4 and Fig. 5 respectively .

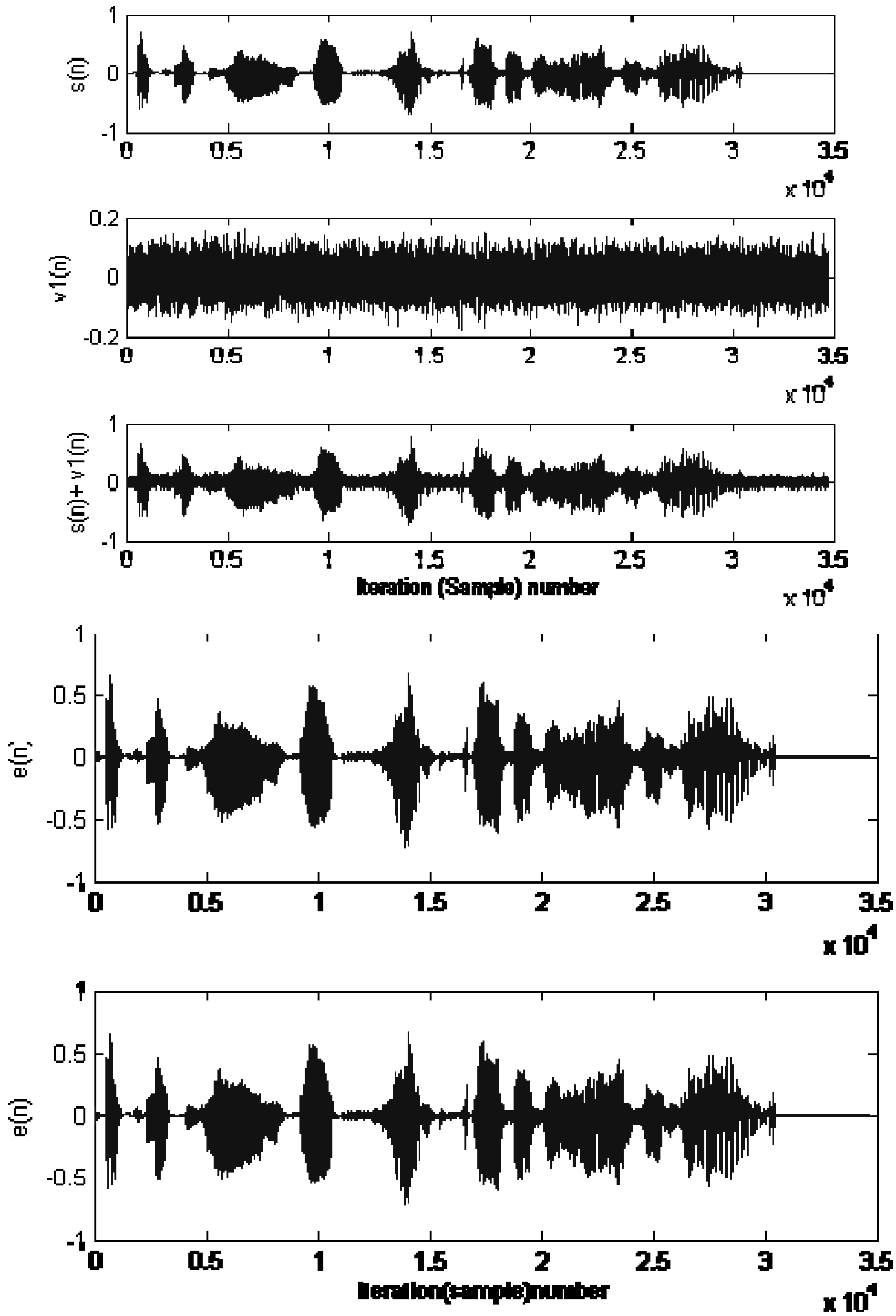

Figure 4: From top to bottom: Original Speech Signal s(n), noise that corrupts speech v(n), corrupted speech d(n), de-noised speech signal using Conventional EDNSS LMS algorithm e(n), de-noised speech signal using WT- EDNSS LMS algorithm e(n).

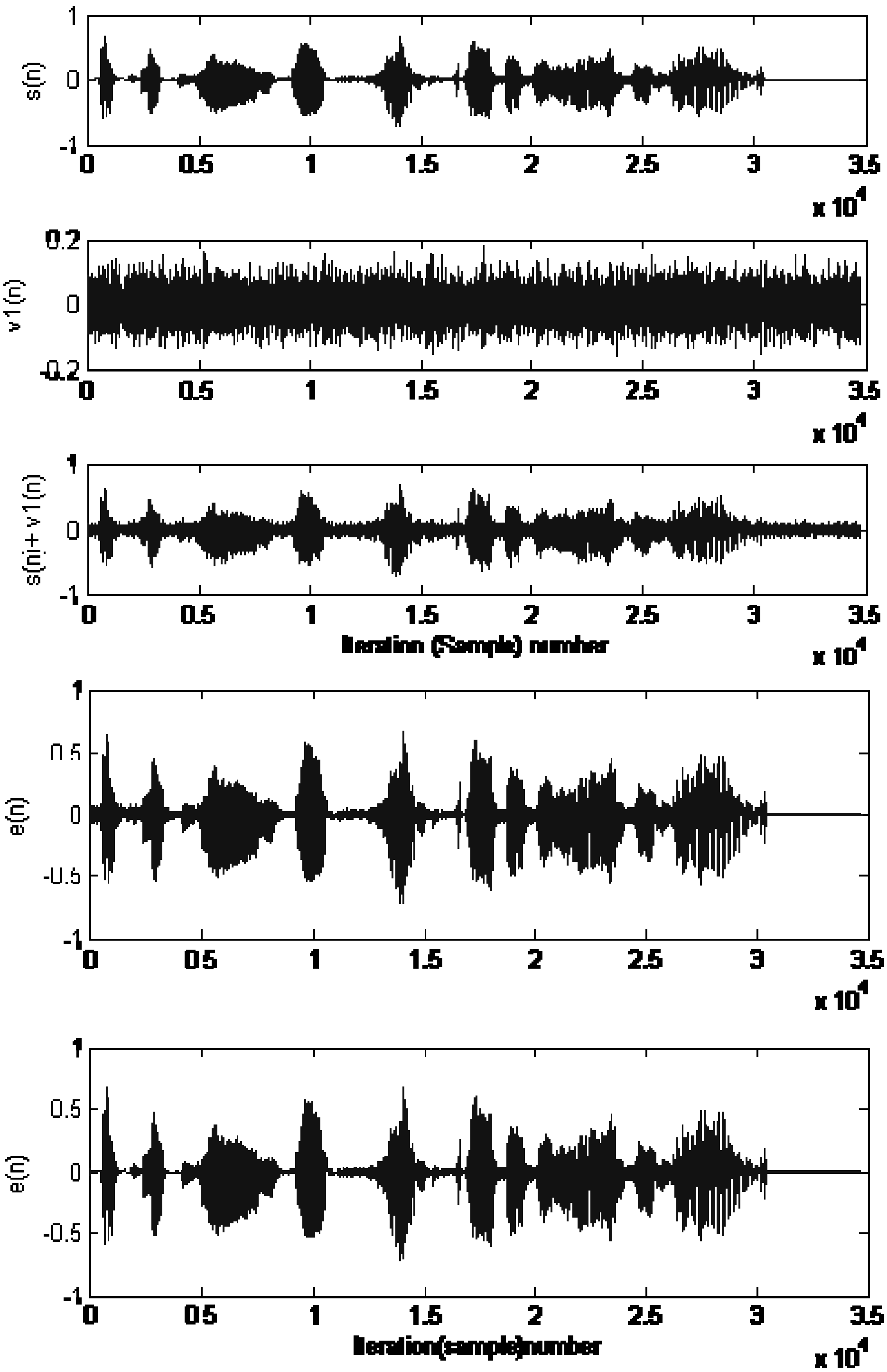

Figure 5: From top to bottom: Original Speech Signal s(n), colored noise that corrupts speech v(n), corrupted speech d(n), de-noised speech signal using Conventional EDNSS algorithm e(n), de-noised speech signal using WT-EDNSS LMS e(n) .

The convergence curve for excess mean squared error (EMSE) in dB versus iterations for white & colored noise are plotted in Fig.6 and Fig.7 respectively.

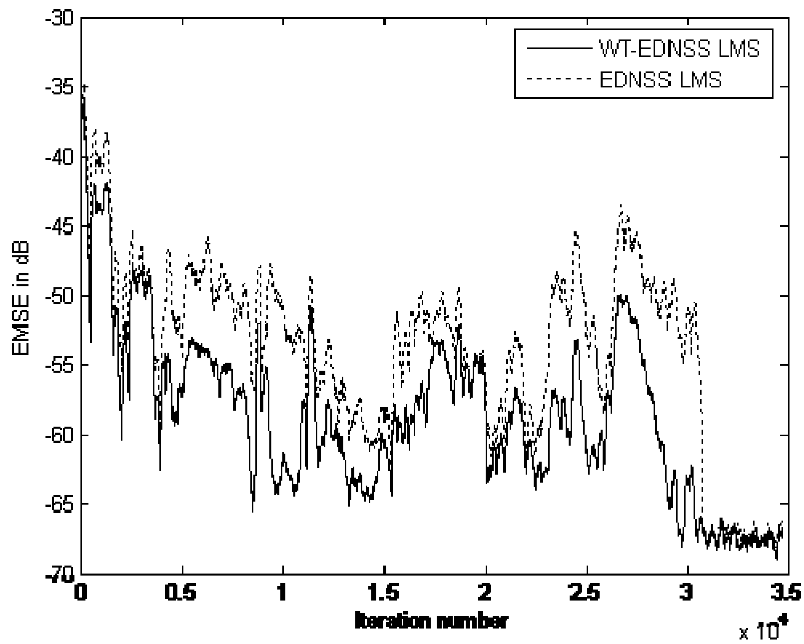

Figure 6: EMSE in dB of the WT-EDNSS LMS and Conventional EDNSS LMS for white noise

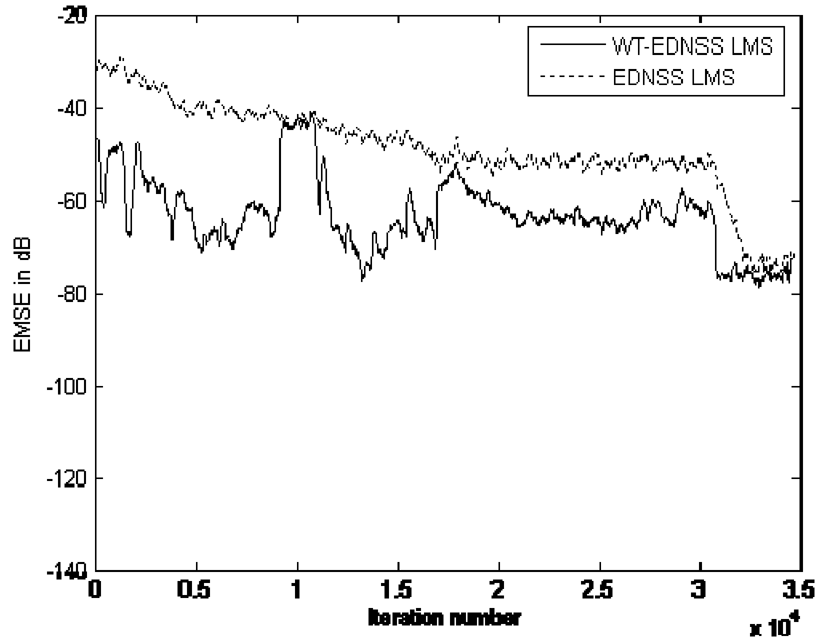

Figure 7: EMSE in dB of the WT-EDNSS LMS and Conventional EDNSS for colored noise.

The simulation results for average EMSE and SNR are presented in Table.1 and Table.2 for white and colored noise respectively.

Table 1: Comparison of the average EMSE and Output SNR in dB of the WT-EDNSS LMS and Conventional EDNSS LMS for white noise.

Algorithm	average EMSE	Output SNR in dB
EDNSS LMS	-49.292	29.759
WAVELET EDNSS LMS	-53.04	33.5164

Table 2: Comparison of the EMSE and Output SNR in dB of the WT-EDNSS LMS and Conventional EDNSS LMS for colored noise.

Algorithm	Average EMSE	Output SNR in dB
EDNSS LMS	-40.8670	21.3486
WAVELET EDNSS LMS	-54.7109	35.1702

Example 2: Echo & Noise Cancellation (white & colored)

The original speech signal ”near speech” and echo signal ”far speech” signals having duration 33.5 seconds and 8 kHz sampling rate were taken from MATLAB 7.0.1. White Gaussian and colored noise were generated and added to the original speech signal. The SNR for both the cases is 7.776dB. The original speech signal corrupted by noise as well as echo signal is taken as the input signal to the summer circuit which is sketched in Fig.1. The noise and echo signal which is uncorrelated with the original speech signal is fed to the filters h1 and h2 which have some fixed filter length. The output of the filter h2 is input to the wavelet transform domain LMS filter, where the projections of the signals for signal input levels are calculated and wavelet transform domain adaptive algorithm technique is adopted to cancel the unwanted signals from the mixed signal. The original speech signal, noise plus echo, noisy speech signal, de-noised speech signal for both cases of white & colored noise experiments are shown in Fig 8 and Fig. 9 respectively.

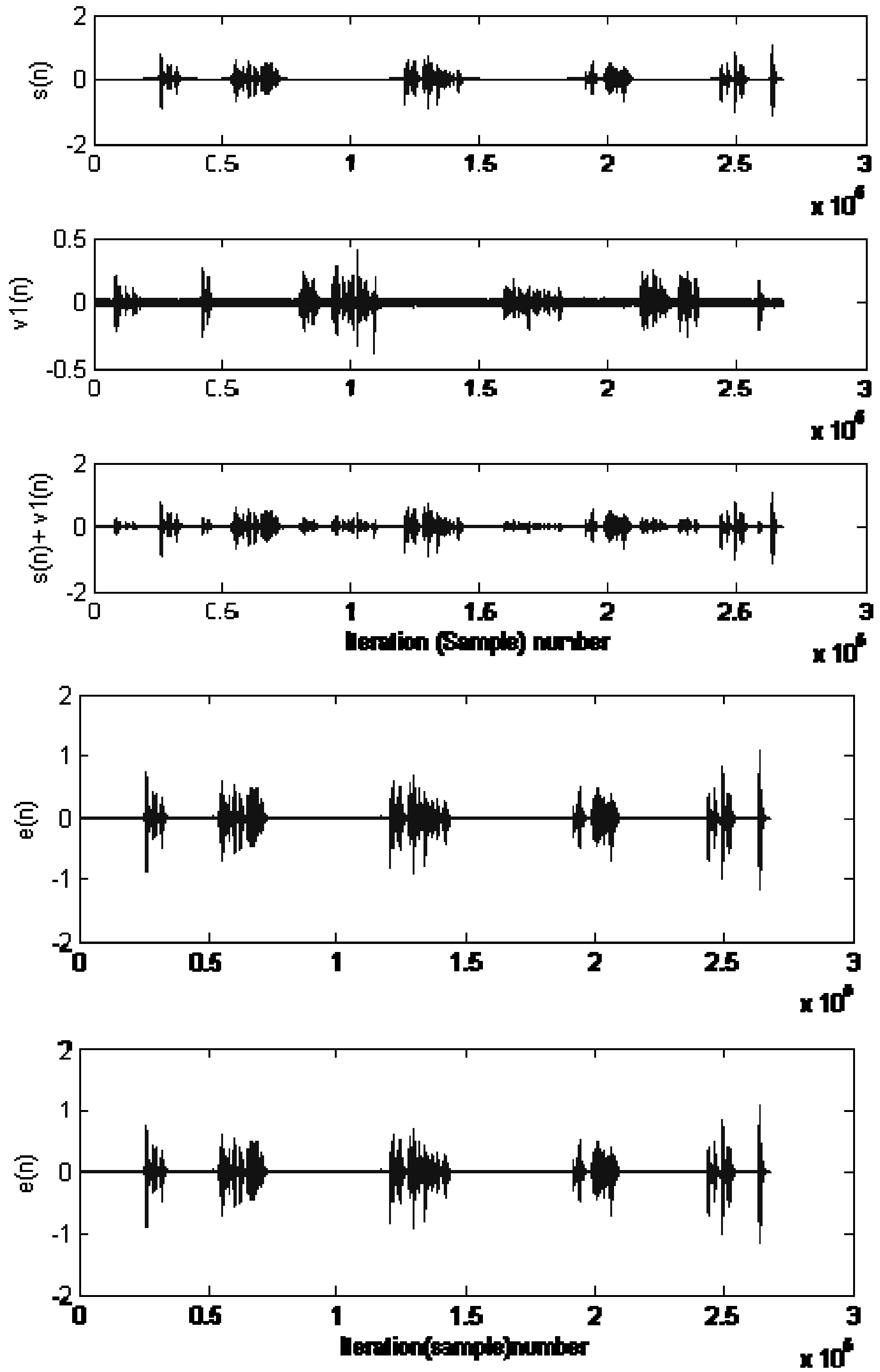

Figure 8: From top to bottom: Original Speech Signal s(n), echo & white noise that corrupts speech v(n), corrupted speech d(n), de-noised speech signal using Conventional EDNSS LMS algorithm e(n), de-noised speech signal using WT-EDNSS LMS algorithm e(n) .

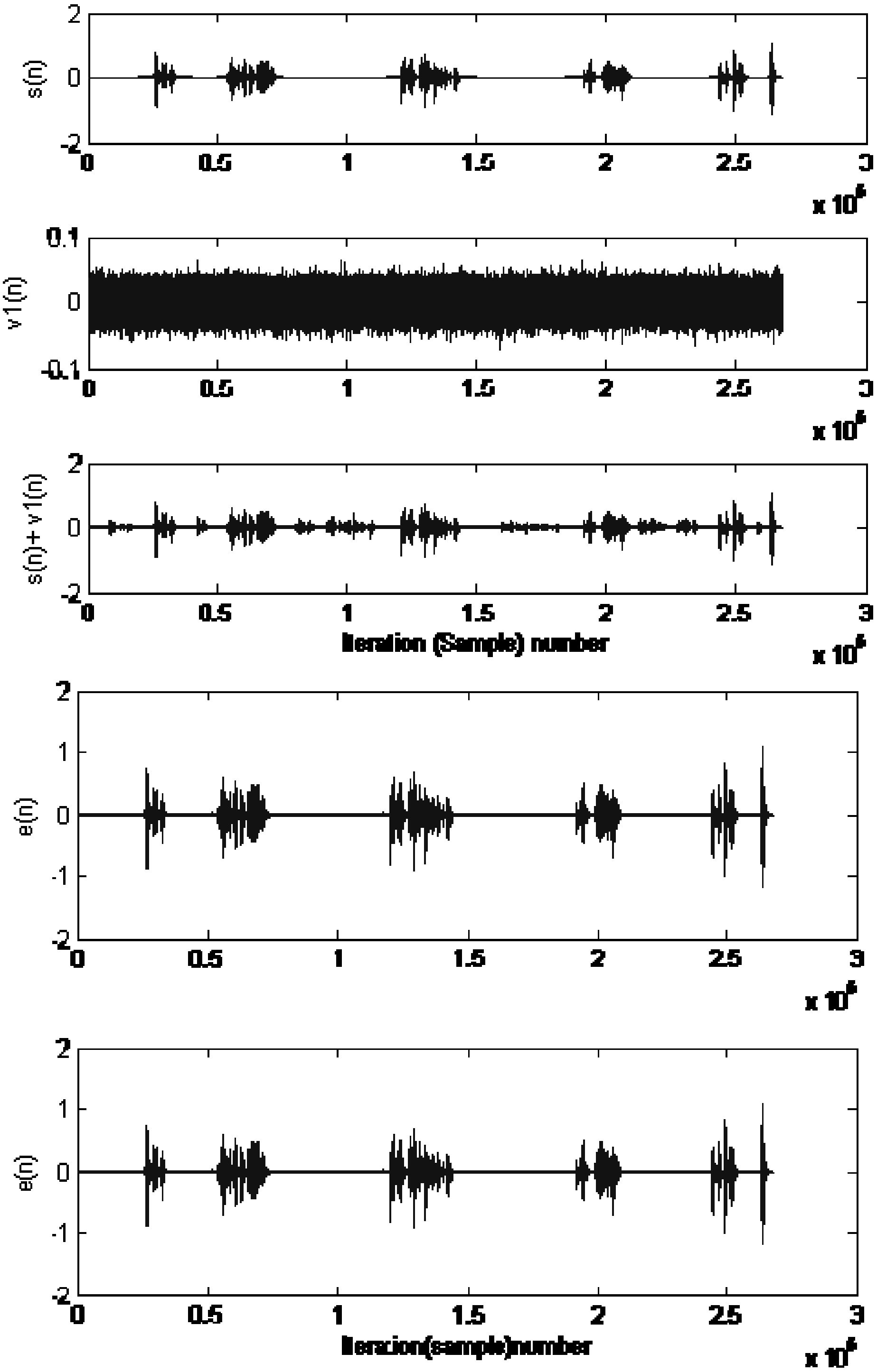

Figure 9: From top to bottom: Original Speech Signal s(n), echo & colored noise that corrupts speech v(n), corrupted speech d(n), de-noised speech signal using Conventional EDNSS LMS algorithm e(n), de-noised speech signal using WT-EDNSS LMS algorithm e(n) .

The EMSE in dB convergence curve are also shown in Fig.10 and Fig.11 for white and colored noise experiments respectively.

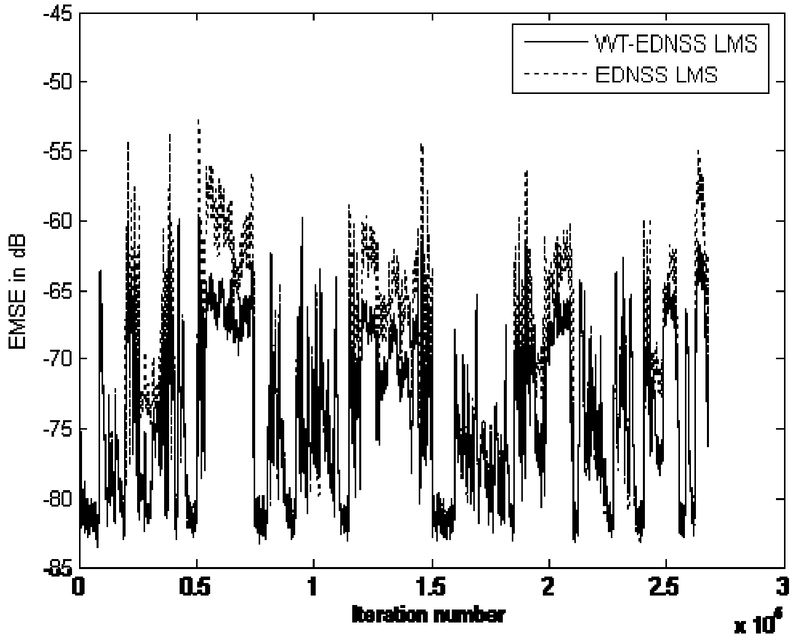

Figure 10: EMSE in dB of the WT-EDNSS and Conventional EDNSS LMS for echo and white noise

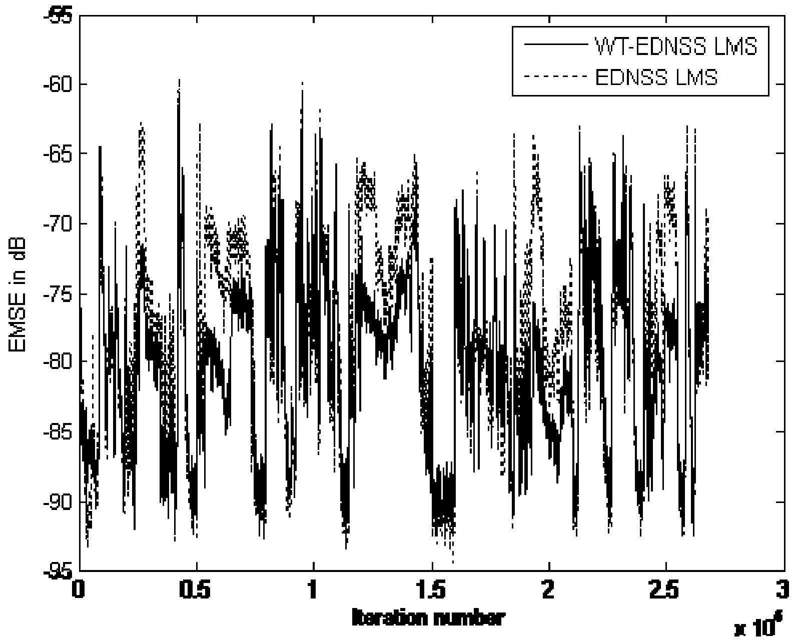

Figure 11: EMSE in dB of the WT-EDNSS and Conventional EDNSS LMS for echo and colored noise.

The average EMSE and output SNR simulation results are given in Table.3 and Table.4 for echo with white and colored noise experiments respectively.

Table 3: Comparison of the average EMSE and Output SNR in dB of the WT-EDNSS LMS and Conventional EDNSS LMS for echo and white noise.

Algorithm	Average EMSE	Output SNR in dB
EDNSS LMS	-65.6426	41.8672
WT-EDNSS-LMS	-69.7279	45.9523

Table 4: Comparison of the EMSE and Output SNR in dB of the WT-EDNSS LMS and Conventional EDNSS LMS for echo and colored noise.

Algorithm	Average EMSE	Output SNR in dB
EDNSS LMS	-72.7114	48.933
WAVELET EDNSS LMS	-75.5273	51.75

Conclusion

In our present paper, the wavelet domain EDNSS algorithm has shown an improved average EMSE and SNR performance compared to the conventional EDNSS algorithm in denoising the speech signals. Listening tests show that the recovered speech is of high quality and is very close to the original speech for WT-EDNSS LMS algorithm. The performance of the wavelet transform domain adaptive filtering is better than conventional EDNSS LMS which can be seen from the tables given in this paper. This improvement of the result is due to time-frequency pursuits of the wavelets. Since speech signals are non stationary signals, it can be easily denoised with the help of wavelet transforms because of time frequency characteristics.

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