Investigation of Denoising of Speech Signal using WaveShrink Method in Deaf Persons

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Abstract

Speech is vital parameter in human cognitive and socio-emotional development. Deaf speech is even more complex to understand unless the noise is removed and improved its fidelity. Denoising of speech signal is an important pre-processing stage in speech signal processing. Denoising of speech signal not only removes the redundant coefficients (leads to data compression) but also improve the quality of speech signal. Waveshrink is a technique used to in this paper to suppress the redundant wavelet coefficient through threshold concept. Denoising concept find application in both signal and image processing. Denoising of the signal will improve in processing the deaf signal speech with any assistive technologies. Digital devices can use this denoised speech to compare and reproduce the deaf speech signal for emotional analysis and comparison of various speech parameters in real time environment.

Keywords- Deaf speech, Denoising, Shrinkage, Wavelet transform, Speech Signal

1. Introduction

Speech and language are vital skillset of human cognitive and socio emotional development. The human voice is generated in the vocal folds makes the human to produce their speech in different voice frequency as voiced and the unvoiced sounds. The laryngeal airflow through the larynx emanates strong or weaken sound. The variation in the larynx muscles based on the length of the vocal fold fine tunes as pitch and tone of the speech [1]. The normal communication is a great challenge for the Deaf person to express their thoughts. The National Deaf Children's Society has classified the deafness from mild to intense deafness in the range from (21- 40) dB for mild and intense deafness above 95 dB [2].

The rehabilitation techniques and hearing aids support the deaf person as an assistive method. Generally, the children with speech disorders have poor articulations, misplacement of articulators and excessive nasality [3]. The deaf speech characteristics has been stated by Hudgins' in his study as extremely slow and breathy speech with excess strain in the vocal folds, long duration during the vowel production leading to replaced syllable in the speech, a bent when the devoice stops in landing its positions during speech production, the excessive use of the nasal breathe during the vowels and consonants production and also abnormal rhythm sequence during the word utterance [4]. Further in their study about the deaf speech they found two major errors which involves consonants, vowels and errors of rhythm [5].

Speech signal is a one-dimensional function of time and this signal is processed in a digital representation to study about the signal [6]. The comparison of the normal and deaf speech deviated in pitch, formants and energy levels which is a challenge for the assistive technologies. In order to produce the enhanced speech signal by eliminating the errors from the assistive devices various clustering algorithms has been proposed by Nirmaladevi which enhanced the speech signal using the energy entropy. [7,8,9,10].

The statistical estimation method stated (Srinath, Rajasekaran and Viswanathan 2003) is used is to findthe useful information about a signal from an observed random process.This information could reconstruct the speech signal completely or else it consists the maximum speech signal parameters and is generally used to obtain the necessary information during the process. Noise reduction is the process to eliminate the undesired frequency added in addition with the original deaf speech signal. Biggest challenge is to extract the attributes of the speech signal from the noise. Noise reduction may greatly alter the properties of the any kind of speech signals. Many researchers have recommended even for various types of algorithms for extracting the speech signals from the buried noise. Digital device might generate random or white noise along with the speech signals with an event of frequency distribution, or frequency dependent noise based on the device's signal processing algorithms or mechanisms. There are three different sources of noise in speech signals viz., physiological variability, environmental noise or interference and noise due to instrumentation.

With the prior qualitative or quantitative knowledge about an undesired noise affecting the signal should be estimated to improve the speech signal quality without noise. Also, an estimator on the directionof orthogonal basis can be implemented will be basically useful when thereis a distribution of added noise energy in the signal. This which in turn provides the vital information to discriminate the signal generated with the noise to a great extent and supports the estimator could obtain a good approximation of the signal. [11,12,13,14,15].

2. WaveShrink

2.1 Objective

The waveshrink model is used in this research paper to reduce the error difference between the original deaf speech signal f and denoised deaf speech signal $\hat{f}$.

The deaf speech signal input vector is given by

$$f(y_i) = [y_1, y_2, \ldots, y_N] \in \mathfrak{R}^N$$

The noisy deaf speech signal vector is given by

$$f(y, \eta) = f(y_i) + \eta_i, \quad i = 1, 2, \ldots, N$$

Where η is the White Gaussian Noise (WGN) with independent and identically distributed random variables $N(0, \sigma)$.

The minimum mean square error (MME) for the given noisy speech signal function is

$$R(\hat{f}, f) = \frac{1}{N} \left\| \hat{f} - f \right\|^2$$

Where, $\hat{f}$ is the estimated speech signal.

2.2 Wavelet Transform

Wavelet transform has exhibited unique attributes viz., asymptotic, optimal bases, adaptability and reduced computational complexity. The wavelet decomposition using the filter banks concept provides reduced computation. The speech signal is decomposed into detail and approximation coefficients, which provides the exact representation of the speech signal and no information is lost during downsampling. Each wavelet subband level is calculated by passing only the previous wavelet approximation coefficients through discrete-time low and high pass quadrature mirror filters. However, due to the downsampling process the overall number of coefficients is still the same in each subband level and there is no redundancy [16]. The reconstruction of speech signal is performed with reversing the process; up-sampling the approximation coefficients and filtering the un-sampled coefficients.

2.3 WaveShrink

Waveshrink method compares wavelet coefficient with a threshold and is reduces to zero if its magnitude is less than threshold value. The threshold value is point which distinguishes between the significant and redundant wavelet coefficients [17]. In Wavshrink method, energy of the function is concentrated only in few coefficients [18].

Donoho et.al., have proposed several thresholds viz., Universal threshold, SureShrink and Minimax, and developed waveshrink methods for signal denoising [17][19].

Donoho and Johnstone studied *hard* shrinkage $\delta_\lambda^H(x)$ and *soft* shrinkage $\delta_\lambda^S(x)$ functions [22]:

$$\delta_\lambda^S(x) = \mathrm{sgn}(x)(|x| - \lambda)_+$$

$$\delta_\lambda^H(x) = x I_{[|x| > \lambda]}$$

The wavelet coefficients at the coarsest scale were left intact, while the coefficients at all other scales were thresholded *viasoft* shrinkage with the universal threshold,

$$\lambda = \hat{\sigma}\sqrt{2logN}$$

where $\hat{\sigma}^2$ is estimate of noise variance and N is length of the signal.

$$\hat{\sigma} = \frac{\text{median}\left(\left|c_{ij}\right|\right)}{0.6745}$$

where c_{ij} was the empirical wavelet coefficients.

The threshold λ determines the redundant wavelet coefficients. The threshold value is to be set optimally neither too big (leakage of outliers into the signal) nor too small (distortion of the signal). Gnanadurai and Sadasivam (2005) proposed estimation theory wherein random noise is suppressed while preserving the original image details. The choice of the threshold estimation analyzed through the statistical metrics like arithmetic mean, geometrical mean and standard deviation of the wavelet subband coefficients.

Bruce and Gao illustrated that the signal had a large variance value due to the lack of continuity when hard shrinkage function is applied and had major bias when the *soft* shrinkage has applied. The signal shrinkage profile distribution is depicted in figure (1).
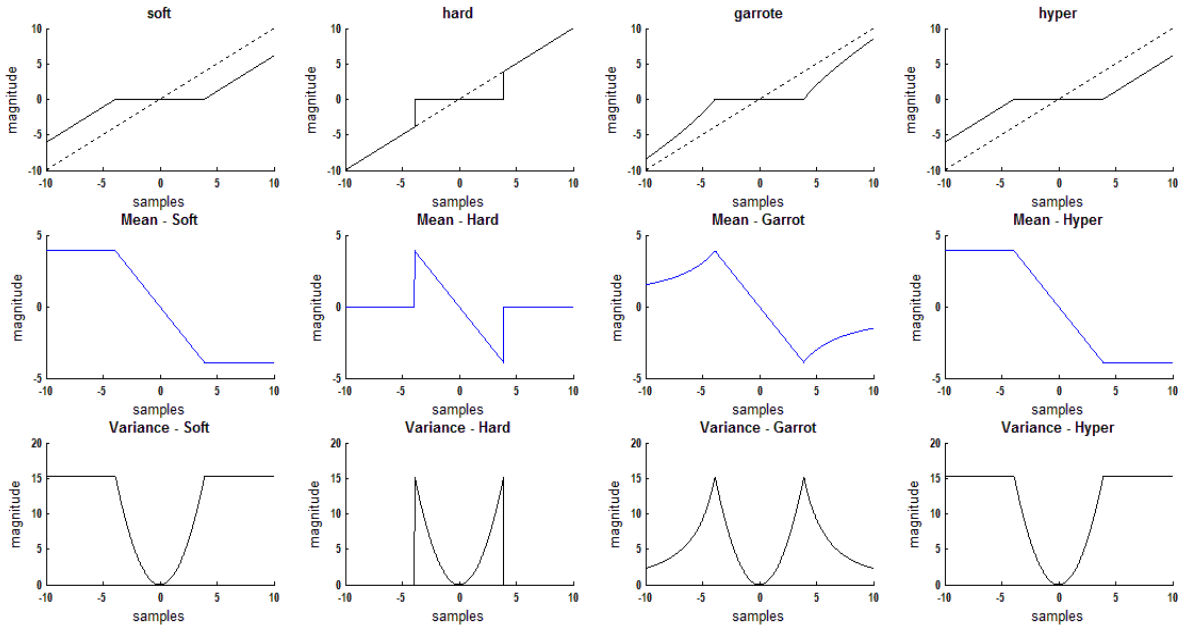

Figure1. a) Shrikage function distribution b) Mean Distribution c) Variance Distribution

Breiman introduced a *non-negative garrote* shrinkage function which overcomes the disadvantages of *hard* and *soft* shrinkage, that is, less sensitive than *hard* shrinkage to small fluctuations and less biased than *soft* shrinkage [18]. The *non-negative garrote* shrinkage function is continuous and approaches the unity for the larger signals [20][23].

The major limitation of linear shrinkage is outperformed by introducing non-linear shrinkage for the signal contains signal attributes preserved in the detail wavelet coefficients. Hyperbolic

function is a nonlinear waveshink model proposed by Poornachandra, unlike hard shrinkage, is a continuously differentiable. The hyper shrinkage model is expressed as,

$$\delta_\lambda^{hyp}(x) = tanh(\rho \times x)(|x| - \lambda)_+$$

Where $\rho = \frac{\lambda}{max|x|}$

ρ is the boundary tuning function to retain the exponential behaviour of the hyperbolic function outside the redundant area as shown in figure (1).

The WaveShrink algorithm is

1. Discrete Wavelet Transform (DWT) is applied to the input speech signal vector *y* and the experimental Wavelet coefficients $C_{j,k}$ is obtained at scale *j*, where *j= 1,2,...,J.*
2. WaveShrink function is applied to coefficients $C_{j,k}$ at each scale *j.*
3. The Estimated coefficients $\hat{C}_{j,k}$ are obtained based on the threshold λ
4. Different threshold values are obtained based on the scales
5. Estimation function $\hat{f}$ obtained by taking inverse DWT.

3. Results &Discussion

The practical deaf speech signals specification taken in this research paper for the evaluation of proposed WaveShrink is as follows;

1. Number of channels: 1 (mono)
2. Time: (0-13.477) seconds of 646,896 sample length
3. Sampling frequency 48KHz,
4. The first sample centred at 1.042e-005 seconds
5. Minimum amplitude -0.951 Pascal, maximum amplitude is 0.915 Pascal, Mean value is -1.577e-005 Pascal & RMS is 0.0861 Pascal.
6. Total energy is 0.0999 Pascal^2 sec (energy in air is 0.000245 Joules/ m^2)
7. Mean power in air is 1.853e-005 Watt/m^2 = 72.68 dB
8. Standard deviation (Channel1) is 0.0861 Pascal.

The simulation was done on 50 different deaf signals from 10 deaf persons. The test was conducted for the chosen deaf persons on normal and uncertain condition for knowing denoising condition of Waveshrink function.

During the simulation for testing the efficiency of denoising in the Waveshrink models, Gaussian noise has been added to the original deaf speech signals. Figure 2 illustrates the denoised Deaf signals from Soft, Hard, Negative Garrot and Hyper Shrinkage functions. It is clear from the figure 2 that hard shrinkage function has an ability to retain the profile of original Deaf signal compare to other shrinkage functions. In this paper, Alpha-trim threshold function has been used in the shrinkage function to identify the redundancy in the coefficiencies.
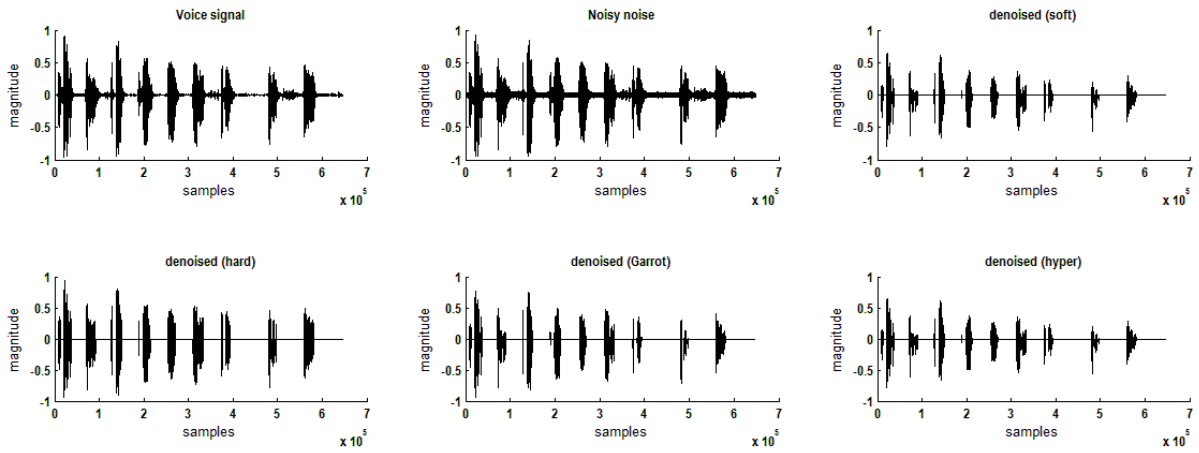
Figure 2. a) Original Deaf signal b) Noisy Deaf Signal c) Denoised Deaf signal using soft shrinkage function d) Denoised Deaf signal using hard shrinkage function e) Denoised Deaf signal using Negative Garrot shrinkage function f) Denoised Deaf signal using Hyper shrinkage function

Figure 3 illustrates the Wavelet subband of Original Deaf signal, Noisy Deaf signal and recovered Deaf signal using Hard shrinkage function. It is quite evident that the Deaf signal is distributed in the all the frequency range as depicted in Approximate range (-1,+1), Detail-3 (D3) in the range (-1,+1), Detail-2 (D2)in the range (-0.05, +0.05) and Detial-1 (D1) in the range (-0.05, +0.05). When the WGN is introduced in the Deaf speech signal, noises are distributed uniformly across the entire wavelet subband. It is quite interesting to see that when the hard shrinkage is introduced for denoising, the redundant coefficients (observed in D1 and D2) were swept away. The speech signal contribution of D1 and D2 would be redundant compared to the D3 and Approx coefficients. The spurious noise distribution in D3 and Approximate level also been filtered as illustrated in figure 3 (3rd column).
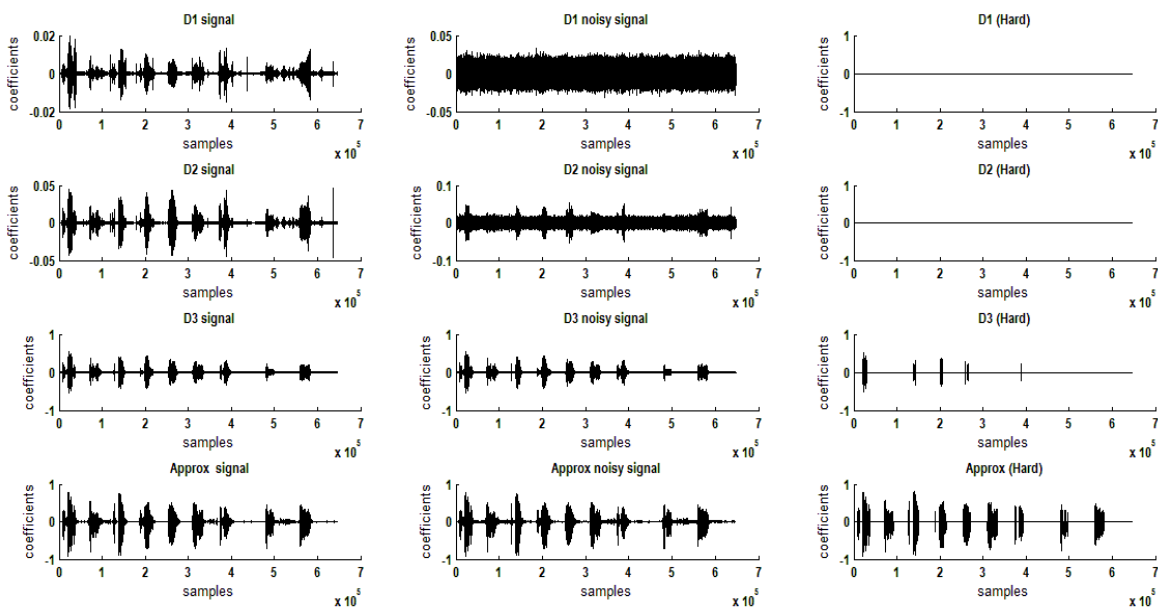

Figure 3. Subband of Deaf Signals a) Original Deaf Signal b) Noisy Deaf Signal c) Recovered Deaf Signal using Hard Shrinkage function
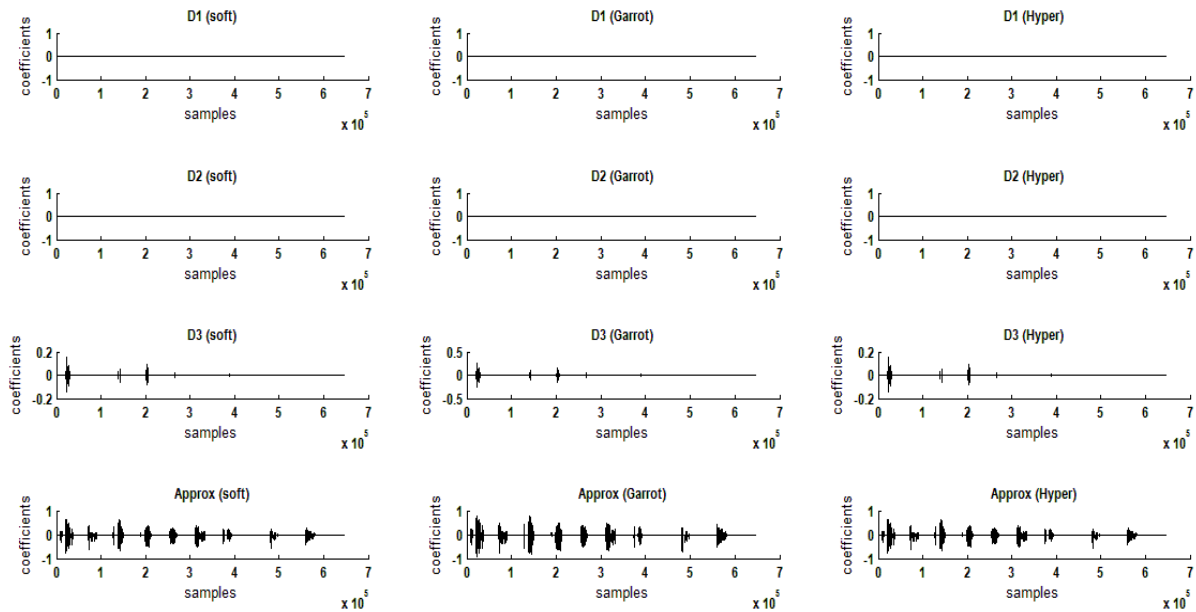
Figure 4. Subband of Deaf Signals a) Recovered Deaf Signal using Soft Shrinkage function b) Recovered Deaf Signal using Negative Garrot Shrinkage function c) Recovered Deaf Signal using Hyper Shrinkage function

Figure 4 depict the subbanding of recovered Noisy Deaf signal using Soft Shrinkage, Negative Garrot Shrinkage and Hyper Shrinkage functions. Though the original Deaf speech signal has been recovered from these shrinkage functions, the loss of signal in the recovered signal is high compared to hard shrinkage function.

Tables 1 to 4 illustrate the statistical analysis *viz.,*of deaf speech signal for various wavelet transforms *viz.,* db9, db10, bior3.7 and bior6.8. Higher value of SNR is observed using hard shrinkage function compared to other shrinkage functions due to its linear functionality.

The compression values after applied the shrinkage model on the deaf speech has been compared for improved performance using Percent RMS difference (PRD) and given in the tables. Hard shrinkage has exhibited lower values of PRD and RMS for all the signals.

Table1. Statistical Analysis of Deaf Speech signal using db9 Wavelet Transform

Wavelet	Subband	WaveShrink	Noise level	SNR	SNR improvement	PRD	RMS
db9	3	Soft	0.001	1.6435	31.6274	82.7611	0.0712
			0.003	1.406	22.3456	85.0546	0.0732
			0.005	1.2222	18.0788	86.8737	0.0748
			0.007	1.0509	15.3261	88.604	0.0763

				0.009	0.9102	13.3021	90.0513	0.0775
				0.01	0.837	12.4501	90.8138	0.0782
				0.03	0.2579	3.4811	97.0742	0.0836
				0.05	0.0975	-0.7847	98.8837	0.0851
				0.07	0.0438	-3.6577	99.4973	0.0857
				0.09	0.0197	-5.8217	99.7734	0.0859
			Hard	0.001	3.7327	29.5382	65.0677	0.056
				0.003	3.3317	20.4199	68.1422	0.0587
				0.005	2.9905	16.3105	70.8722	0.061
				0.007	2.6583	13.7187	73.6347	0.0634
				0.009	2.3508	11.8615	76.2891	0.0657
				0.01	2.2125	11.0746	77.5135	0.0667
				0.03	0.8556	2.8834	90.6192	0.078
				0.05	0.3992	-1.0863	95.5084	0.0822
				0.07	0.2	-3.8139	97.7235	0.0841
				0.09	0.1113	-5.9133	98.7272	0.085
			Hyper	0.001	1.6435	31.6274	82.7611	0.0712
				0.003	1.406	22.3456	85.0546	0.0732
				0.005	1.2222	18.0788	86.8737	0.0748
				0.007	1.0509	15.3261	88.604	0.0763
				0.009	0.9102	13.3021	90.0513	0.0775
				0.01	0.837	12.4501	90.8138	0.0782
				0.03	0.2579	3.4811	97.0742	0.0836
				0.05	0.0975	-0.7847	98.8837	0.0851

			Noise level	SNR	SNR improvement	PRD	RMS
			0.07	0.0438	-3.6577	99.4973	0.0857
			0.09	0.0197	-5.8217	99.7734	0.0859

Table2. Statistical Analysis of Deaf Speech signal using db10 Wavelet Transform

Wavelet	Subband	WaveShrink	Noise level	SNR	SNR improvement	PRD	RMS
db10	3	Soft	0.001	1.533	31.7446	83.8209	0.0722
			0.003	1.3332	22.4093	85.7708	0.0738
			0.005	1.1557	18.1617	87.542	0.0754
			0.007	0.9985	15.3935	89.1408	0.0767
			0.009	0.8719	13.3334	90.4488	0.0779
			0.01	0.8065	12.4619	91.1326	0.0785
			0.03	0.2506	3.4996	97.1555	0.0836
			0.05	0.0883	-0.7681	98.9882	0.0852
			0.07	0.0402	-3.6616	99.5379	0.0857
			0.09	0.0191	-5.8161	99.7807	0.0859
		Hard	0.001	3.308	29.9695	68.328	0.0588
			0.003	2.9847	20.7578	70.9192	0.0611
			0.005	2.6769	16.6405	73.4775	0.0633
			0.007	2.3706	14.0213	76.1151	0.0655
			0.009	2.1307	12.0746	78.2462	0.0674
			0.01	2.0118	11.2566	79.3247	0.0683
			0.03	0.8211	2.9291	90.9801	0.0783
			0.05	0.3572	-1.037	95.9712	0.0826
			0.07	0.1705	-3.7918	98.0567	0.0844

			0.09	0.0907	-5.8877	98.9611	0.0852
			0.001	1.533	31.7446	83.8209	0.0722
			0.003	1.3332	22.4093	85.7708	0.0738
			0.005	1.1557	18.1617	87.542	0.0754
			0.007	0.9985	15.3935	89.1408	0.0767
			0.009	0.8719	13.3334	90.4488	0.0779
		Hyper	0.01	0.8065	12.4619	91.1326	0.0785
			0.03	0.2506	3.4996	97.1555	0.0836
			0.05	0.0883	-0.7681	98.9882	0.0852
			0.07	0.0402	-3.6616	99.5379	0.0857
			0.09	0.0191	-5.8161	99.7807	0.0859

Table3. Statistical Analysis of Deaf Speech signal using bior3.7 Wavelet Transform

Wavelet	Subband	WaveShrink	Noise level	SNR	SNR improvement	PRD	RMS
bior3.7	3	Soft	0.001	1.4468	31.8288	84.6568	0.0729
			0.003	1.336	22.4029	85.7435	0.0738
			0.005	1.1957	18.1102	87.1395	0.075
			0.007	1.0623	15.3222	88.4881	0.0762
			0.009	0.9442	13.2555	89.6995	0.0772
			0.01	0.8902	12.3893	90.259	0.0777
			0.03	0.3761	3.3807	95.7625	0.0824
			0.05	0.1969	-0.8894	97.7588	0.0842
			0.07	0.1232	-3.7419	98.5912	0.0849
			0.09	0.087	-5.8806	99.0036	0.0852

Wavelet	Subband	WaveShrink	Noise level	SNR	SNR improvement	PRD	RMS
		Hard	0.001	1.7627	31.5128	81.6325	0.0703
			0.003	1.7535	21.9854	81.7193	0.0704
			0.005	1.6382	17.6677	82.8114	0.0713
			0.007	1.5077	14.8768	84.0651	0.0724
			0.009	1.3542	12.8455	85.5635	0.0737
			0.01	1.2891	11.9904	86.2072	0.0742
			0.03	0.5829	3.1739	93.5096	0.0805
			0.05	0.2761	-0.9686	96.8717	0.0834
			0.07	0.1291	-3.7477	98.5248	0.0848
			0.09	0.0609	-5.8545	99.3015	0.0855
		Hyper	0.001	1.4468	31.8288	84.6568	0.0729
			0.003	1.336	22.4029	85.7435	0.0738
			0.005	1.1957	18.1102	87.1395	0.075
			0.007	1.0623	15.3222	88.4881	0.0762
			0.009	0.9442	13.2555	89.6995	0.0772
			0.01	0.8902	12.3893	90.259	0.0777
			0.03	0.3761	3.3807	95.7625	0.0824
			0.05	0.1969	-0.8894	97.7588	0.0842
			0.07	0.1232	-3.7419	98.5912	0.0849
			0.09	0.087	-5.8806	99.0036	0.0852

Table 4. Statistical Analysis of Deaf Speech signal using bior6.8 Wavelet Transform

Wavelet	Subband	WaveShrink	Noise level	SNR	SNR improvement	PRD	RMS
bior6.8	3	Soft	0.001	1.7185	31.5666	82.049	0.0706

				0.003	1.4756	22.2687	84.3766	0.0726
				0.005	1.2795	18.0239	86.3027	0.0743
				0.007	1.119	15.2607	87.9119	0.0757
				0.009	0.9691	13.244	89.4424	0.077
				0.01	0.9086	12.352	90.0677	0.0775
				0.03	0.315	3.4224	96.4386	0.083
				0.05	0.1333	-0.8422	98.4768	0.0848
				0.07	0.0621	-3.6852	99.288	0.0855
				0.09	0.0319	-5.8362	99.6335	0.0858
				0.001	3.8877	29.3974	63.9166	0.055
				0.003	3.4398	20.3045	67.2996	0.0579
				0.005	3.0555	16.2479	70.3437	0.0606
				0.007	2.7062	13.6736	73.2299	0.063
				0.009	2.3819	11.8312	76.0156	0.0654
			Hard	0.01	2.2609	10.9998	77.0827	0.0664
				0.03	0.9552	2.7822	89.5858	0.0771
				0.05	0.5157	-1.2245	94.2357	0.0811
				0.07	0.2887	-3.9119	96.7306	0.0833
				0.09	0.1611	-5.9654	98.1621	0.0845
				0.001	1.7185	31.5666	82.049	0.0706
				0.003	1.4756	22.2687	84.3766	0.0726
			Hyper	0.005	1.2795	18.0239	86.3027	0.0743
				0.007	1.119	15.2607	87.9119	0.0757
				0.009	0.9691	13.244	89.4424	0.077

			0.01	0.9086	12.352	90.0677	0.0775
			0.03	0.315	3.4224	96.4386	0.083
			0.05	0.1333	-0.8422	98.4768	0.0848
			0.07	0.0621	-3.6852	99.288	0.0855
			0.09	0.0319	-5.8362	99.6335	0.0858

4. Conclusion

This paper proposes the wavelet domain shrinkage model and the experiment was conducted to various deaf persons. This model has shrinked the redundant empirical wavelet coefficients of the deaf speech signal at every subband level and the reduced noise distribution on the signal. The experiment was conducted for higher noise level and found that linear hard shrinkage model outperforms other shrinkage models. The data compression of speech signal is validated using hard shrinkage function and compression performance showed that the applied waveshrink model is able to achieve good PRD. The hard shrinkage function is further tested with respect to SNR and found better response. The results are clearly seen and it is comparable with the other waveshrink functions. The recommended waveshrink model has various application in the assistive device development for deaf persons where denoising is a prime criterion before processing.

Declarations

Dr. J. Nirmaladevi worked on the data set and analysis related to deaf speech. In addition, she prepared the article as per the structure. Dr. S. Poornachandra worked on the wave shrink evaluation for the deaf signal and carried out grammar corrections and plagiarism checking. RM Mahalakame wrote the introduction of the article. P Jayavardhini collected the literature and developed the information related to it. R V Ragsana created the statistical table analysis for the results and discussion.

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