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A comparison of soft and hard thresholding by using discrete wavelet transforms

S. S .Joshi, V.N.Hainalkar
Department of Electronics & Telecommunication

Abstract**—**This paper about to reduce the noise by Adaptive time-frequency Block Thresholding procedure using discrete wavelet transform to achieve better SNR of the audio signal. . Discrete-wavelet transforms based algorithms are used for audio signal denoising. The resulting algorithm is robust to variations of signal structures such as short transients and long harmonics. Analysis is done on noisy speech signal corrupted by white noise at 0dB, 5dB, 10dB and 15dB signal to noise ratio levels. Here both hard thresholding and soft thresholding are used for denoising. Simulation & results are performed in MATLAB 7.10.0 (R2010a). In this paper we are comparing results of soft thresholding and hard thresholding .

Keywords-Audio denoising, soft thresholding ,Hard thresholding, SNR.

I . INTRODUCTION

Removing noise from audio signals requires a nondiagonal processing of time-frequency coefficients to avoid producing “musical noise”. A nondiagonal audio denoising algorithm through adaptive time -frequency block thresholding is introduced which produces hardly any musical noise and improves the SNR[9]. The time-frequency audio denoising algorithms perform a parameterized filtering of spectrogram coefficients with empirically fixed parameters. Time-frequency audio denoising procedures compute a Discrete Wavelet Transform (DWT) of the noisy signal and process the resulting coefficients to attenuate the noise. The DWT is invertible, that is, the original signal can be recovered from the transform by the Inverse DWT[9].

Wavelets have become a popular tool for audio signal processing, Wavelets are successful front end processors for audio signal processing, this by exploiting the time resolution of the wavelet transform. For the audio signal processing, the mother wavelet is based on the Hanning window. Here, White Gaussian noise can be handled either by hard and soft thresholding with DWT[8].

In non diagonal time-frequency block thresholding procedure, spectrogram coefficients are grouped into blocks to compute attenuation factors. This block grouping regularizes the estimation which removes musical noises. The block size is adapted to the signal properties. An adaptive block threshold nondiagonal estimation procedure described, adjusts all parameters adaptively to signal property by minimizing a Stein estimation of the risk. The adaptive block threshold procedure gives best signal. .Audio signal processing is the intentional alteration of auditory signals, or sound.Our current audio denoising efforts started with the challenge to try to recover as much as possible from a totally corrupted audio signals. Although audio denoising is extremely desirable in many applications, it is a very difficult problem [9].

II. NEED FOR AUDIO DENOISING

Musical noise signals are non stationery signals whose frequency varies. The audio signal range is 20 Hz to 20 KHz. It is a fact that audio signals (both speech and music) are generally not stationary and they cannot always be said to be stationary over each of set intervals of time.

It is non-informative and plays the role of sucking the intelligence of the original signal. Any kind of processing of the signal contributes to the noise addition. Hence to regenerate original signal, it is tried to reduce the power of the noise signal or in the other way, raise the power level of the informative signal, which leads to improvement in the signal to noise ratio (SNR). There are several ways in doing it and here the focus is on audio denoising by time frequency block thresholding.

The signal is corrupted by random white Gaussian noise. The content of noise present in the musical noise signal is reduced using an adaptive

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block thresholding nondiagonal estimation procedure by processing the time-frequency coefficients.

For DWT, Hard thresholding sets all wavelet coefficients below the given threshold value equal to zero and exhibits artifacts. Soft thresholding smoothen the signal by reducing the wavelet coefficients by a quantity equal to the threshold value and modifies the signal energy. For the denoising of the signal it is assumed that the noise can be approximated by a Gaussian distribution. The audio signal Components will have large values compared to the noise. The computation of the coefficients is done using a multi-resolution wavelet filter bank. The filter choice depends on the noise level and other parameters. For a good denoising result, a good threshold level has to be estimated. The wavelet Function and the decomposition level also play an important role in the quality of the denoise signal [8]..

The second step is an attempt made to estimate the non diagonal estimation of an adaptive block Thresholding .The hard or soft thresholding technique is a powerful non-linear estimator. However, its direct application in audio signal denoising is problematic, as it creates some noise. Some improvement may be achieved through more thresholding functions .We study the block size and the thresholding level in time-frequency signal representations [9].

METHOD USED FOR AUDIO DENOISING

Audio signals are often contaminated by background environment noise and buzzing or humming noise from audio equipments. Audio denoising aims at attenuating the noise while retaining the underlying signals.

. The basic methods of audio denoising are “Elimination of the musical noise phenomenon with the Ephraim and Malah noise suppressor” and “Audio signal denoising with adaptive block attenuation”. Depending upon the SNR considered , the Audio Denoising techniques are basically divided in to

- Diagonal Estimation Techniques
- Nondiagonal Estimation Techniques

NON DIAGONAL ESTIMATION

To reduce musical noise as well as the estimation risk, several authors have proposed to estimate a priori SNR with a time-frequency regularization of the posteriori SNR.Resulting attenuation factors thus depend upon the data values in a whole neighborhood of and the resulting estimator is said to be nondiagonal.Some of the Non Diagonal estimation techniques are p-point uncertainty model and Block thresholding (BT)[1]. .

In this thesis , performance of Mozart Signal with different SNR values is done.“Mozart” is a musical excerpt that contains relatively quick notes played by a solo oboe. Mozart Signal is sampled at 11 kHz. The Mozart Signal is corrupted by Gaussian white noise of different amplitude. Short-time Fourier transform and discrete wavelet Transform with half-overlapping windows were used in the experiments and results will be compared. These windows are the square root of Hanning windows of size 50 ms for “Mozart signal ”.The basic steps followed to denoise the musical noise signal are as shown in the following block diagram.

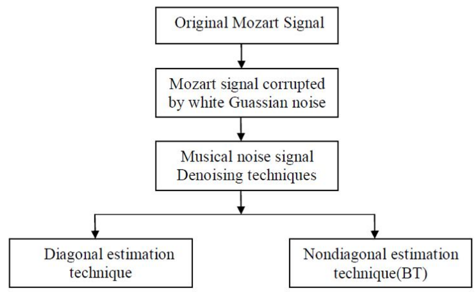


Fig-1: Block Diagram of Denoising Musical noise signal

III. NEED FOR DISCRETE WAVELET TRANSFORM

WAVELET TRANSFORM:

A wavelet is a small wave, which has its energy concentrated in time to give a tool for the analysis of nonstationary, or time varying phenomena [8]. Wavelet transforms convert a signal into a series of wavelets and provide a way for analyzing waveforms, bounded in both frequency and duration. By using wavelet Transform, we can get the frequency information which is not possible by working in time-domain.

There are many different wavelet systems that can be used effectively. A wavelet system is a set of building blocks to represent a signal. One advantage of wavelet transform analysis is the ability to perform local analysis and the calculation of the coefficients from the signal can be done efficiently. Wavelet analysis is able to express signal appearance that other analysis techniques miss such as breakdown points, discontinuities etc. The continuous wavelet transform performs a multi-resolution analysis by contraction and dilatation of the wavelet functions and discrete wavelet transform (DWT) uses filter banks for the construction of the multi resolution time-frequency plane[8]. In DWT decomposition two wavelet decomposition (Analysis) filters which are High Pass and Low Pass respectively followed by down sampling by 2 producing half of input data point of High and Low frequency. The High frequency coefficients are called *Detailed Coefficients* (cD) and Low frequency coefficients are called *Approximation Coefficients* (cA). After decomposition, the signal can be reconstructed back by Inverse Wavelet Transform. The signal can be decomposed in several levels [5] . DWT provides sufficient information both for analysis and synthesis and reduce the computation time sufficiently.

IV. DENOISING SCHEME

A) THRESHOLDING METHOD:

We assume noisy signal:

$y[n]=f[n]+\varepsilon[n], n=0,1,\ldots,N-1$. …………….Eq.(1)

where,

$y[n]$ - Audio Noisy signal, $f[n]$ - Audio Signal

$\varepsilon[n]$ - Noisy signal.

Now, we want to find threshold value that will use to remove noise from noisy signal, but also recover the original signal efficiently. If the threshold value is too high, it will also remove the contents of original signal and if the threshold value is too low, denoising will not work properly[8].

The soft and hard thresholding methods are used to estimate wavelet coefficients in wavelet threshold denoising. Hard thresholding zeros out small coefficients, resulting in an efficient representation. Soft thresholding softens the coefficients exceeding the threshold by lowering them by the threshold value. When thresholding is applied, no perfect reconstruction of the original signal is possible. Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. The hard threshold signal is x if x ≥ thr and is 0 if
x ‹ thr, where 'thr' is a threshold value. 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. If x ≥ thr, soft threshold signal is (sign (x). (x - thr)) .

$$T_{Hard}(f) = \begin{cases} f & |f| \geq thr \\ 0 & |f| < thr \end{cases} \quad (2)$$

$$T_{Soft}(f) = \begin{cases} Sign(f).(f-thr) & f \geq thr \\ 0 & -thr \leq f < thr \\ Sign(f).(f+thr) & f < -thr \end{cases} \quad (3)$$

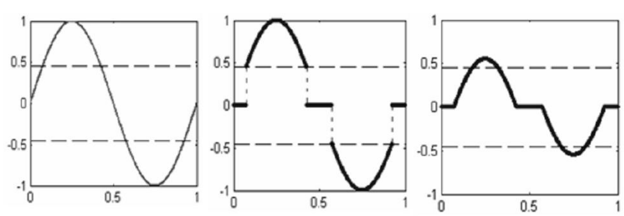


Fig. 2. Original signal, hard thresholding and soft thresholding

Denoising algorithm scheme is showed in Figure 3. Inverse DWT is applied to get denoise time domain signal.

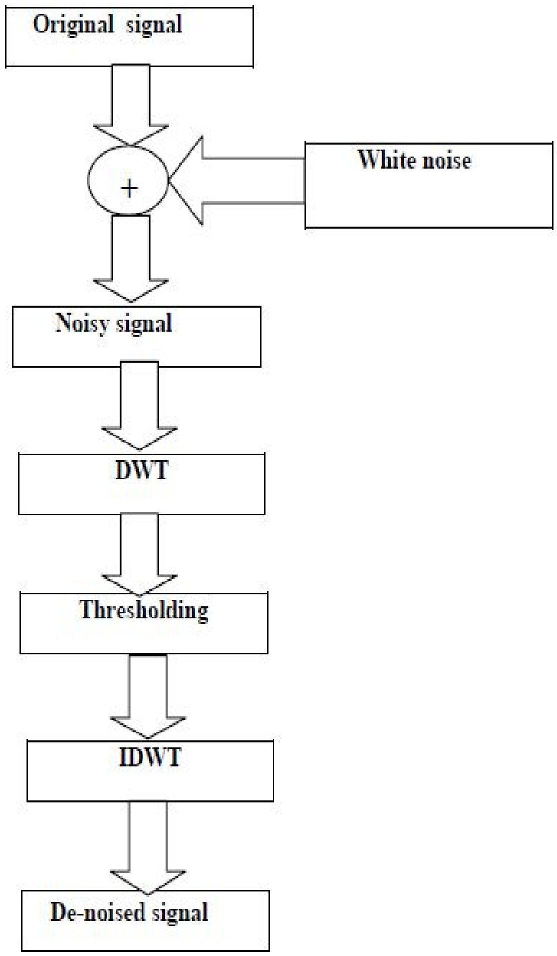


FIG 3. DENOISING ALGORITHM

Algorithm for Adaptive time-frequency Block Thresholding using DWT procedure:

1. Determine the SNR of the musical noise signal.
2. Apply Hanning window.
3. Apply half overlapped window
4. Apply DWT.
5. Determine Block size by considering Stein Unbiased Risk Estimator.
6. Apply Block Thresholding.
7. Apply inverse DWT.
8. Obtain denoised signal.
9. Compare the SNR of the musical noise signal and the denoised signal.

B) THRESHOLD LIMIT*:*

Many methods for setting the threshold have been proposed. The most time-consuming way is to set the threshold limit on a case-by-case basis. The limit is selected such that satisfactory noise removal is achieved. Two rules are generally used for thresholding the coefficients (soft/hard thresholding). Hard thresholding sets zeros for all wavelet coefficients whose absolute value is less than the specified threshold limit.

C) DERIVATION OF FREQUENCY BLOCK TIME-THRESHOLDING ALGORITHM)

To reduce musical noise as well as the estimation risk, several authors have proposed to estimate a priori SNR $\xi[l,k]$ with a time-frequency regularization of the *posteriori* SNR. $\gamma[l,k]$. Resulting attenuation factors $a[l\ ,\ k]$ thus depend upon the data values $Y[l',k']$ for $(\ l'\ ,\ k'\ )$ in a whole neighborhood of and the resulting estimator is said to be nondiagonal and ig given by,

$$\hat{f}[n]=(1/A)\sum_{l,k} a[l,k]Y[l,k]g_{l,k}[n] \ldots \text{Eq.(4)}$$

Ephraim and Malah have introduced a *decision-directed SNR* estimator obtained with a first order recursive time filtering[6] :

$$\hat{\xi}[l,k]=\alpha\hat{\xi}[l-1,k]+(1-\alpha)(\gamma[l,k]-1) \ldots. \text{Eq.(5)}$$

In non diagonal Estimation we consider priori SNR. Pre SNR is the SNR of Audio signal. Non diagonal estimators clearly outperform diagonal estimators but depend upon regularization filtering parameter[9].

D) STEIN UNBIASED RISK ESTIMATE (SURE)

A time-frequency block thresholding estimator regularizes estimation by calculating a single attenuation factor over time-frequency blocks[3]. The signal estimator $\hat{f}$ is calculated from the noisy data *y* with a constant attenuation factor a_i over each block B_i

$$\hat{f}[n] = \sum_{i=1}^{I} \sum_{(l,k)\in B_i} a_i Y[l,k] g_{l,k}[n]$$ … Eq.(6)

To understand how to compute each a_i, one relates the Stein estimation risk, $r = E\{\|f-\hat{f}\|^2\}$ to the frame energy conversion and given by,

$$\gamma = E\left\{\left\|f-\hat{f}\right\|\right\} \le \frac{1}{A}\sum_{i=1}^{I}\cdot\sum_{l,k\in B_i} E\left\{\left|F[l,k]-\hat{F}[L,K]\right|^2\right\}$$ ……………………………………..……Eq.(7)

Since $Y[l,k] = F[l,k] + \varepsilon[l,k]$ one can verify that the upper bound is minimized by choosing

$a_i = 1 - 1/(\xi_i + 1)$. …….. Eq.(8)

A block thresholding estimator can be interpreted as a nondiagonal estimator derived from averaged SNR estimations over blocks[4].

E) ADAPTIVE BLOCK THRESHOLDING

A block thresholding segments the time -frequency plane in disjoint rectangular blocks of length L_i in time and width W_i in frequency[9] . In the following by "block size" we mean a choice of block shapes and sizes among a collection of possibilities. The adaptive block thresholding chooses the sizes by minimizing an estimate of the risk. The risk E $\{\|f-f'\|^2\}$ cannot be calculated since f is unknown, but it can be estimated with a Stein risk estimate. Best block sizes are computed by minimizing this estimated risk[9].

$\Pr ob\{\bar{\varepsilon}^2 > \lambda\sigma^2\}$ is the probability to keep a residual noise.. Adjusting λ and the block sizes $B^{\neq}$ can be interpreted as an optimization between the bias and the variance of our block thresholding estimator.The parameter λ is set depending upon $B^{\neq}$ by adjusting the residual noise probability.

$\Pr ob\{\bar{\varepsilon}^2 > \lambda\sigma^2\} = \delta$ ………… .Eq.(9)

The probability δ is a perceptual parameter. Some specifications about choice of parameters are discussed below.

a) Choice of Block

The block size is $B^{\#}_i = L_i$ X W_i, where L_i and W_i, are respectively the block length in time and the block width in frequency.

For simplicity, lengths L_i = 8, 4, 2 and widths W_i = 16, 8, 4, 2, 1 will be used (the unit being the time-frequency index in spectrogram).

b) Choice of Thresholding Level λ

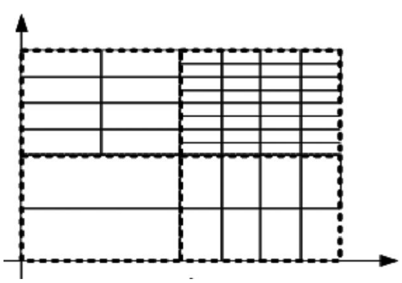
Given a choice of block size and the residual noise probability level δ that one tolerates, the thresholding level λ .For each block width and length, λ is estimated using "Monte Carlo simulation" .The below Table shows the resulting λ with δ = 0.1%.

Table 1: Thresholding level λ calculated with different block size $B^{\#}$ = L X W and with δ = 0.1%.

λ value	W=16	W=8	W=4	W=2	W=1
L=8	1.5	1.6	1.9	2.3	2.5
L=4	1.7	1.9	2.4	3.0	3.4
L=2	1.9	2.5	3.4	3.2	4.8

The partition of macro blocks in to blocks of different sizes is as shown below:

Frequency



Time

Fig - 4: Partition of macro blocks

The adaptive block thresholding chooses the sizes by minimizing an estimate of the risk [9]. The risk cannot be calculated since is unknown, but it can be estimated with Stein risk estimate. The adaptive block thresholding groups coefficients in blocks whose sizes are adjusted to minimize the Stein risk estimate and it attenuates coefficients in those blocks.

V. PERFORMANCE COMPARISION

In this table we also compares soft & hard thresholding SNR value using wavelet transform.From the below comparision we can conclude that the residual noise masks the musical noise.The performance of Block Thresholding of Mozart Signal for different SNR values is shown in the below table.

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Table 2 : Performance of BT for AUDIO signal

Signal	BT with soft thresholding wavelet	BT with hard thresholding wavelet
Mozart 5dB	11.57dB	9.84dB
Mozart 10dB	15.02dB	12.76dB
Mozart 15dB	18.75dB	15.97dB
Mozart 20dB	22.64dB	19.48dB
Mozart 25dB	27.43dB	23.62dB

Comparison between block thresholding method using DWT shown below:

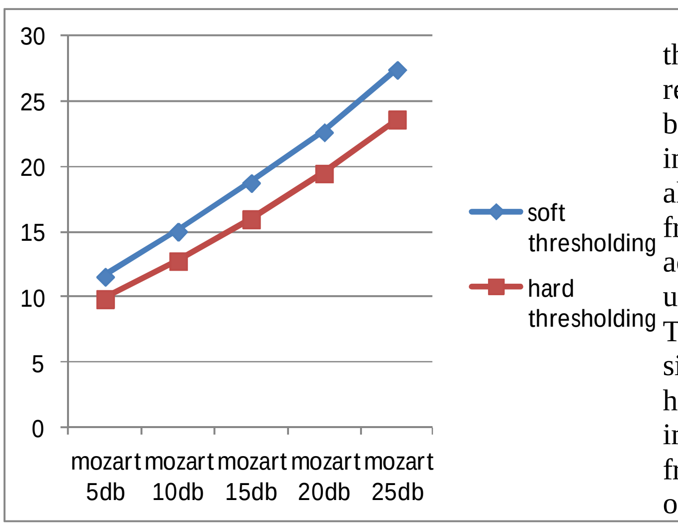
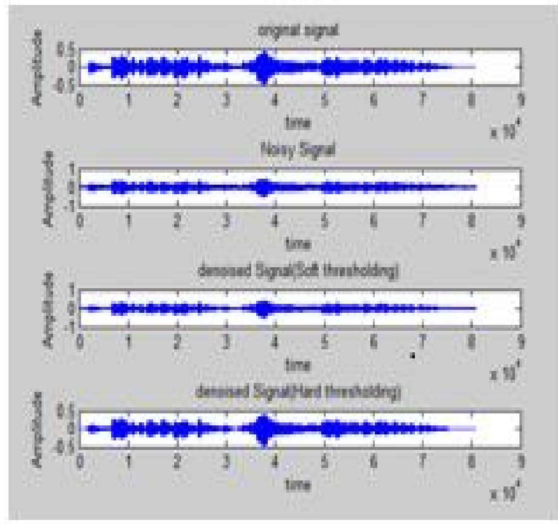


fig-5: comparison graph.

The above graph shows that soft thresholding blue line performs better than hard thresholding red line .

.Fig 6: Comparison of Original, ,Noisy and Denoised Signal



VI. CONCLUSION

Non diagonal estimation teqnique block thresholding with DWT is more advance.Also results shows that soft thresholding performs better than hard thresholding. This paper introduces an adaptive audio block thresholding algorithm that adapts all parameters the time-frequency regularity of the audio signal .The adaptation is performed by minimizing a stein unbiased risk estimator calculated from the data. The resulting algorithm is robust to variations of signal structures such as short transients and long harmonics. Numerical experiment demonstrate improvements with respect to state of the art time-frequecncy audio denoising procedures through objective and subjective evaluations.

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