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Denoising of Image and Audio by using Wavelet Transform

T.V.hyma lakshmi
Assistant professor
Department of Electronics and Communication
S.R.K.R. Engineering college
Bhimavaram ,India.
tvhymalakshmi@gmail.com.

Ramesh Nayak.D
M.Tech
Department of Electronics and Communication
S.R.K.R. Engineering college
Bhimavaram,India.
ramesh.balaji881@gmail.com.

Abstract: This paper proposes real time de-noising algorithms for image and audio based on the Wavelet Transform. White noise is located in all frequencies and is thus especially hard to detect. We use the locality of the wavelet function to single out the frequency domains of the signal itself and thereby able to denoise it. Perfect denoising is not possible, the higher the threshold coefficient is set, the more the noise is detected, but the more the original signal is affected as well. We have implemented a flexible framework for denoising that includes hard and soft thresholding, different Wavelet Transforms and different treatments of the padding coefficients. The presented denoiser is a real-time application that allows direct subjective judgements of a parameter setting.

Keywords: Image denoising, wavelet transform, hard thresholding and soft thresholding.

I. INTRODUCTION

Denoising, the task of removing or suppressing uninformative noise from signals is an important part of many signal processing or image processing applications. Wavelets are commonly used tools in the field of signal processing. The popularity of wavelets in denoising is largely due to the computationally efficient algorithm as well as to the sparsity of the wavelet representation of data. By sparsity we mean that majority of the wavelet coefficients have very small magnitudes where as only a small subset of coefficients have large magnitudes. We may informally state that this small subset contains the interesting informative part of the signal, whereas the rest of the coefficients describe noise and can be discarded to give a noise-free reconstruction. The well known wavelet denoising methods are thresholding approaches. In hard thresholding, all the coefficients with greater magnitudes than the threshold are retained as unmodified as they are comprise the informative part of data, while the rest of the coefficients are considered to represent noise and set to zero. However, it is considerable to assume that coefficients are not purely either noise or informative but mixtures of those. To copeup with this soft thresholding approaches have been proposed. In soft thresholding the coefficients with magnitudes smaller than the threshold are set to zero, but the retained coefficients are also shrunk towards zero by the amount of the threshold value in order to decrease the effect of noise assumed to corrupt all the wavelet coefficients.

Discrete wavelet transform can be used for easy and fast denoising of a noisy signal. If we take only a limited number of highest coefficients of the discrete wavelet transform spectrum, and we perform an inverse transform(with the same wavelet basis) we can obtain more or less denoised signal. There are several ways how to choose the coefficients that will be kept. Here, only two most simple methods were tried – hard and soft thersholding. Wavelets are functions defined over a finite interval and having an average value of zero. The power and magic of wavelet analysis is concept of multi-resolution

II. MULTI RESOLUTION ANALYSIS [4].

The power of wavelets comes from the usage of multi-resolution. Rather than examining entire signals through the same window, different parts of the wave are viewed through size windows (or resolution). High frequency parts of the signal use a small window to give good time resolution; low frequency parts parts of the signal use a big window to get good frequency information. An important thing to note is that the 'window' have equal area even though the height and width may vary in wavelet analysis. The area of the window is controlled by Heisenberg's Uncertainity principle, as the frequency resolution gets bigger the time resolution must get smaller.

Conditions for Multi-Resolution Analysis [4]:

1. Subspace V_j must be contained in all subspaces on higher resolutions.

$$\ldots \subset V_{-1} \subset V_0 \subset \ldots \subset L^2(R) \qquad (1)$$

2. All square integrable functions must be included at the finest resolution level (3) and zero function on the coarsest level (4).

$$\overline{\cup_j V_j} = L^2(R) \qquad (2)$$

$$\cap_j V_j = \{0\} \qquad (3)$$

3. All the spaces $\{V_j\}$ are scaled versions of the central space V_0. If f(t) is in space V_j and it contains no details on scales smaller than $1/2^{j+1}$ and it is from space V_{j+1}(5).

$$f(t) \in V_j \Leftrightarrow f(2t) \in V_{j+1} \qquad (4)$$

4. If f(t) ϵ V_0, so do its translates by integer k, {f(t-k)}.

$$f(t) \in V_0 \Rightarrow f(t-k) \in V_0 \qquad (5)$$

5. There exist a function Ø(t), called scaling function, such that {Ø(t-k)} is an ortho normal basis of V_0.

II(a). WAVELET FAMILIES

There are a number of basis functions that can be used as the mother wavelet for a wavelet transformation. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting Wavelet Transform.

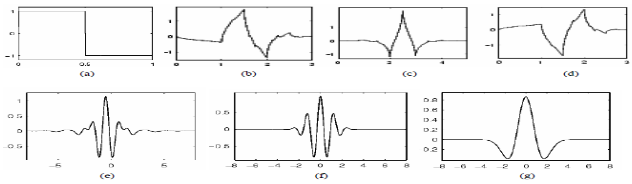

Fig.1.Wavelet Families: (a) Haar (b) Daubechies (c)Coiflets (d) Symlets (e) Meyer (f) Morlet (g) Mexican Hat.

The above figures(fig.1) are some of the commonly used wavelet functions. Haar wavelet is one of the oldest and simplest wavelet. Therefore, any discussion of wavelets starts with the haar wavelet. Daubechies wavelets are the most popular wavelets.

III. WAVELET TRANSFORMS:

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. Often signals we wish to process are in the time-domain, but in order to process them more easily other information. Such as frequency, is required. Mathematical transforms translate the information of signals into different representations. For example, the fourier transform converts a signal between the time and frequency domains, such that the frequencies of a signal can be seen. However the fourier transform cannot provide information on which frequencies occur at specific times in the signal as time and frequency are viewed independently.

The wavelet transform provides a time-frequency representing of the signal. While fourier transform and STFT use waves to analyze signals. The wavelet transform uses wavelets of finite energy.

The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts).

III(a).CONTINOUS WAVELET TRANSFORM

The continuous wavelet transform is the sum over all time of scaled and shifted version of the mother wavelet ψ. Calculating the CWT results in many coefficients c, which are functions of scale and translation.

$$C(s,\tau) = \int_{-\infty}^{\infty} f(t)\psi(s,\tau,t).dt$$

The translation **τ,** is proportional to time information and the scale, s, is proportional to the inverse of the frequency information. To find the constituent wavelets of the signal, the coefficients should be multiplied by the relevant version of the mother wavelet.

III(b).DISCRETE WAVELET TRANSFORM

The DWT provides sufficient information for the analysis and synthesis of a signal, but is advantageously, much more efficient. Discrete wavelet analysis is computed using the concept of filter banks. Filters of different cut-off frequencies analyze the signal at different scales. Resolution is changed by the filtering; the scale is changed by up sampling and downloading. If a signal is put through two filters:

(1) A high pass filter, high frequency information is kept, low frequency information is lost.

(2) A low pass filter, how frequency information is kept, high frequency information is lost.

III(c).TWO DIMENSIONAL DWT (applied for images)

Discrete wavelet transform for two-dimensional signal, or in our case images, can be derived from one dimensional DWT. Easiest way for obtaining scaling and wavelet function for two-dimensions is by multiplying two one-dimensional functions.

Scaling functions for 2-D DWT can be obtained by multiplying two 1-D scaling functions (6). Generally different scaling functions can be used for each direction but in practice those functions are in most cases the same.

$$Ø(x,y)=Ø(x)Ø(y) \qquad (6)$$

Recently, discrete wavelet transform has attracted more and more interest in image de-noising. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges as two signals, approximation and details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse wavelet transform. An image can be decomposed into a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL,LH,HL and HH as shown in figure. The next level of wavelet transforms is applied to the low frequency sub band image LL only. The noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be thresholded.

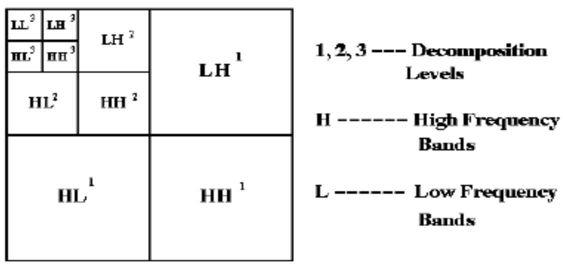

Fig.2.Decomposition levels.

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IV. DENOISING USING WAVELET TRANSFORMS

Applications of signal processing all struggle with a major problem, noise. A pure and undisturbed signal is superimposed by another-unwanted-signal. How to separate the one from the other without deterioration of the signal itself? This question accompanies the search for a good representation of the signal throughout its encoding process. Though the fourier transform (FT) and the windowed fourier transform are successfully used, new methods focus on the wavelet transform (WT) [4] in order to overcome the FT's disadvantages. Its construction through multi resolution analysis proves to reflect the frequency resolution of the human ear: lower frequencies are resolved well, while high frequencies are only loosely resolved. Furthermore, the implementation of the WT is fast enough to allow real-time application.

All digital images contain some degree of noise. Image denoising algorithm attempts to remove this noise from the image. Ideally, the resulting de-noised image will not contain any noise or added artifacts. De-noising of natural images corrupted by Gaussian noise using wavelet technique is very effective because of its ability to capture the energy of a signal in few energy transform values. The methodology of the discrete wavelet transform based image de-noising has the following three steps as shown in fig3.1.Transform the noisy image into orthogonal domain by discrete 2D wavelet transform. 2. Apply hard or soft thresholding the noisy detail coefficients of the wavelet transform. 3. Perform inverse discrete wavelet transform to obtain the de-noised image. Here, the threshold plays an important role in the de-noising process[5].

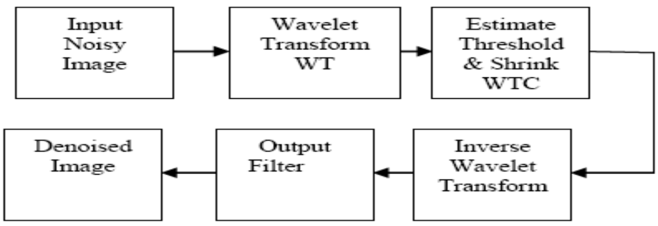

Fig.3.Discrete wavelet transform based image denoising.

SYSTEM MODEL :

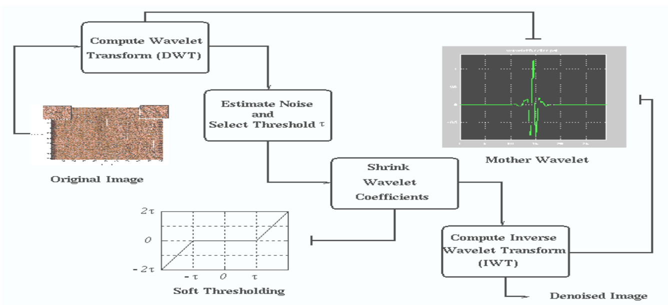

Fig.4.Block diagram of proposed wavelet transform algorithm .

IV(a).THRESHOLDING

The wavelet coefficient corresponding to the signal contain important information and their magnitude are large but the number is small. However, the coefficients corresponding to the noise are commonly distributed and the number is large but the magnitudes are relatively small. Due to the above fact, the wavelet coefficients which are larger than a given threshold are kept or shrunk and the other coefficients are eliminated. This technique is called thresholding [2].

The wavelet coefficients calculated by a wavelet transform represent change in the time series at a particular resolution. By looking at the time series in various resolutions it should be possible to filter out noise. However, the definition of noise is a difficult one. One of my colleagues commented once that "one person's noise is another's signal". In part this depends on the resolution one is looking at. One algorithm to remove Gaussian white noise is summarized in section 10.5, chapter 10, of wavelet methods for time series analysis by Percival and walden. The algorithm is:

1. Calculate a wavelet transform and order the coefficients by increasing frequency. This will result in an array containing the time series average plus a set of coefficients of length 1,2,4,8….The noise threshold will be calculated on the highest frequency coefficient spectrum(this is the largest spectrum).

2. Calculate the median absolute deviation on the largest coefficient spectrum. The median is calculated from the absolute value of the coefficients. The equation for the median absolute deviation is shown

$\delta(mad)=\mathrm{median}\{|c_0|,|c_0|,\ldots\ldots|c_2^{\,n-1}-1|\}/0.6745$

Here C_0, C_1, etc… are the coefficients. The factor 0.6745 in the denominator rescales the numerator so that δ_{mad} is also a suitable estimator for the standard deviation for Gaussian white noise (Wavelet methods for time series analysis).

3. For calculating the noise threshold I have used a modified version of the equation in wavelet methods for time series analysis. This equation has been discussed in papers by D.L.Donoho and I.M.Johnstone. this equation is shown below:

$$\tau = \delta_{mad}\sqrt{\ln(N)}$$

In this equation N is the size of the time series.

4. Apply a threshold algorithm to the coefficients. There are two popular versions

(i). Hard thresholding: Hard thresholding sets any coefficients less than or equal to the threshold to zero.
If (coef[i]<=thresh)
Coe[i]=0.0;

(ii). Soft thresholding: Hard thresholding sets any coefficient less than or equal to the threshold to zero. The threshold is subtracted from any coefficient that is greater than the threshold. This moves the time series toward zero.
If(coef[i]<=thresh)
Coef[i]=0.0
Else
Coef[i]=coef[i]-thresh;

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Soft thresholding not only smooths the time series, but moves it toward zero.

In this section we consider the problem of recovering the regression function from noisy data based on wavelet decomposition.

The upper two plots in the display show the underlying regression function (left) and noisy data (right). The lower two plots show the distribution of the wavelet coefficients in the time-scale domain for the regression function and the noisy data.

For simplicity we deal with a regression estimation problem. The noise is assumed to be additive and Gaussiam with zero mean and unknown variance. Since the wavelet transform is an orthogonal transform we can consider the filtering problem in the space of wavelet coefficients. One takes the wavelet transform of the noisy data and tries to estimate the wavelet coefficients. Once the estimator is obtained one takes the inverse wavelet transform and recovers the unknown regression function.

To suppress the noise on the data two approaches are normally used. The first one is the so-called liner method. The wavelet decomposition reflects well the properties of the signal in the frequency domain. Roughly speaking, higher decomposition scales correspond to higher frequency components in the regression function. If we assume that the underlying regression is allocated in the low frequency domain then the filtering procedure becomes evident. All empirical wavelet coefficients beyond some resolution scale are estimated by zero. This procedure works well if the signal is sufficiently smooth and when there is no boundary in the data. But for many practical problems such an approach does not seem to be fully appropriate, e.g. images cannot be considered as smooth functions.

IV(b).HARD THRESHOLODING

To suppose the noise we apply the following nonlinear transform to the empirical wavelet coefficients:

$$F(x) = x.I(|x| > t)$$

Where t is a certain threshold. The choice of the threshold is a very delicate and important statistical problem.

On the hand, a big threshold leads to a large bias of the estimator. But on the other hand, a small threshold increase the variance of the smoother. Theoretical considerations yield the following value of the threshold:

$$t = \sqrt{2\sigma^2 \log(n)/n},$$

Where n is the length of the input vector and σ^2 is the variances of the noise. The variance of the noice is estimated based on the data. We do this by averaging the squares of the empirical wavelet coefficients at the highest resolution scale.

IV(c).SOFT THRESHOLDING

Along with hard thresholding [2] in many statistical applications soft thresholding procedures are often used. In this section, we study the so-called wavelet shrinkage procedure for recovering the regression function from noisy data.

.The only difference between the hard and the soft thresholding procedure is in the choice of the nonlinear transform on the empirical wavelet coefficients. For soft thresholding [2] the following nonlinear transform is used:

$$S(x) = sign(x)(|x|-t)I(|X|>T),$$

Where t is a threshold. The menu provides you with all possibilities for choosing the threshold and exploring the data.

IV(d).DIFFERENCE–SOFT AND HARD THRESHOLDING

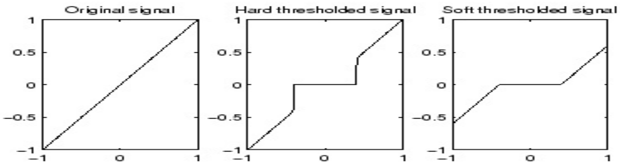

Fig.5.Difference between soft and hard thresholding

In hard thresholding we kept those wavelet coefficients remains constant which are larger than threshold level and we eliminate the smaller magnitude ones. Hard threshold, however, provides better edge preservation in comparison with the soft one.

In soft thresholding we shrunk the larger magnitude coefficient by threshold level and we eliminate the smaller magnitude coefficients. It is known that soft thresholding provides smoother results in comparison with the hard thresholding.

IV. RESULTS

For testing the performance of proposed technique one image and one dog barking signal taken as input.

If we consider a image as shown in fig(6) and add noise to it and if we apply both techniques for this current picture.

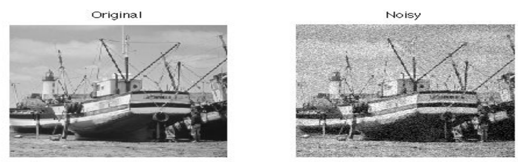

Fig.6.Original image and Noisy image

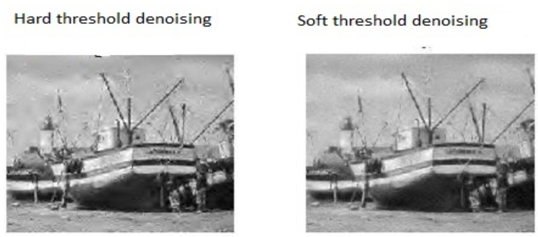

Fig.7. Hard and Soft thresholding images

The above fig (6) shows the original and noisy images and fig.(7) shows the comparison of denoised images of hard and soft thresholding techniques.

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The Audio can also be denoised by using this soft thresholding technique. Fig.8.shows original audio signal. fig.(9) shows noisy audio signal and fig(10) shows denoised audio signal

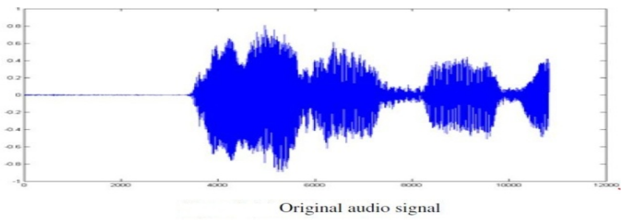

Fig.8.Original Audio signal

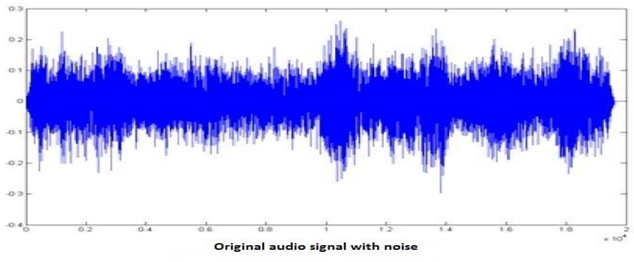

Fig.9.Noisy Audio signal

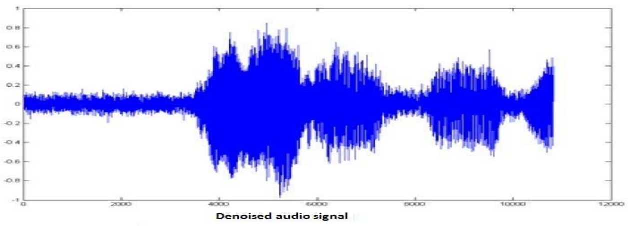

Fig.10.Denoised Audio signal

V. CONCLUSION:

In this paper we have denoised audio and image signals using an advanced technique of wavelet transform. As a whole, the taken input image and audio were denoised using soft thresholding technique. Considering perfect threshold levels and taken ideal characteristic input signals, the process of denoising can be further optimized. As we used random noise in this paper, it can also be implemented to other types of noise and better denoising can be achieved. Choosing real-time signals as input for this paper can be accomplished by choosing the input signal's characteristics as needed for the coding employed internally.

Using complex wavelet basis functions and employing more than one type of threshold techniques this paper can be further developed into a good audio and image denoiser.

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