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Elimination of Noise in Image Using Soft Thresholding with Haar Wavelet Transform

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Abstract

In this project, we intend a new technique of noise removal from an image degraded with Gaussian noise using soft thresholding. In this project, we also compare Peak Signal-to-Noise Ratio (PSNR) of different technique. There are two types of thresholding: Soft and Hard thresholding. The Universal thresholding technique i.e. VisuShrink is based on the Hard-thresholding and it is not suitable for Soft-thresholding. In this we proposed simple method and adaptive since the estimation of thresholding parameters depends on the data of wavelet coefficients. According to the experimental results, this proposed method has higher Peak Signal-to-Noise Ratio (PSNR) than the Mantosh and VisuShrink methods.

Key words: *Image Denoising, Peak Signal-to-Noise Ratio (PSNR), soft thresholding.*

Introduction

An image is a two dimension function f(x,y), where x and y are plane coordinates, and the amplitude off at any pair of coordinates(x, y) is called the gray level or intensity of the Image at that point. There are two types of images i.e. gray scale image and RGB image. An image is often corrupted by noise in its acquition and transmission. Basically image noise is unwanted fluctuations. There are different types of image noise present in the image like Gaussian noise, salt and pepper noise, speckle noise, shot noise, white noise. Image denoise is used to remove the additive noise while retaining as much as possible the important signal features. There are various noise reduction techniques which are used for removing the noise. Most of the standard algorithm used to denoise the noisy image and perform the individual filtering process. Denoise generally reduce the noise level but the image is either blurred or over smoothed due to losses like edges or lines. In the recent years there has been a fair amount of research on wavelet thresholding and threshold section for image denoising, because wavelet provides an appropriate basis for separating noisy signal from the image signal. Wavelet transform is good at energy compaction, the small coefficient are more likely due to noise and large coefficient due to important signal feature. These small coefficients can be threshold without affecting the significant features of the image.[1]

The wavelet transform (WT) is a powerful tool of signal processing for its multi-resolution possibilities. Unlike the Fourier transform, the wavelet transform is suitable for application to non-stationary signals with transitory phenomena, where frequency response varies in time. The wavelet coefficient represents a measure of similarity in the frequency content between a signal and a chosen wavelet function. These coefficient are computed as a convolution of the signal and the scaled wavelet function, which can be interpreted as a dilated band pass filter because of its band pass like spectrum. By wavelet analysis from a signal at high scales, extracted global information called approximations, and at two scales, extracted fine information called details. The discrete wavelet transform (DWT) requires less space utilizing the space saving coding based on the fact that wavelet families are orthogonal or biorthogonal bases, and thus do not produce redundant analysis. The discrete wavelet transform corresponds to its continuous version sampled usually on a dyadic grid, which means that the scales and translations are power of two. Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is threshold by comparing against threshold. If the coefficient is smaller than threshold then it set to be zero; otherwise it is kept or modified. We replace the small noisy coefficient by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and with less noise. Since the work of Donoho and Johnstone[2] there has been much research on finding thresholds, however few are specifically designed for images.[3]

The soft and hard shrinkage (thresholding) functions are basic functions widely used for estimating a signal *via* projection in the wavelet domain. The soft and hard shrinkages involve forcing to zero the coefficients with amplitudes lower than the selected threshold, and preserving (hard) or shrinking (soft) any coefficient, with amplitude above this threshold, by a value that equals the threshold height. Threshold selection for calibrating soft and hard thresholding functions has also been addressed by Donoho and Johnstone. These authors proposed the use of the universal and minimax thresholds: the estimation by soft or hard thresholding with any of these thresholds yields near-optimal risk in the sense that, asymptotically, the estimator achieves within a factor of $2\log N$ of the ideal risk, which is the risk achieved with the aid of an oracle.[4]

However, in practice, the hard and the soft WaveShrink estimators present drawbacks such as an important variance, when using hard thresholding, or a large bias, when using soft thresholding. Many suggestions have been made in order to improve the performance of these Wave Shrink estimators. The different contributions proposed in the literature and aiming at improving the denoising performance have resulted in a huge number of wavelet based methods for image denoising. In addition, there exist many ways to improve a given method.[4]

Image Denoising

Images obtain from the world are always varied with noise. The noise bring in is derived from multiple sources. The deficient instrument itself would produce a certain amount of noise when the image is taken. When transform the optical signal into a digital signal, the pixel's value at specific location is dependent to the number of photons the corresponding captor has received. So the volatility of the number of receiving photons can cause the construction of noise. Moreover, throughout images intensification and broadcast, additional perturbations can be introduced by electronic devices and transmission lines. There are several different types of noise in digital images. For instance, shot noise is generated by the random way photons are emitted from a light source especially when the light intensity is limited and it is usually characterized by Poisson distribution. Thermal noise, also known as dark current noise, is produced by thermal agitation of electrons at sensing sites and highly dependent on the sensor's temperature and the exposure time. Images with impulsive noise, which is generally caused by the malfunctioning of elements in the camera sensors or timing errors in the data transmission process, have bright pixels in dark areas and dark pixels in bright areas. And quantization noise often happens due to the errors when an analog signal is converted to a number of discrete digital values.

Since noise seriously compromises the details of the image and hampers image understanding and image analysis in scientific and commercial applications, image denoising is extensively required. Thus it is highly necessary to use an appropriate and efficient denoising approach to eliminate or reduce noise while keeping the important image features when pre-processing images.

Figure 1 : (a) A noise-free Image *Pepper*, (b) A noisy version of it

Image denoising attempt to recuperate a noise-free image by eliminating or reducing the noise on the observed image. This dispensation can be modeled as obtaining an optimal estimate of the unknown noise-free image from the obtainable noise-corrupted image. A large number of scientific literatures have emphasized on image denoising in the last decade and there does still exist a wide range of interest in the subject nowadays. Although various algorithms and tools have been proposed, derived and improved, the problem is that many denoising techniques always suffer over-softening the crucial image features as well as introducing artifacts. Thus the searching for an efficient image denoising method is still a challenging task.

Wavelet thresholding

Suppose x={x_{ij} , i=1,2,…,M and j=1,2,…,N}is an image of M x N pixels, which is corrupted by independent and identically distributed (i.i.d) zero mean, white Gaussian noise n_{ij} with standard deviation σ_n. The noise signal can be denoted as $n_{ij} \sim N(0,\sigma_n^2)$. This noise may corrupt the signal in a transmission channel. The observed, noise contaminated, image is y={y_{ij} , i=1,2,…,M and j=1,2,…,N}. Therefore, the noised image can be expressed as:

$$y_{ij} = x_{ij} + n_{ij} \qquad (1)$$

The object of a de-noising process is to estimate image x from the noised image y, so that the Mean Square Error (MSE) to be minimum. Let *W* and *W* $^{-1}$ denote the two dimensional DWT and its inverse respectively. Then, the original signal, its noised version and the noise have a matrix form in the transform domain that includes the subband coefficients.

$$X = W x , Y = W y , V = W n$$

Fig . shows the two level DWT of a 2-D signal, which consists of the subbands LL_2 (low frequency or approximation coefficients), HL_2 (horizontal details), LH_2 (vertical details), HH_2 (diagonal details) and the first level details HL_1, LH_1, HH_1.

The one dimensional wavelet transform can be applied to the columns of the already horizontal transformed image as well. The result is shown in Figure 2 and is decomposed into four quadrants with different interpretations.

LL: The upper left quadrant consists of all coefficients, which were filtered by the analysis low pass filter along the rows and then filtered along the corresponding columns with the analysis low pass filter again. This sub-block is denoted by LL and represents the approximated version of the original at half the resolution.

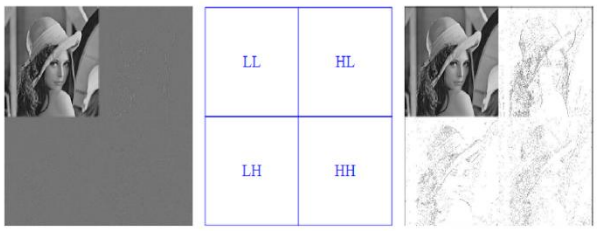

Figure 2: one dimensional CDF(2,2) wavelet transform applied to the rows of the benchmark image *lena* with reflection at the image boundaries

HL/LH: The lower left and the upper right blocks were filtered along the rows and columns alternatively. The LH block contains vertical edges, mostly. In contrast, the HL block shows horizontal edges very clearly.

HH: The lower right quadrant was derived analogously to the upper left quadrant but with the use of the analysis high pass filter which belongs to the given wavelet. We can interpret this block as the area, where we find edges of the original image in diagonal direction.

Therefore equation 1, in the spatial domain, becomes in the transform domain as follows:

$$Y = X + V$$

where X, Y and V are the transform domains of the original image, its noised version and the noise respectively. The orthogonal property of the transform insures that the noise in the transform domain is also of Gaussian nature. The de-noising algorithms, which are based on thresholding, suggest that each coefficient of every detail sub-band is compared to a threshold level and is either retained or killed if its magnitude is greater or less respectively. The approximation coefficients are not submitted in this process, since on one hand they carry the most important information about the image and on the other hand the noise mostly affects the high frequency sub-bands.

The type of the threshold is either hard or soft. Fig. Indicates the two types of thresholding, which can be expressed analytically as follows.

Hard threshold:

$$y = x \text{ if } |x| > T$$
$$y = 0 \text{ if } |x| < T$$

Soft threshold:

$$y = \text{sign}(x)\,(|x| - T)$$

where x is the input signal, y is the signal after threshold and T is the threshold level.

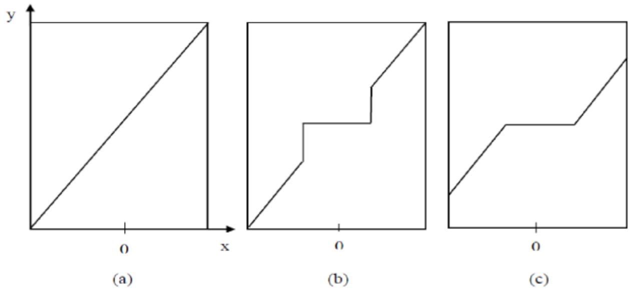

Fig 3 Threshold types: (a) Original signal; (b) Hard; (c) Soft

The hard type does not affect the coefficients that are greater than the threshold level, whereas the soft type causes shrinkage to these coefficients. In the present work, both types of threshold are evaluated but hard thresholding may create abrupt artifacts because of its discontinuous nature. The reconstructed image is a de-noised estimate of x, which is produced by the inverse DWT.

The threshold level is estimated by various methods called thresholding criteria, which are based on the minimization of the averaged squared error

NOISE MODELS

The noise models give the detailed information of the noise that applied in our work. The following are the noise that are used for our proposed work are:

A. Salt and Pepper noise

Salt and Pepper noise is a kind of impulse noise and is also referred to as intensity spikes. Error in data transmission is the main cause of this type of noise. Error in data transmission occurs when there is interference in the channel that passes the data. The salt and pepper noise gives a “salt and pepper” like appearance to the image and the affected (or corrupted) pixels are given a minimum and maximum values alternatively and leave the unaffected pixels unchanged. For an 8-bit image, the minimum value i.e. pepper noise is set as 0 and the salt noise which has maximum value is set as 255. Salt and pepper noise is occurred due to the defected pixels in the camera sensors, timing errors or faulty memory locations.

B. Speckle noise

Images are corrupted with additive or multiplicative noise. Speckle noise is also known as multiplicative noise. Speckle noise results in poor contrast of image. The phenomenon known as “Imaging speckle” occurs when a coherent source and a non-coherent detector are used to interrogate a medium, which is detected rough on the scale of the wavelength. The superposition of acoustical replication coming with random phases and amplitudes results in producing an intricate pattern, known as speckle noise. Depending on whether interference is destructive or constructive, it scales from zero to a maximum. Speckle noise tends to unclear and masks diagnostically important details, thereby distracting the color images.

C. Gaussian noise

Gaussian noise is also known as Additive noise which is evenly distributed over the signal. So, each and every pixel results in the sum of the true pixel value and a random Gaussian distributed noise value.

WAVELET FILTERS

A. Median filter

A median filter comes under the category of nonlinear filters unlike the mean filter. Like as mean filter, the median filter also follows the moving window principle. A 3× 3 kernel of pixels is scanned over pixel matrix of the whole image. The computed pixel values in the window are the resulted median, and the center pixel of the window is replaced with the computed median. Median filtering is applied by sorting all the pixel values from the surrounding neighborhood into numerical order and then the considered pixel is being replaced with the middle pixel value.

B. VisuShrink

VISUShrink follows the hard thresholding rule and is also known as "Universal Threshold". It uses a threshold value, say t and it is proportional to the standard deviation of noise. It is defined as:

$$T= \sigma\sqrt{2\log n}$$

σ implies the noise variance present in the signal or AWGN and n implies the signal size or number of pixels in the image.

C. SureShrink

SureShrink is a threshold based method and here SURE refers to Stein's Unbiased Risk Estimator (SURE) which was proposed by Donoho and Johnstone and therefore called as SureShrink. It is an assemblage of the universal threshold and the SURE threshold. SureShrink method is also known as level dependent thresholding because it provides a threshold value for each resolution level in the wavelet transform. SureShrink follows the rule of soft thresholding.

D. Bayes Shrink

The Bayes Shrink minimizes the Bayesian risk, and hence its name, Bayes Shrink. It follows soft thresholding rule and is sub-band-dependent, so the thresholding is done at each and every band of resolution in the wavelet decomposition. Similarly as Sure Shrink procedure, it is smoothness-adaptive. The Bayes threshold, th_B, is defined as:

$$th_B = \sigma^2 / \sigma_s,$$

where σ^2 denotes the noise variance and σ_S denotes the signal variance without noise.

Result

The experimental evaluation is performed on two gray scale images like "Lena" and "Cameraman" of size 512 X 512 pixels at different noise levels. The wavelet transform employs Haar wavelet at four levels of decomposition. The objective quality of the reconstructed image is measured by:

$$PSNR=10\log10(255^2/mse)$$

where *mse* is the mean square error between the original (i.e. x) and the de-noised image (i.e.) with size M x N:

$$mse = \frac{1}{MxN}\sum_{i=1}^{M}\sum_{j=1}^{N} [x(i,j) - \hat{x}(i,j)]^2$$

Fig 4. Original test images with 512×512 pixels: (a) Cameraman; (b) Lena

We have performed experiments on different images using our proposed method. The results of our proposed method have been compared with that of the VisuShrink and Mantosh denoising thresholding technique[8]. In our experiments, we have used 'haar' wavelet and three level of decompositions (Level 1, Level 2, and Level 4). In Level 1 and Level 4 decomposition, we use mantosh and proposed method. And In level 2 decomposition we use visushrink[1], mantosh and proposed method to calculate PSNR. The experiments are conducted on the following test images: Cameraman and Lena of size 512×512 at different noise levels: 10, 20, 30, and 50. The quality of test images is measured in terms of PSNR. The experimental results of our proposed method are depicted in Table 1-3,

Table 1. Numerical results (i.e. PSNR in db) for Cameraman, and Lena on Level 1 decompostion

Method (PSNR in db)		Noise Level	Image Name
Proposed	Mantosh		
43.07	43.00	10	Cameramen
40.99	40.98	20	
39.61	39.53	30	
37.81	37.70	50	
35.84	35.78	10	Lena
33.15	33.02	20	
31.46	31.36	30	
29.44	29.37	50	

Table 2. Numerical results (i.e. PSNR in db) for Cameraman, and Lena on Level 4 decompostion

Method (PSNR in db)		Noise Level	Image Name
Proposed	Mantosh		
34.44	34.84	10	Cameramen
32.95	32.94	20	
32.04	31.98	30	
30.85	30.77	50	
30.48	30.44	10	Lena
29.27	29.25	20	
28.76	28.71	30	
28.01	27.94	50	

Table 3. Numerical results (i.e. PSNR in db) for Cameraman and Lena on Level 2 decomposition

Method (PSNR in db)			Noise Level	Image Name
Proposed	Mantosh	Visu Shrink		
38.13	28.63	27.42	10	Cameramen
36.38	26.48	24.77	20	
35.46	24.95	23.41	30	
34.32	23.12	21.97	50	
34.92	30.77	28.34	10	Lena
33.22	28.42	26.09	20	
32.17	26.48	24.82	30	
30.71	23.79	23.35	50	

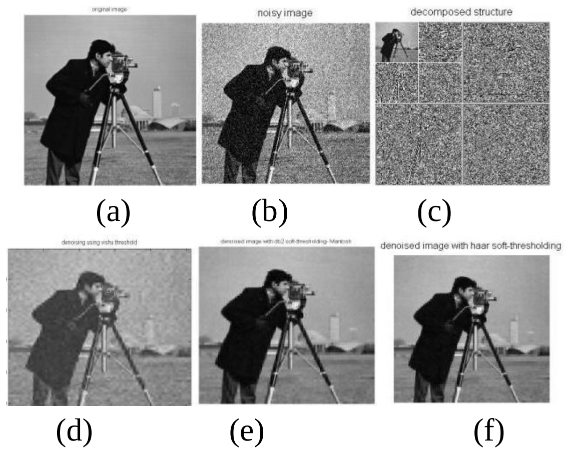

Fig 5. Cameraman Image: (a) Original, (b) Noisy image with noise level 20, (c) Decomposed image with level 2, (d)Denoising using Visu Shrink; (e) Denoising using Mantosh method. (f) Denoising using proposed method.

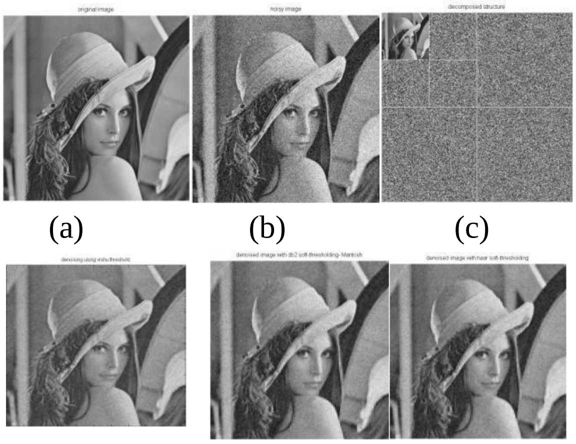
(a) (b) (c)
(d) (e) (f)

Fig 6. Lena Image: (a) Original, (b) Noisy image with noise level 20, (c) Decomposed image with level 2, (d)Denoising using Visu Shrink; (e) Denoising using Mantosh method. (f) Denoising using proposed method.

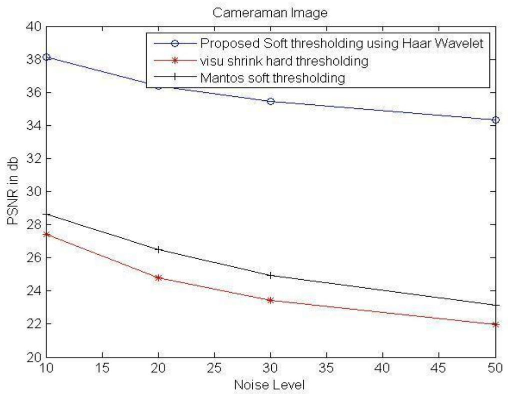

Fig 7. PSNR gains vs. noise levels of Proposed, Mantosh and VisuShrink methods with images: Cameraman

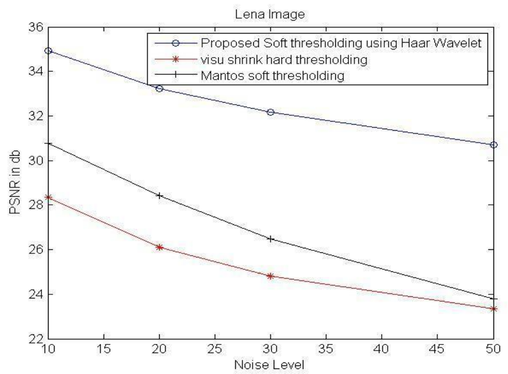

Fig 8. PSNR gains vs. noise levels of Proposed, Mantosh and VisuShrink methods with images: Lena

In Table 1, we have shown the PSNR gains to each test images for our proposed, Mantosh and VisuShrink techniques. The PSNR gains of our proposed method are higher than that of the Mantosh and VisuShrink for all noise levels. The first image i.e. (a) represents the original one, and the second image i.e. (b) represents the noisy one with noise level 20 in Figs. In Figs, the third ones i.e. (c) decomposed image with level 2 (d) are denoised images using VisuShrink and the fourth ones i.e. (e) are the denoised images using Mantosh method and the fifth ones i.e. (e) are the denoised images using our proposed method. It is evident from these figures that the above denoised images using our proposed method have better visual quality than that using VisuShrink. From the above results and analysis, we can say that our method outperforms over the VisuShrink and Mantosh method.

Conclusion

In this project, we have successfully reduced noise from noisy image. We compare our result with Mantosh and VisuShrink Denoising methods and get better result. We implement Gaussian noise in images of level 10db, 20db, 30db and 50 db. At all level we got significant noise reduction and better visual quality from noisy images.

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