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Image Enhancement by Thresholding on Wavelet Coefficient

M. E. Akbarpour, M. R. Karami Mollaei

Abstract: ***The different wavelet transform-based methods of the image De-noising by thresholding on wavelet coefficients are discussed in this paper. These methods include different ways of adaptive calculating of threshold value and also kinds of thresholdig function. After examining the existing methods, a simple and efficient method based on local features of each pixel has been proposed. At last the proposed method has been compared the other existing methods and it is obtained that the proposed method, despite of the simplicity, has the same efficiency as some of the common complex methods. In addition some times it has better response than the complex methods.***

Keywords: discreet wavelet transform (DWT), image enhancement, wavelet thresholding.

I. INTRODUCTION

If y, x and v are noised image, clean image and noise that is added with image respectively, it is known that:

$$y = x + v \tag{1}$$

If it is assumed that the added noise and the clean image are independent, the following equation can be derived [1, 2, 3]:

$$\sigma_y^2 = \sigma_x^2 + \sigma_v^2 \tag{2}$$

In which σ^2_y ، σ^2_x و σ^2_v are the variance of the noised image, the clean image and the noise added to image, respectively.
As it is understood from the relationship2, the estimate of added noise variance should be available to estimate cleaned image variance, therefore the wavelet transform is used for estimating this parameter. If we use wavelet transform for equation1 we have:

$$Y = X + V \tag{3}$$

In which Y, X and V are wavelet transform of y, x and v signals respectively. If wavelet transform is used on a two dimensional signal like image, we will face four subband images LL, HL, HH and LH.

The LL piece comes from low pass filtering in both directions and it is the most like original picture and so is called the approximation. The remaining pieces are called detailed components. The HL comes from low pass filtering in the vertical direction and high pass filtering in the horizontal direction and so has the label HL. The visible detail in the sub-image, such as edges, have an overall vertical orientation since their alignment is perpendicular to the direction, of the high pass filtering and they are called vertical details. The LH comes from low pass filtering in the horizontal direction and high pass filtering in the vertical direction and so has the label LH, called horizontal details. The HH comes from high pass filtering in the horizontal and vertical direction and so has the label HH. For two-level wavelet transform in the image, wavelet transform must be used again for LL1 [2, 3, 4].
Because HH1 coefficient shows the high frequency in image, in the other hand the noise in image contain high frequency, therefore these coefficients can be used for estimating added noise with image. For this reason noise variance which is estimated from the subband HH1, using the formula[1, 2, 3, 5]:

$$\hat{\sigma}_v = \frac{median\left(\left|Y_{ij}\right|\right)}{0.675}\ ,\ Y_{ij} \in HH1 \tag{4}$$

Estimated variance of the noisy image also can be calculated by using the wavelet coefficient and it is described as [1, 2, 3]:

$$\hat{\sigma}_y^2 = \frac{1}{L}\sum_{i,j} Y_{ij}^2 \tag{5}$$

In which L is the number of all wavelet coefficient of noisy image, therefore the estimated variance of clean image can be derived as [1, 2, 3]:

$$\hat{\sigma}_x^2 = \max\left\{\sigma_y^2 - \sigma_v^2, 0\right\} \tag{6}$$

That max operator prevents the negative value for variance.

II. CALCULATING THE THRESHOLD VALUE:

One of methods for calculating of thresholdig value is Bayes shrink that threshold value is given as [1, 3]:

$$T_{BS} = \begin{cases} \dfrac{\hat{\sigma}_v^2}{\hat{\sigma}_x} & \hat{\sigma}_v^2 > \hat{\sigma}_y^2 \\ \max\left|Y_{ij}\right| & \hat{\sigma}_v^2 \geq \hat{\sigma}_y^2 \end{cases} \tag{7}$$

The second criterion in above equation prevents from infiniting of the amount of thresholdig value when estimated variance of noise is more than estimated variance of noisy image. Because in this condition according to the two above equation $\hat{\sigma}_x$ is zero. Noise effect on different frequency and so in various wavelet-level is different, therefore threshold value in various wavelet-level is different. In higher level,

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Mohammad Esmaeil Akbarpour, Dept. of Electrical Engineering, Shomal university, Amol, Iran.
M. R. Karami Mollaei, Faculty of Electrical & Computer Engineering, Noushirvani University of Technology**,** Babol, Iran.

threshold value should be decreased because there is a little noise in these levels. Therefore equation (7) corrected in the following form [1, 2]:

$$T_{MBS} = \beta T_{BS} \quad (8)$$

$$\beta = \sqrt{\frac{\log(L)}{2j}} \quad (9)$$

In which j is the wavelet-level number, this method is called modified Bayes shrink. Normal shrink method can reduce noise in higher level, and its relationship has been illustrated in following [1]:

$$T_{NS} = \lambda \frac{\hat{\sigma}_v^2}{\hat{\sigma}_y} \quad (10)$$

Where, the scale parameter λ is computed once for each scale using the following equation:

$$\lambda = \sqrt{\log(\frac{L_k}{J})} \quad (11)$$

Lk is the length of the subband at kth scale. and j is the number of wavelet-level. In addition to dependency of wavelet-level to level number, threshold value depends on the kind of the region that pixel is in. For example threshold value for edge pixels should be less than non-edge pixels.
Following equation is one based on number of level and the kind of the region [4]:

$$T = C_k \sigma_v - \left| AM_k \quad GM_k \right| \quad (12)$$

In which C_k is a coefficients depends on wavelet-level:

$$C_k = 2^{J-k} \quad (13)$$

AM_k and GM_k are arithmetic and geometric mean of kth wavelet-level respectively [4].

$$AM_k = \frac{1}{L_k} \sum_{i,j} Y_{ij} \quad (14)$$

$$GM_k = \prod_{i,j} Y_{ij}^{\frac{1}{L_k}} \quad (15)$$

In both of above equations:

$$Y_{ij} \in LL_k, HL_k, LH_k, HH_k$$

In addition to of methods that depend on wavelet-level, there is a general method called Donoho. In this method [5]:

$$T_{Universal} = \hat{\sigma}_v \sqrt{2\,Ln(L)} \quad (16)$$

This method is called visual shrink too.

III. THRESHOLDING FUNCTIONS:

The wavelet transform-based methods are mostly based on the thresholding on wavelet coefficient**,** to do this thing, first we use wavelet transform for the noisy image, then use thresholding on wavelet coefficients and finally we use inverse wavelet transform, for this modified wavelet coefficient. Therefore the major part of these things are thresholding. In last part we examined methods for calculating threshold value, in this part we should familiar the method of thresholding (thresholding function).

There are two famous thresholding function, hard thresholding function and soft thresholding function, that are explained with following equation [2, 3, 4, 5]:

$$\eta_{Hard}(Y_{ij}) = \begin{cases} Y_{ij} & \left|Y_{ij}\right| > T \\ 0 & \left|Y_{ij}\right| \le T \end{cases} \quad (17)$$

$$\eta_{Soft}(Y_{ij}) = \begin{cases} Y_{ij} - T & \left|Y_{ij}\right| > T \\ 0 & \left|Y_{ij}\right| \le T \end{cases} \quad (18)$$

Expect two above thresholding functions we can name Garrote and semi-soft thresholdig functions [5].

Problems of above functions are discontinuing in threshold point, so many changes around threshold point, unused space and so many changes of wavelet coefficient. For solving these problems Zhang proposed his thresholdig function, he presented the first thresholding function in 1998 that is so-called Zhang1998 [5]:

$$\eta_{Zhang1998}(Y_{ij},k) = \begin{cases} Y_{ij} + T - \frac{T}{2k+1} & Y_{ij} < -T \\ \frac{1}{(2k+1)T^{2k}} Y_{ij}^{2k+1} & \left|Y_{ij}\right| \le T \\ Y_{ij} - T + \frac{T}{2k+1} & Y_{ij} > T \end{cases}$$

(19)

In above relationship k parameter determines the amount of function curvature then he represented his second thresholding function in 2001 that is so-called Zhang2001:

$$\eta_{Zhang2001}(Y_{ij}) = Y_{ij} + 0.5\left[\sqrt{(Y_{ij} - T)^2 + \lambda} - \sqrt{(Y_{ij} + T)^2 + \lambda}\right] \quad (20)$$

As we said before, in calculating threshold value, region of pixel and so the neighbors of pixel are important and efficient.
Therefore it is better that in thresholding function, wavelet coefficient of the neighbors of pixel should be used. Therefore the neighborhood thresholding function was proposed in 2008 [6]:

$$\eta_{Neighborhood}(Y_{ij}) = \begin{cases} 0 & aT^2 > S_{ij}^2 \\ Y_{ij}\,(1 - a\frac{T^2}{S_{ij}^2}) & otherwise \end{cases} \quad (21)$$

$$S_{ij}^2 = \sum_{i=\ B}^{B} \ \sum_{j=\ B}^{B} Y_{i-k,\,j-k}^2 \quad (22)$$

In above relationship B is a parameter that indicates the number of neighborhood pixels. In 2009, Nasri and Nezamabadipour proposed a new thresholding function that in fact is combination of hard and soft thresholding function [5].

$$\eta_{Nasri...}(Y_{ij}) = \begin{cases} Y_{ij} - 0.5\frac{T^2}{Y_{ij}} & \left|Y_{ij}\right| > T \\ 0.5\frac{Y_{ij}^3}{T^2} & \left|Y_{ij}\right| \le T \end{cases} \quad (23)$$

The following thresholdig function also has been proposed by them having three criterions [5]:

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$$\eta_{\text{Im proved Nasri...}}(Y_{ij},m,n)=\begin{cases} Y_{ij}-0.5\dfrac{kT^{m}}{Y_{ij}^{m-1}}+(k-1)T & Y_{ij}>T \\ 0.5\dfrac{k\left|Y_{ij}\right|^{n}}{T^{n-1}}sign(Y_{ij}) & \left|Y_{ij}\right|\leq T \\ Y_{ij}+0.5\dfrac{k(-T)^{m}}{Y_{ij}^{m-1}}-(k-1)T & Y_{ij}<-T \end{cases} \quad (24)$$

m, n and k are three parameters that affect on amount of function curvature, the meaning of T is $T_{\text{Universal}}$. In this method in addition to continuing in threshold point, function change should be continuing too. Therefore the following relationship is obtained between three parameters [5]:

$$n=m+\frac{2-k}{k} \quad (25)$$

By combining of two above equation it can be expanded to:

$$\eta_{\text{Im proved Nasri...}}(Y_{ij},m,n)=\begin{cases} Y_{ij}-0.5\dfrac{kT^{m}}{Y_{ij}^{m-1}}+(k-1)T & Y_{ij}>T \\ 0.5\dfrac{k\left|Y_{ij}\right|^{m+[(2-k)/k]}}{T^{m+[(2-2k)/k]}}sign(Y_{ij}) & \left|Y_{ij}\right|\leq T \\ Y_{ij}+0.5\dfrac{k(-T)^{m}}{Y_{ij}^{m-1}}-(k-1)T & Y_{ij}<-T \end{cases} \quad (26)$$

IV. PROPOSED METHOD:

In the above methods, the HH1 wavelet coefficients are used to estimate the noise variance. These coefficients are obtained by using the wavelet transform on all pixels of an image. Accordingly, it is possible that the estimates obtained are not accurate enough for all parts and regions of an image. Because some areas of the image such as edges, have some features that other areas do not have them. Thus, the estimate on all areas of an image is obtained; it can not provide necessary details for this area. On the other hand, the existence of the edges in an image, prevents accurate calculation of the threshold value for non-edges area. For above reasons and in order to calculate the noise variance locally, for noisy image at first block scheduling is necessary and then we calculate the variance of noise in each block.

$$\hat{\sigma}_{v,b}=\frac{median\left(\left|Y_{ij,b}\right|\right)}{1.25}\ ,\ Y_{ij,b}\in HH1_{b} \quad (27)$$

In above method index b is number of block, for example $HH1_b$ is approximate coefficient for b block. This method in addition to increasing care in the estimating of the noise variance like the neighborhood shrink method only uses the neighborhoods of the pixel for calculating threshold value. Semi-soft thresholding function has been selected for the proposed method.

V. SIMULATION AND COMPARE METHODS:

if x and $\hat{x}$ are clean and enhanced images respectively, MSE is defined as [1, 2, 4]:

$$MSE=10\log\left\{\frac{1}{M}\sum_{i,j}\left[x_{ij}-\hat{x}_{ij}\right]^{2}\right\} \quad (28)$$

M is the total number of pixels of clean image, if this parameter is lower, it means that difference between clean and enhanced image is less. This parameter compares pixels, lightness intensity of images. Another similar parameter called LVMSE can compare neighborhood pixels variance [7].

$$LVMSE=\frac{1}{M}\sum_{i,j}\left[\sigma_{A}^{2}(x(i,j))\quad\sigma_{A}^{2}(\hat{x}(i,j))\right]^{2} \quad (29)$$

$\sigma_{A}^{2}(x(i,j))$ is the variance of neighborhood pixels of pixel(i,j) which are in a square window. SNR is a suitable parameter for comparing image De-noising methods. In SNR, the power ratio of clean signal to noise signal per unit is measured in decibels which is obtained from the following equation [1]:

$$SNR=10\log\left\{\frac{\sum_{i,j}\left[x_{ij}\right]^{2}}{\sum_{i,j}\left[x_{ij}-\hat{x}_{ij}\right]^{2}}\right\} \quad (30)$$

Improved SNR is ISNR which is obtained from [8]:

$$ISNR=10\log\left\{\frac{\sum_{i,j}\left[y_{ij}-x_{ij}\right]^{2}}{\sum_{i,j}\left[\hat{x}_{ij}-x_{ij}\right]^{2}}\right\} \quad (31)$$

Except the two above parameters, another parameter is used for comparing which is called SSIM. This parameter illustrates likeness between clean and enhanced image [9]:

$$SSIM=\frac{(2\mu_{x}\mu_{\hat{x}}+C_{1})(2\sigma_{x,\hat{x}}+C_{2})}{(\mu_{x}^{2}+\mu_{\hat{x}}^{2}+C_{1})(\sigma_{x}^{2}+\sigma_{\hat{x}}^{2}+C_{2})} \quad (32)$$

SSIM value is between 0 and 1. 1 means two images are completely the same. C_1 and C_2 are two low numbers for preventing denominator to be zero, and obtained from [9]:

$$C_{1}=(K_{1}N)^{2}\ ,\ C_{2}=(K_{2}N)^{2}\qquad K_{1},K_{2}<<1 \quad (33)$$

N is the maximum of change in lightness in the image, for example in a gray-scale image N is 255. By examining the above methods we understand that VS and NS threshold values are better than BS and MBS, furthermore hard thresholding function is better than soft thresholding function.

In table (1) hard thresholdig function is used for comparing efficiency of three threshold value (VS, NS and Am & GM) for cell image and Gaussian white noise with σ_v = 0.01. This comparison is based on five parameters MSE, LVMSE, SNR, ISNR and SSIM. In this comparison, for LVMSE method we use 7*7window.

Table (1): compare of calculating threshold value

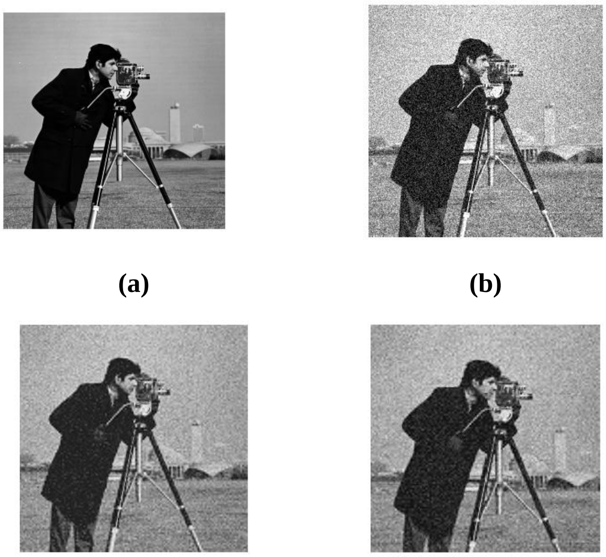
	MSE	LVMSE	SNR	1SSIM
Noisy	28.22	673.53	58.11	37%
VS	29.97	292.21	63.35	68%
NS	26.25	428.50	60.08	48%
AM & GM	22.75	236.41	63.59	68%

In table (2) with VS threshold value is used for comparing efficiency of five thresholding function (Hard, Zhang2001, Nasri…., improved Nasri…. And neighborhood shrink) for circuit image and Gaussian white noise with $\sigma_v = 0.01$. This comparison is based on five parameters MSE, LVMSE, SNR, ISNR and SSIM. In this comparison for LVMSE method we use 7*7window, too. In addition in this comparison we consider $\lambda = 10$, $n = 2$, $m = k = 1$, $B = 2$ and $a=1.05$.

Table (2): compare of different thresholdig function

	MSE	LVMSE	SNR	|ISNR|	SSIM
Noisy Image	31.11	714.61	56.73	0	84%
Hard	29.46	874.37	58.39	1.65	88%
Zhang2001	25.27	184.09	62.58	5.84	95%
Nasri …	24.75	376.70	63.10	6.35	96%
Improved Nasri…	22.70	179.94	65.16	8.41	96%
Neighbor … Shrink	22.28	178.94	65.57	5.57	96%

In table (3) the proposed method is compared with Nasri…. proposed method on three images Cameraman, Circuit and Coins, by keeping constant values of Table 2 and size of blocks are 64 × 64. It is seen that despite of simplicity in the proposed method, it is equal to the complex method, in terms of the quality of the improved image and even in some cases, it acts better. In Fig1, the proposed method has been compared with Nasri… proposed method for improving Cameraman noisy image.



(a) (b) (c) (d)

Fig (1): (a) clean image, (b) noisy image, (c) improved image by Nasri… proposed method, (d) improved image by proposed method

Table (3): Comparison of the proposed method with nasri and ... proposed method

Cameraman				
	MSE	LVMSE	SNR	SSIM
Noisy	30.52	770.59	59.69	91%
Improved Nasri…	23.96	388.58	66.75	97%
Proposed	23.56	359.85	66.65	97%
Coins				
	MSE	LVMSE	SNR	SSIM
Noisy	30.64	666.63	59.32	89%
Improved Nasri…	23.42	224.96	66.63	97%
Proposed	23.72	233.12	66.88	97%
Cicuit				
	MSE	LVMSE	SNR	SSIM
Noisy	31.11	714.61	56.73	84%
Improved Nasri…	22.70	179.94	65.16	96%
Proposed	22.56	210.63	64.92	96%

VI. RESULTS:

According to Table 1, which can be understood that calculating the threshold value with VS and NS methods, are better than BS and MBS methods in image improving.

On the other hand, with attention to table (2), it can be understood that Nasri ... proposed method and Neighborhood Shrink are better than other thresholding functions, because there are no thresholding functions discontinuity, dead space (Nasri... proposed method) and connecting between threshold value of each pixel to neighboring pixels (Neighborhood Shrink).

Accordingly, the proposed method by modeling of the table (1) and Neighborhood Shrink in using the VS threshold value and image blocking, through soft thresholding function is able to respond like complex methods and in some cases be better than them.

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