



## NOISE REMOVAL IN IMAGE BY SOFT THRESHOLDING TECHNIQUE

Y. Kumari and N. V. Seshagiri Rao

Department of Electronics and Communication Engineering, PSCMR College of Engineering and Technology, Vijayawada, AP, India  
E-Mail: [nvsrab@gmail.com](mailto:nvsrab@gmail.com)

### ABSTRACT

Image acquisition is the process of obtaining a digitized image from a real world source. Each step in the acquisition process may introduce random changes into the values of pixels in the image. These changes are called noise and to remove noise from images so many researchers proposed different methods and techniques. This article is presenting a technique called soft thresholding technique, which will remove the noise like discrete wavelet transform from the images.

**Keywords:** discrete wavelet transform (DWT) noise removal, soft thresholding, acquisition.

### 1. INTRODUCTION

There are three standard noise models which model well the types of noise encountered in most images: additive, multiplicative, and impulse noise.

Additive noise is independent of the pixel values in the original image. Typically  $n(x, y)$  is symmetric about zero. This has the effect of not altering the average brightness of the image, or large parts thereof. Additive noise is a good model for the thermal noise within photo-electronic sensors. Multiplicative noise, or speckle noise, is a signal dependent form of noise whose magnitude is related to the value of the original pixel. Multiplicative noise is an approximation to the noise encountered in images recorded on film slides and from synthetic aperture radar [1-3].

Impulse noise has the property of either leaving a pixel unmodified with probability  $1-p$ , or replacing it altogether with probability  $p$ . The source of impulse noise is usually the result of an error in transmission or an atmospheric or man-made disturbance. *Quantization noise* is due to the quantization of pixel values during the analog to digital conversion. For example, imagine an analog image with brightness values ranging from 0 to 10. If it is quantized to accuracy 0.1, the digitized image will have 101 distinct grey levels. A given intensity  $z$ , could have

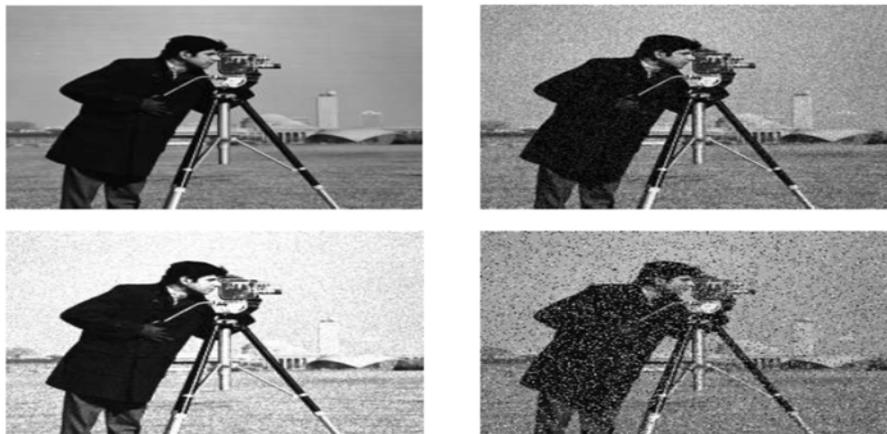
originally been anywhere in the range  $z \pm 0.05$ . This uncertainty in the true value of  $z$  is called quantization noise [4].

### 2. REMOVING NOISE BY LINEAR FILTERING

You can use linear filtering to remove certain types of noise. Certain filters, such as averaging or Gaussian filters, are appropriate for this purpose. For example, an averaging filter is useful for removing grain noise from a photograph. Because each pixel gets set to the average of the pixels in its neighbourhood, local variations caused by grain are reduced.

### 3. REMOVING NOISE BY MEDIAN FILTERING

Median filtering is similar to using an averaging filter, in that each output pixel is set to an average of the pixel values in the neighbourhood of the corresponding input pixel. However, with median filtering, the value of an output pixel is determined by the *median* of the neighbourhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values (called outliers). Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.



**Figure-1.** Different types of noise: (a) original image; (b) additive noise; (c) Multiplicative noise; (d) impulse noise.



#### 4. DISCRETE WAVELET TRANSFORM

The Wavelet Transform provides a time-frequency representation of the signal. A wavelet series is representation of a square-integral (real or complex value) function by a certain orthonormal (two vectors in an inner product space are orthonormal if they are orthogonal (when two things can vary independently or they are perpendicular) and all of unit length).

There are two classifications of wavelets, (a) orthogonal (the low pass and high pass filters have same length) and (b) bi-orthogonal (the low pass and high pass filters do not have same length). Based on the application, either of them can be used. The Wavelet transforms contribute to the desired sampling by filtering the signal with translations and dilations of a basic function called "mother wavelet". The mother wavelet can be used to form orthonormal bases of wavelets, which is particularly useful for data reconstruction [5].

In DWT, the most prominent information in the signal appears in high amplitudes and the less prominent information appears in very low amplitudes. Data compression can be achieved by discarding these low amplitudes [6-7]. The wavelet transforms enables high compression ratios with good quality of reconstruction. Recently, the Wavelet Transforms have been chosen for the JPEG 2000 compression standard. The discrete wavelet transform uses low-pass and high-pass filters,  $h(n)$  and  $g(n)$ , to expand a digital signal. They are referred to as analysis filters. The dilation performed for each scale is now achieved by a decimator [8]. For image enhancement different techniques are proposed by the researchers in the literature [9-12].

The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere, e.g. the dilation equation

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k) \quad (1)$$

where  $S$  is a scaling factor (usually chosen as 2). Moreover, the area between the function must be normalized and scaling function must be orthogonal to its integer translations, i.e.

$$\int_{-\infty}^{\infty} \phi(x) \phi(x + l) dx = \delta_{0,l} \quad (2)$$

There are several types of implementation of the DWT algorithm. The oldest and most known one is the Mallat (pyramidal) algorithm. In this algorithm two filters - smoothing and non-smoothing one - are constructed from the wavelet coefficients and those filters are recurrently used to obtain data for all the scales. If the

total number of data  $D = 2^N$  is used and the signal length is  $L$ , first  $D/2$  data at scale  $L/2^{N-1}$  are computed, then  $(D/2)/2$  data at scale  $L/2^{N-2}$ , ... up to finally obtaining 2 data at scale  $L/2$ . The result of this algorithm is an array of the same length as the input one, where the data are usually sorted from the largest scales to the smallest ones.

Within Gwyddion the pyramidal algorithm is used for computing the discrete wavelet transform. Discrete wavelet transform in 2D can be accessed using DWT module.

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. Within Gwyddion, the universal thresholding, scale adaptive thresholding [2] and scale and space adaptive thresholding [3] is implemented. For threshold determination within these methods we first determine the noise variance guess given by

$$\hat{\sigma} = \frac{\text{Median } |Y_{ij}|}{0.6745} \quad (3)$$

Where  $Y_{ij}$  corresponds to all the coefficients of the highest scale sub band of the decomposition (where most of the noise is assumed to be present). Alternatively, the noise variance can be obtained in an independent way, for example from the AFM signal variance while not scanning. For the highest frequency sub band (universal thresholding) or for each sub band (for scale adaptive thresholding) or for each pixel neighbourhood within sub band (for scale and space adaptive thresholding) the variance is computed as

$$\hat{\sigma}_Y^2 = \frac{1}{n^2} \sum_{i,j=1}^n Y_{ij}^2 \quad (4)$$

Threshold value is finally computed as

$$T(\hat{\sigma}_X) = \hat{\sigma}^2 / \hat{\sigma}_X \quad (5)$$

Where

$$\hat{\sigma}_X = \sqrt{\max(\hat{\sigma}_Y^2 - \hat{\sigma}^2, 0)} \quad (6)$$

When threshold for given scale is known, we can remove all the coefficients smaller than threshold value (hard thresholding) or we can lower the absolute value of these coefficients by threshold value (soft thresholding).



## 5. RESULTS AND DISCUSSIONS

### Basic steps are used to apply DWT in MATLAB

- a) Read an image.
- b) Convert an input image into a gray scale image.
- c) Perform a single-level wavelet decomposition (we get for information approximation, horizontal, vertical and diagonal details of an image)
- d) Construct and display approximations and details from the coefficients.
- e) To display the results of the level 1 decomposition.
- f) Regenerate an image by zero-level inverse Wavelet Transform.
- g) Perform multilevel wavelet decomposition.
- h) Extract approximation and detail coefficients. To extract the level 2 approximation coefficients from step 5.
- i) Reconstruct the Level 2 approximation and the Level 1 and 2 details.
- j) Display the results of a multilevel decomposition.
- k) Reconstruct the original image from the multilevel decomposition.

Figures 2 and 3 displayed images are decomposed into level 2 using DWT algorithm.



The dwt image



The soft thresholding idwt image



**Figure-2.** (a). Gray scale image, (b). Noise added image, (c). DWT image, (d). Soft threshold IDWT image.



The dwt image



The Hard thresholding idwt image



**Figure-3.** (a). Gray scale image, (b). Noise added image, (c). DWT image, (d). Hard threshold IDWT image.



The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. The two dimensional discrete wavelet transform is essentially a one dimensional analysis of a two dimensional signal. It only operates on one dimension at a time, by analyzing the rows and columns of an image in a separable fashion. The first step applies the analysis filters to the rows of an image. This produces two new images, where one image is set of coarse row coefficients, and the other a set of detail row coefficients. Next analysis filters are applied to the columns of each new image, to produce four different images called sub bands. Rows and columns analyzed with a high pass filter are designated with an H. Likewise, rows and columns analyzed with a low pass filter are designated with an L. For example, if a sub-band image was produced using a high pass filter on the rows and a low pass filter on the columns, it is called the HL sub-band.

When we apply high frequency (use high pass filter) on an image, there are high variations in the gray level between the two adjacent pixels. So edges are occurred in image. When we apply low frequency (use low pass filter) on an image, there are smooth variations between the adjacent pixels. So edges are not generated or very few edges are generated. All information of image is remaining same as real image information.

## 6. CONCLUSIONS

When we apply high frequency on an image, there are high variations in the gray level between the two adjacent pixels. So edges are occurred in image. When we apply low frequency on an image, there are smooth variations between the adjacent pixels. So edges are not generated or very few edges are generated. All information of image is remaining same as real image information. The discrete wavelet transform has a huge number of applications in science, engineering, and mathematics and computer science. The wavelet domain representation of an image, or any signal, is useful for many applications, such as compression, noise reduction, image registration, watermarking, super-resolution etc.

## ACKNOWLEDGEMENTS

Authors like to express their gratitude towards the department of ECE and management of PSCMR College of Engineering and Technology for their support and encouragement during this work.

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