Novel Image Denoising using TV Model and Coiflet Wavelet Decomposition

Syed Rameez Ali[1], Prof. Zuber Farooqui[2]
[1]M-Tech Research Scholar, [2]Research Guide, Department of Computer Science and Engineering
All Saints' College of Technology, Bhopal

***Abstract* - The denoising of images is novel techniques used in the various multimedia devices which offers post correction in captured images. For example Digital Cameras, Scanners, Mobiles etc. The main reason to research on such techniques is outdoor conditions are not in our control e.g. temperature, weather, moisture and air, which are the major causes of noises in the images captured. These different noises are collectively formulated as Additive White Gaussian Noises(AWGN). In this paper such scenarios are considered and developed a denoising technique which significantly improve the performance. The proposed methodology considered Total Variation Model followed by Coiflet Filter Decomposition with Hard thresholding.**

***Keywords* - AWGN, Coiflet, Total Variation(TV) Model, Denoising.**

I. INTRODUCTION

Wavelet theory is one of the most modern areas of mathematics. Masterfully developed by French researchers, such as Yves Meyer, Stéphane Mallat and Albert Cohen, this theory, is now used as an analytical tool in most areas of technical research: mechanical, electronics, communications, computers, biology and medicine, astronomy and so on. In the field of signal and image processing, the main applications of wavelet theory are compression and denoising.

In the context of denoising, the success of techniques based on the wavelet theory is ensured by the ability of de-correlation (separation of noise and useful signal) of the different discrete wavelet transforms [1, 2]. Because the signal is contained in a small number of coefficients of such a transform, all other coefficients essentially contain noise. By filtering these coefficients, most of the noise is eliminated. Thus, each method of image denoising based on the use of wavelets follows the classic method, in three steps: computing a discrete wavelet transform of the image to be denoised, filtering in the wavelet domain and the computation of the corresponding inverse wavelet transform. Throughout recent years, many wavelet transforms (WT) have been used to operate denoising. The first one was the discrete wavelet transform, [3]. It has three main disadvantages [5]: lack of shift invariance, lack of symmetry of the mother wavelet and poor directional selectivity. These disadvantages can be diminished using a complex wavelet transform [5, 4]. More than 20 years ago, Grossman and Morlet [6] developed the continuous wavelet transform [7]. A revival of interest in later years has occurred in both signal processing and statistics for the use of complex wavelets [8], and complex analytic wavelets, particularly in [9, 10]. It may be linked to the development of complex-valued discrete wavelet filters [11] and the clever dual filter bank [9, 7]. The complex WT has been shown to provide a powerful tool in signal and image analysis [12]. In [13], the authors derived large classes of wavelets generalizing the concept of 1-D local complex-valued analytic decomposition introducing 2-D vector-valued hyper analytic decomposition.

The present work is situated in this context, and, by introducing a new version of the Hyper analytic Wavelet Transform and by combining this transform with various parametric and non-parametric filtering techniques attempts to provide a solution to the denoising problem. The new transform, by allowing the use of all the mother wavelet families that are usually used with the discrete wavelet transform, while achieving the desirable properties of complex wavelet transforms, such as quasi shift-invariance and a good directional selectivity, in association with different filters selected has provided good denoising results both when applied to images affected by additive noise or by multiplicative noise, as is the case of SAR images.

II. WAVELET DECOMPOSITION

The term ‘wavelet’ refers to an oscillatory vanishing wave with time-limited extend, which has the ability to describe the time-frequency plane, with atoms of different time supports (see Fig.1). Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. They represent a suitable tool for the analysis of non-stationary or transient phenomena.

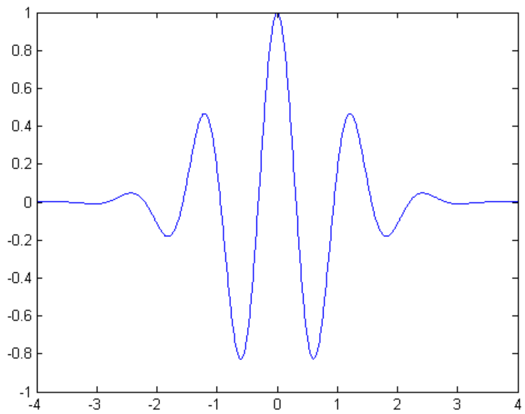


Fig. 1: Wavelet

Mathematically, the wavelet , is a function of zero average, having the energy concentrated in time:

$$\int_{-\infty}^{\infty} \psi(t)\, dt = 0$$

In order to be more flexible in extracting time and frequency informations, a family of wavelets can be constructed from a function *Ψ* (t), also known as the 'Mother Wavelet', which is confined in a finite interval. 'Daughter Wavelets', *Ψ* u;s (t) are then formed by translation with a factor u and dilation with a scale parameter s:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}} \cdot \psi\left(\frac{t-u}{s}\right)$$

Wavelet Transforms are adopted for a vast number of applications, often replacing conventional Fourier Transform.

Due to DWT's lack of redundancy and to the property to concentrate important data in a small number of coefficients (also known as 'sparsity'), it is very appropriate for signal and image compression. Compared to techniques previously used in compression, such as those using the Discrete Cosine Transform, wavelet-based coding [14] provides substantial improvements in picture quality at higher compression rates. One example of image compression is JPEG 2000, which uses biorthogonal wavelets. Another use is that of denoising data based on wavelet coefficients filtering [3]. By adaptively thresholding the wavelet coefficients that correspond to undesired frequency components smoothing and/or denoising operations can be performed. Besides compression and denoising, we can also use wavelets in image watermarking ([15]).

Apart from signal and image processing, wavelet transforms are starting to be used in communication applications where traditional FFT OFDM systems are losing field in favor of newer, more performance, Wavelet OFDM systems ([16]).

Coiflets:

Take a look at the discrete filters and the scaling/wavelet functions of Daubechies wavelets. These functions are far from symmetry. That's because Daubechies wavelets select the minimum phase square root such that the energy concentrates near the starting point of their support. Coiflets select other set of roots to have closer symmetry but with linear complex phase.

III. PROPOSED METHODOLOGY

An image is often corrupted by noise in its acquisition or transmission. The underlying concept of denoising in images is similar to the 1D case. The goal is to remove the noise while retaining the important signal features as much as possible.

The wavelet decomposition of an image is done as follows: In the first level of decomposition, the image is split into 4 subbands, namely the HH, HL, LH and LL subbands. The HH subband gives the diagonal details of the image; the HL subband gives the horizontal features while the LH subband represent the vertical structures. The LL subband is the low resolution residual consisting of low frequency components and it is this subband which is further split at higher levels of decomposition. The different methods for denoising we investigate differ only in the selection of the threshold. The basic procedure remains the same:

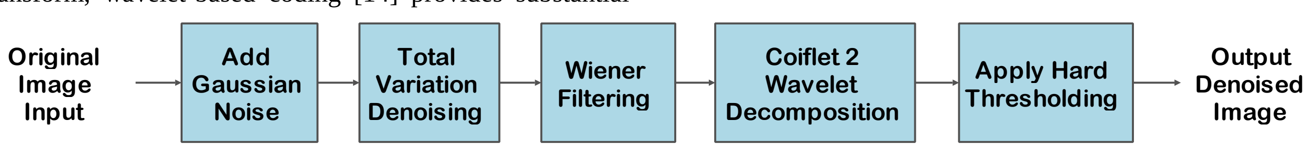


Fig. 2 Block diagram of the proposed denoising technique

Hard thresholding is found to introduce artifacts in the recovered images. Hard threshold is a "keep or kill" procedure and is more intuitively appealing. The transfer function of the same is shown in Fig 3.

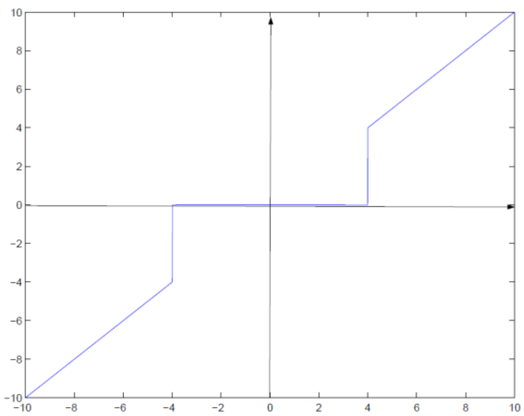


Fig. 3 Transfer function of hard thresholding

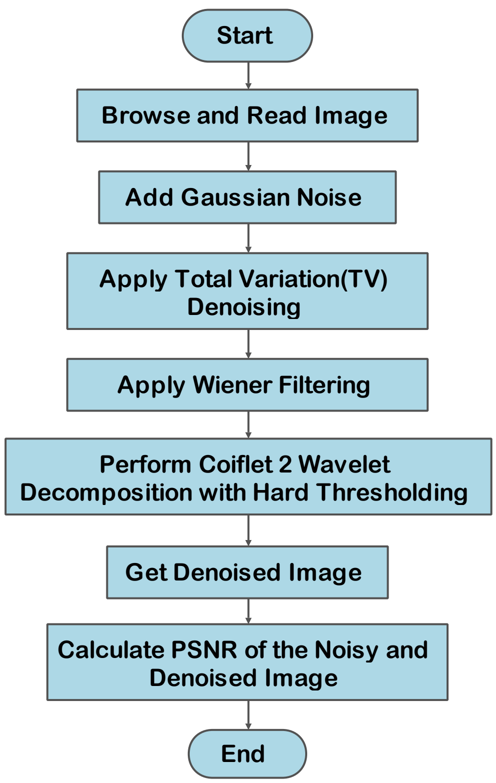


Fig. 4 Flow chart of the proposed denoising methodology

The simulation algorithm of the proposed denoising technique as a flow chart is given in the Fig. 4. The main steps are:

a. Start of simulation
b. Browse image and select for the denoising operation
c. Add Gaussian noise to make noisy image and save it
d. For the denoising approach first Total Variation (TV) model is applied with lambda=0.01
e. After that image is followed by Weiner filtering of 3x3 to remove small noises
f. Next step is to apply Coiflet2 wavelet decomposition with Hard Thresholding
g. Now we have Final Denoised Image and save it
h. Calculate PSNR of Noisy and Denoised Image for comparison
i. End of simulation

IV. SIMULATION RESULTS

The image denoising technique proposed and explained in the previous section is simulated on MATLAB R2011a and the outcomes of the various images is given below. The images taken for the experiments are grayscale images and these are: angela, palace (as taken in the existing work), lena, peppers, house etc. The results given below are contained three versions of each image. First image is original image(without any noise), second image is noisy image(after addition of Gaussian Noise) and last one is denoised image(after applying proposed TV and Coiflet based denoising technique)

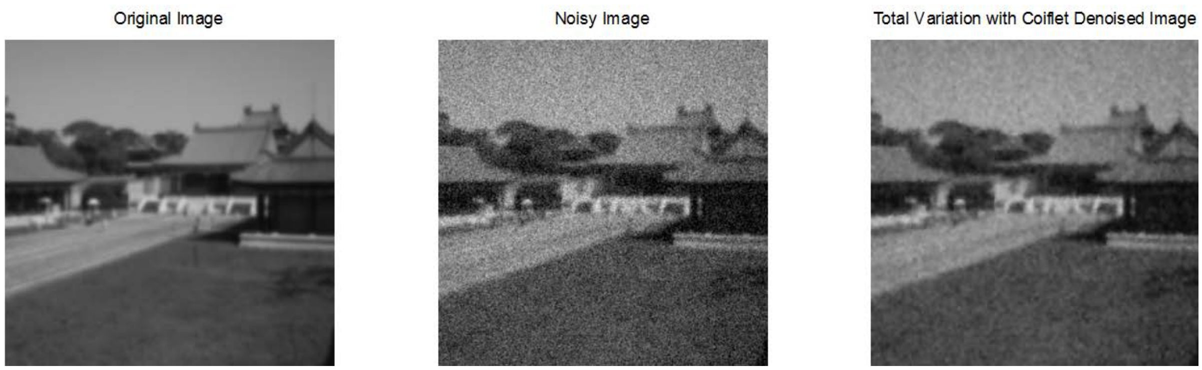
During the simulation of the proposed denoising technique PSNR is calculated after addition of Gaussian Noise and after applying denoising technique. The comparison table of PSNR calculated of noisy image, existing denoising technique and proposed denoising technique is given below in Table -I.

Table-I: PSNR comparison of various images

File	**Noisy Image**	**Existing Work**	**TV + Weiner + Coiflet Wavelet Decomposition**
Palace	21.879 dB	24.437 dB	32.091 dB
Angela	21.908 dB	26.270 dB	31.771 dB
House	21.847 dB	-	30.310 dB
Peppers	21.938 dB	-	28.182 dB
Lena	21.839 dB	-	27.900 dB


Original Image
Noisy Image
Total Variation with Coiflet Denoised Image

(a)


Original Image
Noisy Image
Total Variation with Coiflet Denoised Image

(b)

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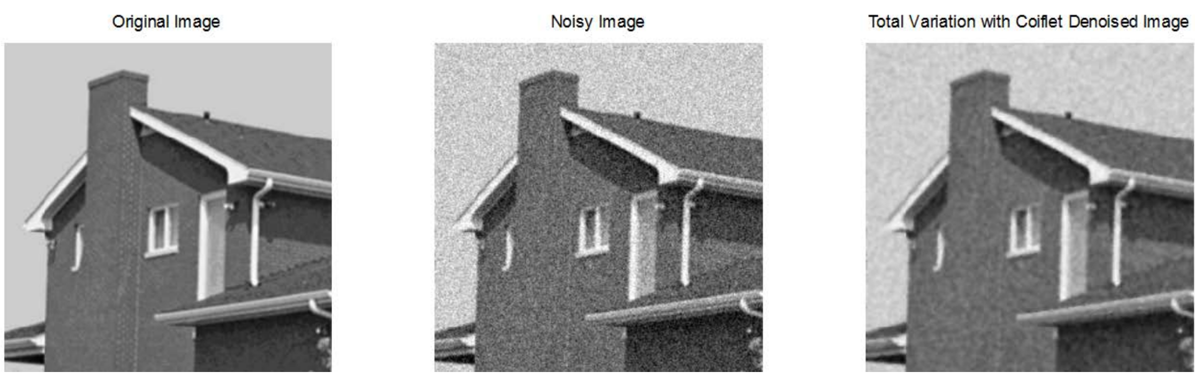
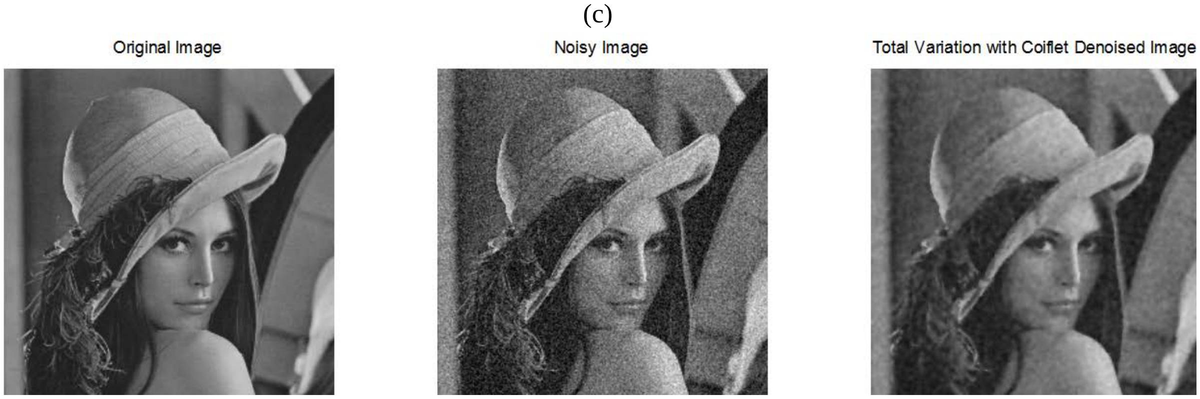
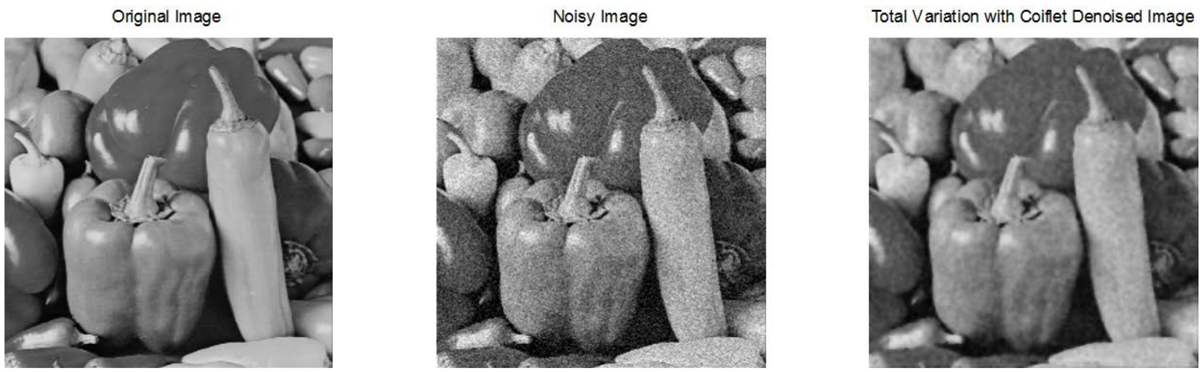

Original Image
Noisy Image
Total Variation with Coiflet Denoised Image

(c)


Original Image
Noisy Image
Total Variation with Coiflet Denoised Image

(d)



(e)

Fig. 5 Images at various stages (i-Original Image, ii-Noisy Image and iii-Denoised Image), (a) Angela, (b) Palace, (c) House, (d) Lena and (e) Peppers

From the Table-I it is clear that the PSNR for the proposed denoising technique is quiet better than the previous denoising technique. So it can be better implementable in imaging devices.

V. CONCLUSION AND FUTURE SCOPE

The denoising techniques are the most efficient way to remove noises in the imaging devices after taken or scanning picture. The denoising technique explained and simulated in this paper is shown the better performance compared to the existing denoising technique, the comparison is shown in terms of peak signal to noise ratio(PSNR). The PSNR for angela image is achieved 31.551dB which is 5dB more than the existing value, and for palace image is 31.830dB which is about 7db more than existing value. So it can be say that the proposed methodology is preferable over existing technique. In the future denoising techniques proposed methodology will play a very important role such that the TV model can be replaced by any other efficient method to improve the denoising performance of the method.

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