Efficient Image Denoising using Coiflets Filters and Thresholding

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Abstract - There are several research has been carried out to make digital imaging system better and better. The increasing trends of imaging devices is making image processing research to explore more facilities with automatic image denoising imaging system in digital capturing devices for images and videos. Such research is very useful in the denoising of medical images where the limitation of the particular imaging devices always exists. In this paper an efficient denoising technique is proposed by utilizing the Coiflets Filters of discrete wavelet transform (DWT). The proposed approach is having two Coiflet Filters connected in series with soft thresholding to reduce the effect of gaussian noises of various intensities.

Keywords - Coiflet Filters, Soft Thresholding, DWT and Denoising.

I. INTRODUCTION

A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained [2]. Degradation comes from blurring as well as noise due to electronic and photometric sources. Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus [1]. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contribute to the degradation.

Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality.

Image denoising is the problem of finding a clean image, given a noisy one. In most cases, it is assumed that the noisy image is the sum of an underlying clean image and a noise component, see Fig.1.1. Hence image denoising is a decomposition problem: The task is to decompose a noisy image into a clean image and a noise component. Since an infinite number of such decompositions exist, one is interested in finding a plausible clean image, given a noisy one. The notion of plausibility is not clearly defined, but the idea is that the denoised image should look like an image, whereas the noise component should look noisy. The notion of plausibility therefore involves prior knowledge: One knows something about images and about the noise. Without prior knowledge, image denoising would be impossible.

During any physical measurement, it is likely that the signal acquisition process is corrupted by some amount of noise. The sources and types of noise depend on the physical measurement. Noise often comes from a source that is different from the one to be measured (e.g. read-out noise in digital cameras), but sometimes is due to the measurement process itself (e.g. photon shot noise). Sometimes, noise might be due to the mathematical manipulation of a signal, as is the case in image deconvolution or image compression.

noisy = clean + noise

Fig. 1.1 A noisy image is assumed to be the sum of an underlying clean image and noise

Often, a measurement is corrupted by several sources of noise and it is usually difficult to fully characterize all of them. In all cases, noise is the undesirable part of the signal. Ideally, one seeks to reduce noise by manipulating the signal acquisition process, but when such a modification is impossible, denoising algorithms are required.

The characteristics of the noise depend on the signal acquisition process. Images can be acquired in a number of ways, including, but not limited to: Digital and analog cameras of various kinds (e.g. for visible or infra-red light), magnetic resonance imaging (MRI), computed tomography (CT), positron-emission tomography (PET), ultra sonography, electron microscopy and radar imagery such as synthetic aperture radar (SAR).

The following is a list of possible types of noise.

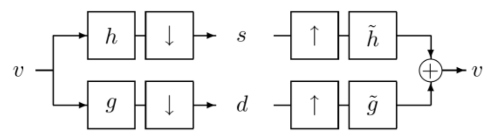
- Additive white Gaussian noise
- Photon shot noise
- Thermal noise
- Salt-and-pepper noise
- Compression artifacts
- Rician noise
- Colored noise

II. COIFLET FILTERS

Over the last two decades, wavelets have gained a lot of popularity and become a standard tool for many disciplines. Despite all the attention, it can be difficult to obtain filter coefficients for even the most commonly used wavelets.

- Wavelets are indexed by the number of vanishing moments.
- Wavelets can have more than one name
- There are different conventions for filter scale factors.

Let h and g be the wavelet decomposition (analysis) filters, where h is a lowpass filter and g is a highpass filter. Let the dual filters h˜ and ˜g be the wavelet reconstruction (synthesis) filters. One stage of decomposition followed by reconstruction is.



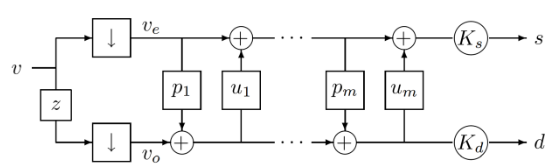
The wavelet filters h, g, h˜, ˜g must satisfy the perfect reconstruction conditions,

$$\begin{aligned} h(z)\tilde{h}(z) + g(z)\tilde{g}(z) &= 2, \\ h(z)\tilde{h}(-z) + g(z)\tilde{g}(-z) &= 0. \end{aligned}$$

Scaling the filters by some scale factors α, β and shifting by some even integers 2j, 2k

$$\begin{aligned} h'(z) &= \alpha z^{2j} h(z), & g'(z) &= \beta z^{2k} g(z), \\ \tilde{h}'(z) &= \alpha^{-1} z^{-2j} \tilde{h}(z), & \tilde{g}'(z) &= \beta^{-1} z^{-2k} \tilde{g}(z), \end{aligned}$$

preserves the perfect reconstruction conditions. Exchanging the primal filters h, g with the dual filters h˜, ˜g also produces a valid wavelet.



Any FIR (compact support) wavelet transform can be expressed as a lifting scheme [2]. The lifting scheme analysis is described with a sequence of "predict" and "update" filters, denoted p1, p2, . . . for predict filters and u1, u2, . . . for update filters. After the filtering steps, xe is multiplied by Ks and xo is multiplied by Kd. For the inverse transform, undo the Ks and Kd scale factors, change additions to subtractions, and perform the filtering steps in the reverse order.

$$h(z) = \sum_k h_k z^{-k}, \qquad g(z) = zh(-z^{-1}),$$
$$\tilde{h}(z) = h(z^{-1}), \qquad \tilde{g}(z) = g(z^{-1})$$

Coiflet 1

$$\begin{aligned}
h_0 &\doteq -0.072\ 732\ 619\ 513,\\
h_1 &\doteq 0.337\ 897\ 662\ 458,\\
h_2 &\doteq 0.852\ 572\ 020\ 212,\\
h_3 &\doteq 0.384\ 864\ 846\ 864,\\
h_4 &\doteq -0.072\ 732\ 619\ 513,\\
h_5 &\doteq -0.015\ 655\ 728\ 135
\end{aligned}$$

Coiflet 2

$$\begin{aligned}
h_0 &\doteq 0.016\ 387\ 336\ 464,\\
h_1 &\doteq -0.041\ 464\ 936\ 782,\\
h_2 &\doteq -0.067\ 372\ 554\ 722,\\
h_3 &\doteq 0.386\ 110\ 066\ 823,\\
h_4 &\doteq 0.812\ 723\ 635\ 450,\\
h_5 &\doteq 0.417\ 005\ 184\ 424,\\
h_6 &\doteq -0.076\ 488\ 599\ 079,\\
h_7 &\doteq -0.059\ 434\ 418\ 647,\\
h_8 &\doteq 0.023\ 680\ 171\ 946,\\
h_9 &\doteq 0.005\ 611\ 434\ 819,\\
h_{10} &\doteq -0.001\ 823\ 208\ 871,\\
h_{11} &\doteq -0.000\ 720\ 549\ 445
\end{aligned}$$

III. PROPOSED DENOISING METHODOLOGY

The image denoising is performed in this paper is using Coiflet Filter of Wavelet Transform. Various image denoising techniques has been carried out with the wavelet filters and here the two Coiflet5 transforms with the soft thresholding working better to reduce the noise levels.

The block diagram of the proposed approach is given below. The main blocks are reading of image, adding of the gaussian noise of different intensities and Coiflet5 transforms with soft thresholding twice followed by the same and the denoised image is in the output.

The above proposed denoising methodology is implemented using an algorithm on simulation tool which is explained in the below steps:

a) Start simulation
b) Browse an image want to transfer denoising on it
c) Read image (Load image in simulation environment)
d) Add Gaussian Noise of different intensitites
e) Save Noisy image
f) Calcualte PSNR of Noisy Image
g) Perform Wavelet Decomposition with Coiflet5 Filter and Soft Thresholding twice one by one
h) Save Denoised Image
i) Calculate PSNR to Check the effectiveness of the technique
j) End of Simulation

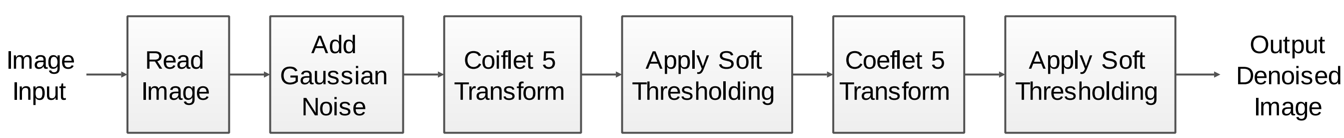


Fig. 3.1 Block Diagram of the Proposed Methodology

IV. SIMULATION RESULTS

Image denoising using the Coiflet5 Wavelet Filters Decomposition is performed on the standard grayscale images e.g. Lena, Barbara, Boats, House and Peppers are of size 512×512. All these images are attacked with the Gaussian Noises with standard deviation σ = 10, 20, 30, 40 and 50.

The results obtained after proposed denoising method are shown in the below figures. The proposed method is combine form of two Coiflet5 Wavelet Filters and Soft Thresholding.

From the Table I and From Table II it is clear that the proposed denoising method giving us better PSNR than the previous works performed on the standard images for image processing.

TABLE I: PSNR OF DIFFERENT GAUSSIAN NOISE LEVELS AND DENOISED IMAGE

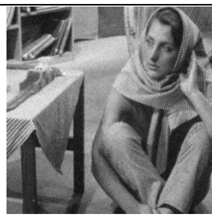
Gaussian Noise	σ =10	σ =20	σ =30	σ =40	σ =50
Noisy Image	 PSNR = 30.0dB	 PSNR = 27.0dB	 PSNR = 25.3dB	 PSNR = 24.0dB	 PSNR = 23.1dB
Denoised Image	 PSNR = 31.3dB	 PSNR = 29.3dB	 PSNR = 28.0dB	 PSNR = 27.0dB	 PSNR = 26.3dB

TABLE II: COMPARISON OF PSNR PERFORMANCE

Image	**Technique**	**PSNR (dB) of Denoised Image**				
		σ =10	**σ =20**	**σ =30**	**σ =40**	**σ =50**
Boats	Proposed	32.6	30.4	29.0	28.0	27.2
	Existing	32.3	29.0	27.1	26.0	24.9
Lena	Proposed	33.3	30.9	29.4	28.3	27.4
	Existing	33.9	31.0	29.7	28.4	27.0
Pepper	Proposed	33.9	31.2	29.6	28.5	27.6
	Existing	35.1	31.7	29.8	28.2	27.1
House	Proposed	35.7	32.8	31.0	29.9	28.9
	Existing	36.9	34.1	31.7	30.3	29.2
Barbara	Proposed	32.1	29.8	28.4	27.4	26.6
	Existing	31.7	29.4	26.9	24.5	24.1

V. CONCLUSION AND FUTURE SCOPE

The image denoising techniques using wavelet decomposition are used, but working towards the efficient techniques is always a need of research and development industry. In this paper the Coiflet Wavelet Filter is used to denoise the images affected by Gaussian Noise of different intensities. The percentage improvement from the previous method is about four percent. In the future the series of different wavelet filter followed by different thresholding technique will much more productive for the future denoising needs.

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