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Edge Preserving Image Denoising Using Wavelet Approach and Local Linear SURE Method

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Abstract

In this paper, we propose a new approach for performing edge-preserving image filtering. This paper deals with wavelet decomposition, local linear Stein's unbiased risk estimate as an estimator for the mean squared error from the noisy image only, we derive a simple explicit image filter which can filter out noise while preserving edges and fine-scale details. Moreover, this filter has a 6 db better PSNR and minimum Standard Deviation algorithm whose computational complexity is independent of the filtering kernel size; thus, it can be applied to real time image processing tasks. The experimental results demonstrate the effectiveness of the new filter for various applications, including noise reduction.

Index Terms: Edge-preserving image filtering, wavelet decomposition, local linear Stein's unbiased risk estimate (SURE).

1. Introduction

FILTERING is perhaps the most important operation of image processing and computer vision, and it is used extensively in a wide range of applications, including image smoothing and sharpening, noise removal, resolution enhancement and reduction, feature extraction, and edge detection. The simplest filtering should be explicit linear translationinvariant (LTI) filtering, which can be implemented using a convolution mask. For example, box filter, also known as "moving average," is implemented by a local averaging operation where the value of each pixel is replaced by the average of all the values in the local neighborhood. Box filter is the quickest blur algorithm, but its smoothing effect is often not sufficient. Another widely used LTI filter is Gaussian filter with the weights chosen according to the shape of a Gaussian function. Gaussian filter is a very good filter for removing noise drawn from a normal distribution. And the multi-scale space representation of an image can be obtained easily by Gaussian smoothing with increasing variance. Although LTI filtering is very simple and is used extensively in early vision processing, it also has some disadvantages. LTI filtering not only smooths the noise but also blurs important structures along with noise, and outliers exert large influence on filtered output.

To reduce these undesirable effects of linear filtering, a variety of edge preserving filtering techniques have been proposed over the past few years. Since taking into account local structures and statistics during the filtering process, edgepreserving filtering is non-linear and can preserve the image details and local geometries while removing the undesirablenoise. Most of popular filtering techniques in this class have been developed based on partial differential equations (PDE's) and variational models. For example, non-linear/anisotropic diffusions (AD) [1], as well as regularization methods based on the total variation (TV) [3], are most popular and widely used non-linear filtering methods in signal and image processing.

In general, an initial image is progressively approximated by filtered versions which are smoother or simpler in some sense. Actually, this process introduces a hierarchy into the image structures, thus one can use a scale-space representation for extracting semantically important information. These methods are very effective tools for edge preserving filtering, however they are implemented as an iterative process which is usually slow and may raise issues of stability. As a good alternative to the iterative algorithm, the bilateral filter was first termed by Tomasi and Manduchi [8] based on the work [5], [7], and later modified and improved in [9]. Since its formulation is simple, and method is non-iterative which achieving satisfying results with only a single pass, bilateral filtering has been proven to be a valuable tool in a variety of areas of computer vision and image processing [10]–[11]. However the direct implementation of bilateral filter is known to be slow. Although several techniques [12]–[14] are proposed to speed up the evaluation of the bilateral filter, its fast implementation is still a challenging problem. And it has recently been noticed that bilateral filter may have the gradient reversal artifacts in detail decomposition and high dynamic range (HDR) compression [15].

Recently, some novel edge-preserving smoothing filters have been proposed, including weighted least squares filter (WLS) [15], edge avoiding wavelets (EAW) [16], and domain transform (DT) method [17] to approximate geodesic distance by iterating 1D-filtering operations. In particular, based on a local linear model, He *et al.* [18] proposed a new filtering method - guided filter that can perform effective edge-preserving smoothing by considering the content of a guidance image. To avoid a trivial solution, He *et al.* introduced a regularization parameter which determines the amount of smoothing. Although edge-preserving smoothing filters are wildly used as useful tools for a variety of image editing and manipulation tasks, most of them are originally proposed to remove noise while preserving fine details and geometrical structures in the original image. It is well known that the denoising performance of an algorithm is often measured in terms of peak signal-to-noise ratio (PSNR). A higher PSNR would normally indicate that the reconstruction is of higher quality. To maximize the PSNR, an alternative approach is to minimize the mean square error (MSE) which can be estimated accurately by Stein's unbiased risk estimate (SURE) from the noisy image only. As it does not depend on a priori knowledge of the unknown signal, SURE has already turn out to be a flexible and effective tool which can be applied by directly parameterizing the estimator and finding the optimal parameters that minimize the MSE estimate. The best-known use of the SURE for wavelet denoising is Donoho's SureShrink algorithm [19]. Recently, an analytical form of SURE for the NLM algorithm has been derived [20] and further extended and studied [21]. In particular, Luisier *et al.* [22], [23] have proposed a very appealing denoising algrithm - Stein's unbiased risk estimator-linear expansion of thresholds (SURE-LET) and later been extended to color images, video and mixed Poisson Gaussian noise condition [24], [25]. Similar idea has been early and independently proposed by Pesquet and his collaborators [26], [27]. Inspired by the SURE-LET method and He's guided filter, we present a novel edge-preserving smoothing filter, called Wavelet based LLSURE filter which is based on a local linear model and the principle of Stein's unbiased risk estimate (SURE)[28]. In our case, input image is decomposed into level 1 using Haar Wavelet and then the filtered output in a local window are considered as a very simple affine transform of input signal in the same window, and the optimal transform coefficients are determined by minimizing the SURE. The Wavelet Based LLSURE filter has the edge preserving smoothing property that can filter out noise while preserving edges and fine scale details. Moreover, it is very simple and has an exact linear-time algorithm which can be applied to various image processing tasks.

2. Problem Formulation

2.1. Digital images and noise

The need for efficient image restoration methods has grown with the massive production of digital images and movies of all kinds, often taken in poor conditions. No matter how good cameras are, an image improvement is always desirable to extend their range of action.

A digital image is generally encoded as a matrix of grey level or color values. In the case of a movie, this matrix has three dimensions, the third one corresponding to time. Each pair (i; u(i)) where u(i) is the value at i is called pixel, for \picture element". In the case of grey level images, i is a point on a 2D grid and u(i) is a real value. In the case of classical color images, u(i) is a triplet of values for the red, green and blue components. All of what we shall say applies identically to movies, 3D images and color or multispectral images..The two main limitations in image accuracy are categorized as blur and noise. Blur is intrinsic to image acquisition systems, as digital images have a finite number of samples and must satisfy the Shannon-Nyquist sampling conditions. The second main image perturbation is noise.

2.2 Problem Setting

We consider the measurement model

yi = xi + ni , i = 1, . . . , N

where xi is the underlying latent signal of interest at a position i , yi is the noisy measured signal (pixel value), and ni is the corrupting zero-mean white Gaussian noise with variance σ2. The standard simplified denoising problem is to find a reasonably good estimate ˆ**x** of **x** = [x1, . . . , xN]T from the corresponding data set **y** = [y1, . . . , yN]T . To restate the problem more concisely, the complete measurement model in vector notation is given by

y = **x** + **n**.

2.3 Signal to Noise ratio

A good quality photograph (for visual inspection) has about 256 grey level values, where 0 represents black and 255 represents white. Measuring the amount of noise by its standard deviation, $\sigma(n)$, one can define the signal noise ratio (SNR) as

$$SNR = \frac{\sigma(u)}{\sigma(n)}$$

where $\sigma(u)$ denotes the empirical standard deviation of u,

$$\sigma(u) = \left(\frac{1}{|I|}\sum_{i\in I}(u(i) - \bar{u})^2\right)^{\frac{1}{2}}$$

and $\bar{u} = \frac{1}{|I|}\sum_{i\in I} u(i)$ is the average grey level value. The standard deviation of the noise can also be obtained as an empirical measurement or formally computed when the noise model and parameters are known.

The mean squared error (MSE) of the denoised image with respect to its noise-free version is

$$MSE(\hat{x}) = \frac{1}{N}\|x - \hat{x}\|^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2$$

Where $\|\cdot\|^2$ is the Euclidean norm.

In denoising applications, the performance is often measured in terms of peak signal-to noise ratio (PSNR), which can be defined as follows:

$$PSNR = 10log_{10}\,(\frac{MAX(x^2)}{MSE(\hat{x})})$$

The higher the PSNR is, the better the performance of denoising algorithm. Since **x** is the noise-free signal which does not affect the value of PSNR in any algorithm, maximizing PSNR is equivalent to minimizing MSE. However, one cannot approximate MSE without the original signal **x**.

3. Proposed Method

Basic steps for the proposed algorithm are as follows:-

Step-1 Image Acquisition
Step-2 RGB to Gray Scale Conversion
Step-3 Perform Discrete Wavelet Transform ie. Haar Wavelet
Step-4 Local Linear windowing
Step-5 Perform Thresholding using Sure shrink.
Step-6 Perform IDWT
Step-7 Edge detection
Step-8 Final Denoised Image

3.1 Haar Wavelet

Wavelets are functions generated from a single function by its dilations and translations. The Haar transform forms the simplest compression process of this kind. In 1-dimension, the corresponding algorithm [2] transforms a 2-element vector $[x(1), x(2)]^T$ into $[y(1), y(2)]^T$ by relation:

$$\begin{bmatrix} y(1) \\ y(2) \end{bmatrix} = T \begin{bmatrix} x(1) \\ x(2) \end{bmatrix}$$

where $\mathbf{T} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$

is an orthonormal matrix as its rows are orthogonal to each other (their dot products are zero). Therefore $\mathbf{T}^{-1} = \mathbf{T}^{\mathrm{T}}$ and it is possible [4] to recover **x** from **y** by relation

$$\begin{bmatrix} x(1) \\ x(2) \end{bmatrix} = \mathrm{T}^{\mathrm{T}} \begin{bmatrix} y(1) \\ y(2) \end{bmatrix}$$

In 2-dimensions **x** and **y** become 2 × 2 matrices. We can transform at first the columns of **x**, by pre-multiplying by **T**, and then the rows of the result by post-multiplying [4] by **T**T to find $\mathbf{y} = \mathbf{TxT}^{\mathrm{T}}$ and in the next step $\mathbf{x} = \mathbf{T}^{\mathrm{T}}\ \mathbf{yT}$ (3)

To show more clearly what is happening we can use a specific matrix **x** of the form

$$\mathbf{x} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

imlying that

$$\mathbf{y} = \frac{1}{\sqrt{2}} \begin{bmatrix} a+b+c+d & a-b+c-d \\ a+b-c-d & a-b-c+d \end{bmatrix}$$

These operations correspond to the following filtering processes:
Top left: 2-D lowpass filter (Lo-Lo).
Top right: horizontal highpass and vertical lowpass filter (Hi-Lo).
Lower left: horizontal lowpass and vertical highpass filter (Lo-Hi).
Lower right: 2-D highpass filter (Hi-Hi).
To apply this transform to a complete image grouping of pixels into 2 × 2 blocks is done .

3.2 Threshold Estimation
A great challenge in the wavelet shrinkage process is to find an adequate threshold value. A small threshold will hold the majority of the coefficients associated with the noisy signal, then resulting a signal that may still be noisy. On the other hand, a large threshold will shrink more coefficients, which leads to a smoothing of the signal that may suppress important features of the image.

Three threshold estimation criteria, called VisuShrink, SureShrink and BayesShrink, are described as follows.

VisuShrink is a thresholding scheme that uses a single universal threshold proposed by Donoho and Johnstone [4], defined as

$$\lambda_v = \hat{\sigma}_{noise}\sqrt{2\log L}$$

where $(\hat{\sigma}_{noise})^2$ is the estimated noise deviation and L = M ×N is the number of pixels in the image. The same threshold is applied to all levels of decomposition. Although the resulting image is very smooth and has a pleasant visual appearance, it is known that VisuShrink tends to oversmooth the signal [14].

SureShrink is a thresholding scheme that applies a subband adaptive threshold [6]. A separate threshold is computed for each subband based on Stein's unbiased risk estimator (SURE)

$$\lambda_S = \arg\min_{t\geq=0} SURE(t, Gs)$$

which minimizes the risk

$$SURE(t,GS) = N_S - 2[1 : NS] + \sum_{x,y=1}^{Ns}[\min(Gxy, t)]^2$$

Adaptive Edge-Preserving Image Denoising Using Wavelet Transforms (7) where G_S is the detail coefficients from subband S and N_S is the number of coefficients Gxy in $\{G_S\}$. As pointed out by Donoho and Johnstone [4], when the coefficients are not very sparse, then SureShrink is applied, if not, universal threshold is applied.

BayesShrink uses a Bayesian mathematical framework and assumes generalized Gaussian distribution for the wavelet coefficients in each detail subband to find the threshold that minimizes the Bayesian risk [3, 20], expressed as

$$\lambda_B = \frac{(\hat{\sigma}\text{noise })2}{\hat{\sigma}\text{signal}} = \frac{(\hat{\sigma}\text{noise })2}{\sqrt{\max\left((\hat{\sigma}\text{G })2-(\hat{\sigma}\text{noise }),0\right)}}$$

$$\hat{\sigma}_G{}^2 = \frac{1}{Ns}\sum_{x,y=1}^{Ns}(\text{Gxy})\text{^}2$$

and N_S is the number of wavelet coefficients G_{xy} on the subband under consideration. As it can be observed in the previous equations, most thresholding algorithms require an estimate of the noise variance.

For images, the noise level can be estimated from the highest frequency coefficients. A robust estimate of noise variance uses the median absolute value of the wavelet coefficients [32], which is insensitive to isolated outliers of potentially high amplitudes, defined as

$$\hat{\sigma}\text{noise} = \frac{\text{median(Gxy)}}{0.6745} \text{ and Gxy } \varepsilon \text{ subband HH}$$

where Gxy are the HH wavelet coefficients that form the finest decomposition level. It is assumed that the noise follows a Gaussian distribution with zero mean and variance σ^2.

4. Experimental Results

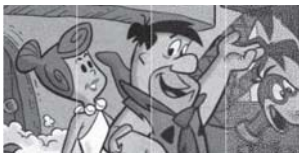
The simulation is done on MATLAB with Intel Pentium V Processor and 4 GB RAM. Three image denoising algorithms are carried out in these experiments: Bayes shrink algorithm, LLSURE and the proposed method. To measure the perceptual quality of images, the signal-to noise ratio (SNR) and standard deviation can be well used. PSNR will be measure in dB.

The results shown hereafter are obtained from previously described algorithms applied to noisy images. Many images have been tested , the result for each image in terms of PSNR and standard deviation is tabulated below:

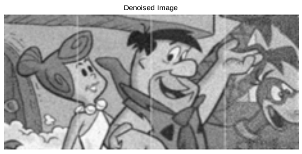
Sr. No	Methods	Standard Deviation	PSNR
1.	LLSURE	0.0871	36.3701
2.	Bayes shrink	0.15856	36.5824
3.	Proposed Method	0.0857	42.215

Sr. No	Methods	Standard Deviation	PSNR
1.	LLSURE	0.0316	60.840
2.	Bayes Shrink	0.12473	40.2545
3.	Proposed Method	0.0334	68.835

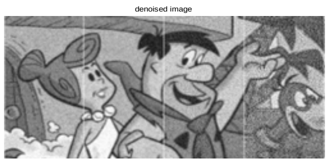
Input Image 1



Denoised image1 using LLSURE



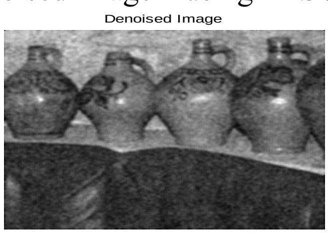
Denoised image1 using Bayes shrink



Denoised image1 using proposed method

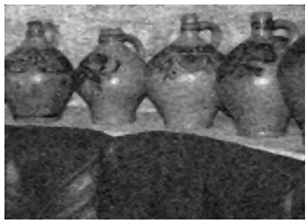
Input Image 2

Denoised image 2 using LLSURE



Denoised image 2 using Bayes shrink

Denoised image 2 using proposed method



5. Conclusion

The presented algorithm has shown a good response on preserving the edges on the input images. Further, the SURE based estimate is applied in HH sub-band of the wavelet decomposed image, the image is denoised as well. The high value of PSNR and low value of SD indicate that the resultant image is vary close to the original one and therefore information loss is minimum.

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