Denoising Filters Using Image Processing

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ABSTRACT:

In Research field is mainly challenge in digital image processing to remove noise from the original image. Image denoising is the manipulation of the image data to produce a visually high quality image In this paper, some important denoising techniques are discussed and classification of such techniques is listed.In this denoising algorithm various algorithm are produce the assumptions, advantages, applications and limitations. The denoising procedure which can be applied for the various types of noises. There are different types of filters like mean filter, median filter, bilateral filter, wiener filter etc. It is used to remove a tiny particles of noise such as salt and pepper noise, speckle noise, Gaussian noise , Rayleigh noise etc. But if the image is corrupted by mixed noise then these filters do not remove the noise exactly. But Image denoising promises good image outputs.

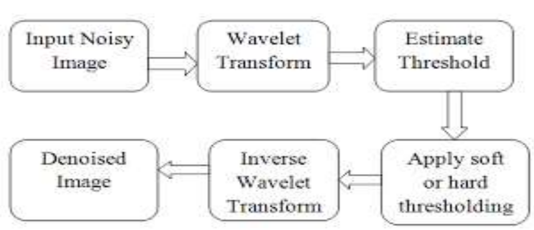
Keywords: Filters, Denoising algorithm, high quality image.

1.Introduction

The Main Thing in Image Processing is to denoise procedure is to reduce the noise level present in the image so as to produce the denoised image closer to the original image. Image Fusion is defined as the task or technique of combining two or more images into a single image. Image fusion is a emerging tool used to **increase the quality of image**. Image fusion increases reliability, decreases uncertainty and storage cost by a single informative image than storing multiple images.

Image fusion technique is of **two types** – Direct Image Fusion and Multi resolution Image Fusion. Multiresolution Image fusion techniques based on pixel level fusion methods. Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Datasets collected by image sensors are generally contaminated by noise.

"**Image denoising** is a restoration process, where attempts are made to recover an image that has been degraded by using prior knowledge of the degradation process".



Flow diagram of denoising images

2.Classification of Denoising Methods

There are two basic approaches to image denoising , **spatial domain filtering methods** and **transform domain filtering methods.**

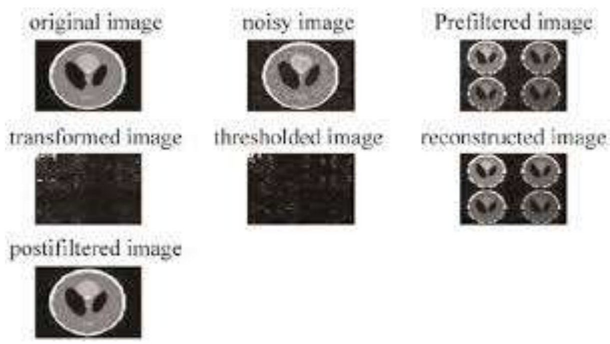


Fig.1 Classification of filtered images

3.Spatial Domain filtering Methods

David L Donoho[1] et.al A traditional way to remove noise from image data is to employ spatial filters. Spatial filters are further classified into two types of filters .There are **linear filters** and **non linear filters**.

3.1Linear Filters

Most classical linear image processing techniques are based on the assumption that image processing applications in which both edge enhancement and noise reduction are desired linear filters too t end to unsharp edges, destroy lines and other fine image details and perform badly in the presence of signal dependent noise.

3.2 Non Linear Filters

Non linear filters modify the value of each pixel in an image based on the value returned by filtering function that depends on the neighbouring pixels. Non linear filters are mostly used for noise removal and edge detection. The traditional non linear filters are the median filter. Non linear Spatial filters employ a low pass filtering on collection of pixels with the assumption that the noise occupies the higher region of frequency spectrum.Generally spatial filters remove noise to a valid reason to extent but at the cost of blurring images which in turn make the edges in pictures invisible.

4.The concept of denoising

L. Yaroslavsky [15] et.al A more precise explanation of the wavelet denoising procedure can be given as follows. Assume that the observed data is $X(t) = S(t) + N(t)$ where S(t) is the uncorrupted signal with additive noise N(t). Let $W(¢)$ and $W_{¡}1(¢)$ denote the forward and inverse wavelet transform operators.Let *D*(*¢; ¸*) denote the denoising operator with threshold ¸. We intend to denoise X(t) to recover ˆ *S*(*t*) as an estimate of S(t). The procedure can be summarized in three steps

$Y = W(X)$

$Z = D(Y;\ ¸)$

ˆ $S = W¡1(Z)$

D(*¢; ¸*) being the thresholding operator.

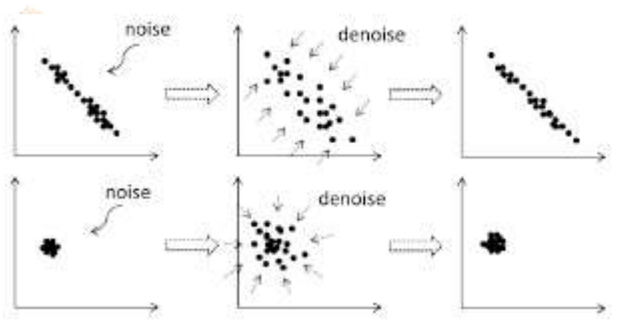


Fig.2 Concept of denoising

6.Color Image of Denoising using Edge detection

Color images contain better visual effects than gray image in terms of visual perception, and the edge information of color images is more abundant than in gray images. Ideally, when removing the additive noise from an image, as many of the important features as possible should be retained. The denoising of color images often results in **the loss of some edge and texture information**, making the image blurred and creating a poor visual effect.**Multi-scale edge detection algorithm** which took soft threshold method to implement detail enhancement and noise reduction of the true color image.

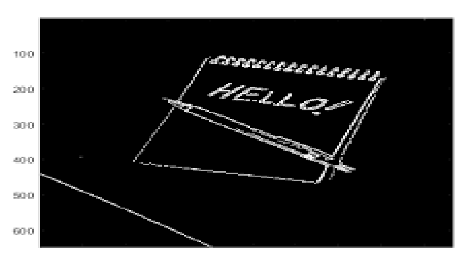


Fig.3 Edge detection

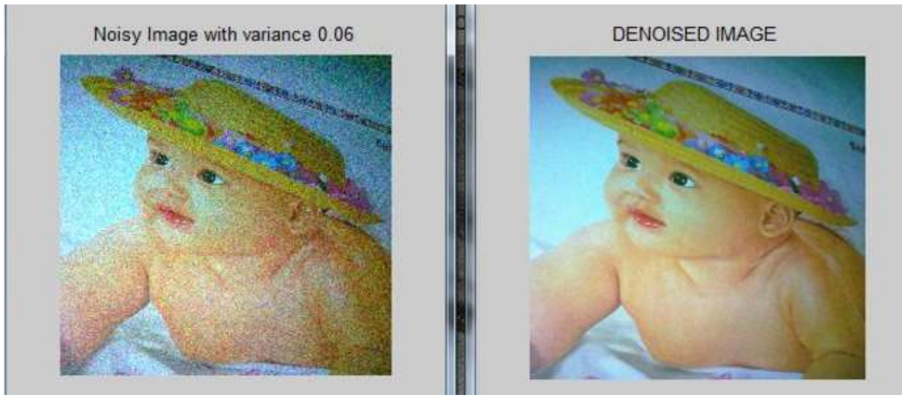


Fig.4: Noisy image into denoising image

7.Thresholding

Wavelet transforms enable us to represent signals with a high degree of scarcity. I. Johnstone [19]et.al Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising**.** Low-level process involves primitive operations such as image processing to reduce noise, contrast enhancement & image sharpening. A low- level process is characterized by the fact that both its inputs & outputs are images.

Let be an orthonormal basis of wavelets . Let us discuss two procedures modifying the noisy coefficients, called *wavelet thresholding methods* (D. Donoho et al. [11]). The firrst procedure is a projection operator which approximates the ideal projection (10). It is called *hard thresholding*, and cancels coefficiients smaller than a certain threshold .

Let us denote this operator by $HWT^1(v)$. This procedure is based on the idea that the image is represented with large wavelet coeffcients, which are kept, whereas the noise is distributed across small coefficients, which are cancelled. The performance of the method depends on the capacity of approximating *u* by a small set of large coefficients. Wavelets are for example an adapted representation for smooth functions.*Let u be an image defined in a grid I. The method noise of a hard thresholding*

Unfortunately, edges lead to a great amount of wavelet coeffcients lower than the threshold,but not zero. The cancellation of these wavelet coefficients causes small oscillations near the edges,i.e. a Gibbs-like phenomenon. Spurious wavelets can also be seen in the restored image due to the cancellation of small coefficients : see Figure 5. D. Donoho [10] showed that these effects can be partially avoided with the use of a soft thresholding,which will be denoted by $SWT^1(v)$. The continuity of the soft thresholding operator better preserves the structure of the wavelet coefficients, reducing the oscillations near discontinuities. Note that a soft thresholding attenuates all coefficients in order to reduce the noise, as an ideal operator does, the *L*2 norm of the method noise is lessened when replacing the hard by a soft threshold , for a comparison of the both method noises.In practice the optimal threshold ^{1} is very high and cancels too many coefficients not produced by the noise. A threshold lower than the optimal is used in the experiments and produces much better results,. For a hard thresholding the threshold is fixed to 3 sigma. For a soft thresholding this threshold still is too high ; it is better fixed at 3/2 sigma

The thresholding is classified into two categories.

A. Hard Thresholding

Hard thresholding can be defined as follow:

D (U, λ) = U for all |D|> λ (1.1)

= 0 otherwise

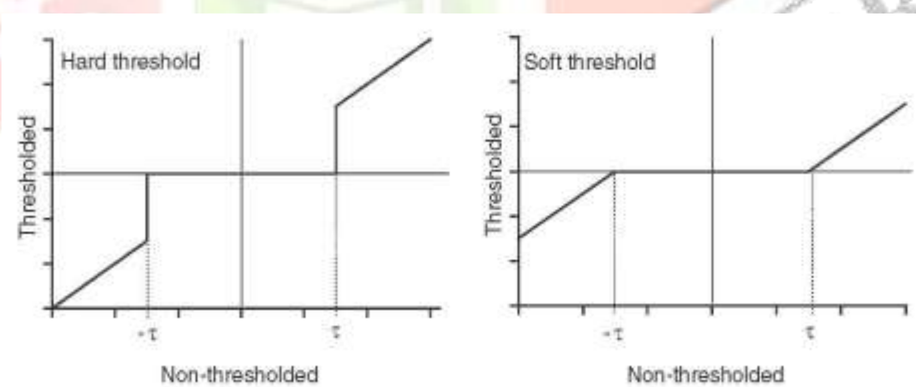
Hard threshold is a "keep or kill" procedure and is more intuitively appealing. The transfer function of the Hard thresholding is shown in the figure. Hard thresholding may seem to be natural. Hard thresholding does not even work with some algorithm such as GCV procedure. Sometimes pure noise coefficients may pass the hard threshold and appear as annoying „blips" in the output.

B. Soft Thresholding

Soft thresholding can be defined as follow:

D (U, λ) =sgn (U) max (0, |U|- λ) (1.2)

Soft threshold shrinks coefficients above the threshold in absolute value. The false structures in hard thresholding can overcome by soft thresholding. Now a days, wavelet based denoising methods have received a greater attention. Important features are characterized by large wavelet coefficient across scales, while most of the timer scales.



8.Conclusion:

Performance of denoising algorithms is measured using quantitative performance measures such as **peak signal-to-noise ratio** (PSNR), **signal-to-noise ratio** (SNR) as well as in terms of visual quality of the images. Many of the current techniques assume the noise model to be **Gaussian.*BayesShrink*** gave the best results. This validates the assumption that the GGD is a very good model for the wavelet coefficient distribution in a subband. Color transfer techniques and some typical image fusion methods based on color transfer the better signal to noise ratio and the detection accuracy.

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