SURVEY OF IMAGE DENOISING METHODS IN SPATIAL DOMAIN AND WAVELET DOMAIN

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Abstract

Images are often corrupted by noise due to errors generated in noisy sensors or communication channels. It is important to eliminate noise in the images before some subsequent processing. In this paper it is proposed to obtain the denoised estimate in spatial domain method using filters like mean filter, Gaussian filter, Weiner filter, median filter, midpoint filter, unsharp filter and progressive switching median filter and combination of these filters. Form the observations of PSNR for various filters, it is inferred that progressive switching median filter is suitable for denoising salt and pepper noise. These methods were simple and easy to apply but their effectiveness is limited since this often leads blur or smoothed out in high frequency regions. New and better approaches perform thresholding in wavelet domain of an image. The idea of wavelet thresholding relies on the assumption that the signal magnitude dominates the magnitude of the noise in wavelet representations, so that wavelet coefficients can be set to zero if their magnitudes are less than a predetermined threshold. In this paper it is proposed that VISU shrink is effective because it is not subband adaptive.

Key words: PSNR, progressive switching median filter, VISU shrink, SURE shrink, Bayes shrink

I. INTRODUCTION

The need for efficient image restoration methods has grown with massive production of photographs often taken in poor conditions or with deficient cameras or acquisition systems. Due to the nature of light, the amount of photons arriving to the camera fluctuates and these perturbations are called noise.

Image denoising is the basic problem in the area of image processing. The digital images play a vital role in day to day applications like medical imaging, astronomy. So there is a need for efficient restoration of the image. It is important to eliminate noise in the images before some subsequent processing such as edge detection, image segmentation and object recognition. Image denoising is a method of removal of noise while retaining as much as possible important information. It is the method of producing a good estimate of the original image from noisy observations. A traditional way to remove noise from image data is to employ spatial filters. With wavelet transform gaining popularity in the last two decades, various algorithms for denoising in wavelet domain were introduced. The most straight forward way of distinguishing information from noise in the wavelet domain consists of thresholding of wavelet coefficients.

II. METHODS AND MATERIALS

A. Spatial filtering techniques

There are a number of filters that can be employed for the purpose of obtaining a denoised estimate from a noisy image. The filters employed here include averaging filter, median filter, midpoint filter, Gaussian filter, Weiner filter and unsharp filter. These filters can be applied by varying the mask size or kernel size. Apart from this another filter employed here includes progressive switched median filter. These filters are applied either individually or along with another filter forming a combination or even performing the filtering operation with the same filter a number of times with the same filter till a better result is obtained. There are various types of noise that affect an image at various time of processing. In such a case a particular filter performs better for a particular type of noise and the other goes worse. The noises taken under consideration include Salt and pepper noise, Gaussian noise, Speckle noise and Poisson noise. One filter has its own advantage and disadvantage over the other filter.

Average Filter

The output or response of the averaging filter is simply the averaging of the pixels contained in the neighborhood of the filter mask. They are also referred to as low pass filters. The value of every pixel is replaced by the average of the gray levels in the neighborhood defined by the filter mask. Mean filtering is a simple, intuitive and easy to implement. In mean filters a single pixel with a very unrepresentative value can significantly affect the mean value of all the pixels in its neighborhood. When the filter neighborhood straddles an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output.

Gaussian Filter

Gaussian filter is a filter whose impulse response is a Gaussian function. A Gaussian filter modifies the input signal by convolution with a Gaussian function.

Weiner Filter

The filter is designed by minimizing the MSE between the restored image and the true image. The expression for the Weiner filter is given as

$$F(u,v)=\left(\frac{H^*(u,v)}{|H(u,v)|^2+K(u,v)}\right)G(u,v) \tag{1}$$

Where, H(u,v) is the degradation function

H*(u,v) is the complex conjugate of H(u,v)
|H(u,v)|^2= H(u,v) . H*(u,v)
K(u,v)= Sη (u,v)/ Sf (u,v)
Sη (u,v)= | N(u,v)|^2 is the power spectrum of noise
Sf (u,v)= |F(u,v)|^2 is the power spectral density of the un-degraded image.

In case of global Weiner filter this expression is used for the entire image and in case of local Weiner filtering technique it is applied on small blocks of an image at a time. It should be noted that the Wiener filter is derived under the assumption that the noise n is not correlated to the true image. Blur and speckles are also removed efficiently by using Weiner filter. Wiener filtering as a linear is often assumed to be unsuitable for images containing edges. The restored image generally exhibits artifacts due to the attenuation of high frequency components.

Median Filter

The median filter response is based on ordering the pixels contained in the image area encompassed by the filter and then replacing the value of the center pixel with the value determined by the ranking result. As the name implies this replaces the value of the pixel by the median of the gray levels in the neighborhood of the pixel. The original value of the pixel is also included in the computation of the median. Median filter belong to the class of edge preserving smoothing filters. Median filtering is comparatively better that mean filter since it preserves some useful details in an image. It helps in reducing mainly speckle and salt and pepper noise. Median filtering is also called rank filtering. The median is more robust average than the mean and so a single very unrepresentative pixel in a neighborhood will not affect the median value significantly. Since the median value must actually be the value of one of the pixels in the neighborhood, the median filter does not create new unrealistic pixel values when the filter straddles an edge. For this reason the median filter is much better at preserving sharp edges than the mean filter. One of the major problems with the median filter is that it is relatively expensive and complex to compute. To find the median it is necessary to sort all the values in the neighborhood into numerical order and this is relatively slow, even with fast sorting algorithms.

Midpoint Filter

Midpoint filters are those that replace the value of the pixel by the midpoint of the maximum and the minimum value of the pixels that are in a sorted order.

Unsharp Filter

The main principle of un-sharp masking is to extract high frequency information by subtracting the blurred version of the image from the image itself and add it onto the original image to enhance edges.

Progressive Switched Median Filter

The algorithm of this PSM filter consists the following two main points: switching scheme—an impulse detection algorithm is used before filtering, thus only a proportion of all the pixels will be filtered and progressive methods—both the impulse detection and the noise filtering procedures are progressively applied through several iterations. PSM filter is said to show better results because it has both impulse detector as well as noise filters and they are applied progressively in iterative manner. The pixels that are processed in the current iteration are used to alter the other pixel in the subsequent iteration. The advantage of this method is that the impulse pixels that are located in the middle of the blotches can be detected and filtered. The method is highly effective especially when the image is highly corrupted. The drawback is the time complexity due to numerous equations involved both in detection and correction phases. The process can't guarantee that all the uncorrupted pixels are identified. And the impulses can also be wrongly identified as uncorrupted pixels. Further the predefined threshold value employed to detect the corrupted pixels need not be an optimum noise detecting value since estimation of optimum threshold is difficult because it may vary from window to window.

B. Wavelet Domain Techniques

Denoising using wavelet transform can generally is carried out in three steps. A linear forward wavelet transforms followed by a non linear shrinkage of denoising and then by performing a linear inverse wavelet transform shown in Fig. 1.

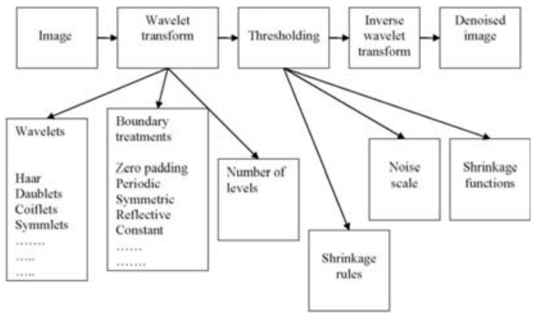

Fig. 1. Wavelet domain thresholding

The method of denoising using wavelet transform can be varied by varying the wavelets used in carrying out the wavelet transform, by varying the type of treatment in case of boundary pixels and finally by varying the level of decomposition. Further variations can be brought by varying the method of calculation of threshold, and also the method of applying threshold, and also the way of determining the noise scale. Several combination results in variation in the performance of a method for a particular type of noise.

Universal Thresholding

The threshold is given as

$$\lambda = \sigma\sqrt{2\ln N} \tag{2}$$

where N being the signal length, σ being the noise variance. It is the optimal threshold in the asymptotic sense and minimizes the cost function of the difference between the function and the soft threshold version of the same.

Visu Shrink

In Visu Shrink threshold is given by

$$\lambda = \sigma\sqrt{2\ln M} \tag{3}$$

where σ is the noise variance and M is the number of pixels in the image.

However, for denoising images, Visu Shrink is found to yield an overly smoothed estimate. Thus, the threshold does not adapt well to discontinuities in the signal.

SURE Shrink

SureShrink is a thresholding by applying subband adaptive threshold, a separate threshold is computed for each detail subband based upon SURE (Stein's unbiased estimator for risk), a method for estimating the loss.

$$SURE(t;X) = d - 2\#\{i : |X_i| \le t\} + \sum_{i=1}^{d} \min(|X_i|, t)^2 \tag{4}$$

For an observed vector x , x is the set of noisy wavelet coefficients in a subband, we could find the threshold that minimizes SURE .

$$t^S = \arg\min SURE(t;X) \tag{5}$$

The results are much better than Visu Shrink. The sharp features of image are retained. This because Sure Shrink is subband adaptive.

Bayes Shrink

BayesShrink is an adaptive data-driven threshold for image denoising via wavelet soft-thresholding. The threshold is driven in a Bayesian framework, and we assume generalized Gaussian distribution (GGD) for the wavelet coefficients in each detail subband and try to find the threshold T which minimizes the Bayesian Risk.
The reconstruction using BayesShrink is smoother and more visually appealing than one obtained using SureShrink.

Shrinkage Functions

Shrinkage functions are the ways in which the threshold is applied. They are classified as follows

• Hard threshold
• Soft threshold

Hard threshold

Hard threshold is kill or keep strategy. Here a wavelet coefficient is kept unchanged if it is larger in absolute value than a positive threshold lambda and it is set to 0 otherwise. Hard threshold can be given as

$$D(U,\lambda) = \begin{cases} U, \text{for all} |U| > \lambda \\ 0, \text{otherwise} \end{cases} \tag{6}$$

The hard threshold produces artifacts when the noise energy is significant. At times pure noise coefficients may pass the hard threshold and appear as annoying 'blips' in the output. Hard thresholding function is discontinuous at |X| = λ due to this it yields artifacts in the denoised signal when the noise level is significant. Hard thresholding is best in preserving edges but worst in reducing noise.

Soft Threshold

A wavelet coefficient is shrunk towards 0 if its absolute value than a positive threshold lambda and it is set to 0 otherwise. Soft threshold can be given as

$$D(U,\lambda) = \text{sgn}(U)\max(0, |U| - \lambda) \tag{7}$$

Soft threshold is used to achieve near minmax rate. Soft threshold yields visually pleasing images. And also that at times the noise coefficients pass through in case of hard threshold whereas soft threshold shrinks these false structures

Soft thresholding makes the algorithm more mathematically traceable whereas hard thresholding is not applicable for certain algorithms.. Soft thresholding would introduce more error or bias than hard thresholding does. On the other hand soft thresholding is more efficient in denoising. Soft thresholding is best in reducing noise but worst in preserving edges.

III. RESULTS AND DISCUSSION

The image quality is measured using the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR).

A. Mean Square Error

It is the square of the difference between the original image and the estimated image. For a given denoised estimate the MSE is given as

$$MSE = \frac{\Sigma[f(i,j) - F(i,j)]^2}{N^2} \quad (8)$$

where, f(i, j) is the original image,
F(I, j) is the estimated image ,
N is the number of pixels in the image,

B. Peak Signal to Noise Ratio

It is the ratio between the maximum possible power of a signal and the power of corrupting noise.

$$PSNR = 20\log_{10}\left(\frac{255}{MSE}\right) \quad (9)$$

When the two original and the estimated images are identical the MSE will be equal to zero, resulting in an infinite PSNR.

Table 1 displays PSNR values of cameraman image with salt and pepper noise, Gaussian noise, different spatial domain filters. For salt and pepper speckle noise and Poisson noise, progressive switched median filter is effective in obtaining the de-noised estimate and for other noises Weiner filter gives better result compared to other filters.

Table 1. PSNR values for the cameraman image influenced by various types of noise with variation in their variance and filtered using different types of filters.

Variance	Salt and pepper			Gaussian		Speckle		Poisson		
	.2	.3	.4	.01	.02	.03	.02	.03	.04	
Noisy Image	11.9927	10.2449	9.0280	20.2952	17.3919	14.6627	22.5748	20.7490	19.5209	27.2835
Spatial Filters										
Average	19.9386	18.4231	17.1798	24.2662	23.0383	21.3440	24.9557	24.5377	24.1343	25.5881
Gaussian	15.5068	13.6519	12.3565	23.6531	20.8911	18.2333	25.7742	24.1645	23.0094	29.4987
Weiner	18.9619	17.4708	14.8914	**26.0336**	**24.1712**	**22.1553**	**27.8611**	**26.4474**	**25.6985**	**30.2558**
Median	23.6346	21.1817	20.2957	24.0735	22.4089	21.0545	24.4334	23.5016	22.7549	26.3093
Midpoint	12.2287	11.9622	11.9642	21.3331	20.2194	18.7107	22.2781	22.2085	22.1342	22.2169
Unsharp	19.6403	17.8596	16.5128	25.0017	23.2775	21.6251	26.0714	25.3774	24.7635	27.1889
PSMF	**24.8031**	**22.9007**	**20.9441**	22.7371	21.2417	19.5053	23.2236	22.3814	21.7332	25.3359
Combination of Spatial Filters										
Average, Average	**20.2338**	**18.4532**	**17.1759**	23.9665	23.2229	22.1039	24.3804	24.1861	23.9890	24.6595
Gaussian, Gaussian	17.6567	15.7268	14.3614	**25.0280**	**23.7401**	**22.3354**	**26.6243**	**25.5064**	**24.8137**	**28.6983**
Weiner, Mean	20.1735	18.5448	17.2882	24.0020	23.2134	22.0863	24.4329	24.1904	23.9629	24.7866
Weiner, Gaussian	20.1733	18.4433	17.0963	23.6662	22.9935	21.9552	24.0425	23.8696	23.7027	24.2896
Unsharp, Mean	20.1540	18.3459	16.9595	24.1225	23.3042	22.1003	24.5770	24.3535	24.1283	24.9010
Unsharp, Gaussian	19.4803	17.5549	16.1470	24.9189	23.5634	21.8242	25.7156	25.2426	24.7985	26.4330

Table 2 shows the PSNR values of cameraman image influenced by salt and pepper noise, Gaussian noise, speckle noise and Poisson noise denoised by wavelet thresholding techniques using haar, db2, db4, sym8 and sym16 wavelets respectively. From the table it is inferred that VISU shrink gives high PSNR for Gaussian noise, speckle noise and Poisson noise and universal hard and soft thresholding is better for salt and pepper noise.

Table 2. PSNR values for the cameraman image influenced by various types of noise with variation in their variance and denoised using thresholding techniques making use of wavelets

wavelet	Salt and pepper		Gaussian	Speckle						Poisson
	.2	.3	.4	.01	.02	.03	.02	.03	.04	
	11.9319	10.2346	9.0082	20.2952	17.4324	15.7461	22.5349	20.7773	19.5300	27.3319
haar	**16.8701**	**15.0962**	**13.8858**	22.9270	21.2762	20.0776	24.3424	23.4185	22.7046	26.5856
Db4	**16.8717**	**15.0989**	**13.8325**	23.5880	21.3114	20.1696	24.3983	23.4274	22.7273	26.8123
Sym 16	**17.0888**	**15.2202**	**13.8519**	23.4702	21.6119	19.4049	24.7863	23.8662	23.1319	26.9894
haar	16.1899	15.0962	13.8858	23.2231	21.3478	20.0979	25.1165	23.9171	23.0295	28.0470
Db4	16.2527	15.093	13.8325	23.2692	21.3613	20.1713	25.1412	23.8355	22.9579	29.1219
Sym16	15.8501	15.2083	13.8519	23.6104	21.6483	19.4074	25.2035	24.0553	23.2582	28.1791
haar	16.5541	15.0843	13.8858	**23.4375**	**21.4802**	**20.1831**	**25.2294**	**24.0704**	**23.1535**	**29.1300**
Db4	16.8288	15.0873	13.8272	**23.5673**	**21.4919**	**20.2559**	**25.3118**	**24.0875**	**23.2456**	**28.1668**
Sym16	16.8906	15.1436	13.8078	**24.1049**	**21.8484**	**19.4462**	**25.8602**	**24.4871**	**23.5001**	**29.0849**
haar	13.2660	14.2475	13.8858	23.7179	21.4402	19.9936	25.1448	23.4795	22.6424	28.1053
Db4	15.5050	14.4421	13.3598	23.7668	21.3211	19.9216	24.9596	23.2719	22.0588	28.1588
Sym16	14.4103	13.4934	12.4962	23.2569	20.6659	17.9880	23.6741	22.0181	20.8361	28.6569
haar	11.9319	10.2346	9.0082	20.2952	17.4324	15.7461	22.5349	20.7773	19.5300	27.3319
Db4	11.9347	10.1882	8.9959	20.3082	17.3957	15.7967	22.5564	20.7771	19.5319	27.3576
Sym16	12.1009	10.1947	8.9284	20.3829	17.4618	14.6457	22.5520	20.8305	19.5802	27.3814
haar	11.9319	10.2346	9.0082	20.2952	17.4324	15.7461	22.5349	20.7773	19.5300	27.3319
Db4	11.9320	10.1872	8.9950	20.3019	17.3923	15.7940	22.5327	20.7610	19.5209	27.3146
Sym16	12.0894	10.1947	8.9208	20.3487	17.4382	14.6300	22.5066	20.7924	19.5473	27.2969
haar	11.9319	10.2346	9.0082	20.2952	17.4324	15.7461	22.5349	20.7773	19.5300	27.3319
Db4	11.9347	10.1882	8.9959	20.3082	17.3957	15.7967	22.5564	20.7771	19.5319	27.3576
Sym16	12.1009	10.1947	8.9284	20.3829	17.4618	14.6457	22.5520	20.8305	19.5802	27.3814
haar	11.9319	10.2346	9.0082	20.2952	17.4324	15.7461	22.5349	20.7773	19.5300	27.3319
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Sym16	12.1009	10.1947	8.9284	20.3829	17.4618	14.6457	22.5520	20.8305	19.5802	27.3814

The following figures 2 to 9 shows noisy and denoised images for salt & pepper noise, Speckle noise, Gaussian noise and Poisson noise by using PSMF, VISU shrink soft thresholding by wavelet sym16 and Weiner filter respectively.

Fig. 2. Image affected by salt and pepper noise

Fig. 3. Denoised Image by PSMF

Fig. 4. Image affected by Gaussian noise

Fig. 5. Denoised Image by Weiner filter

Fig. 6. Image affected by speckle noise

Fig. 7. Denoised Image using sim 16 by VISU soft

Fig. 8. Image affected by Poisson noise

Fig. 9. Denoised Image by Weiner Filter

IV. CONCLUSION

The main aim of the image denoising is to reduce these level while preserving the image features. In this paper denoised estimate is proposed using both spatial domain method and wavelet domain method. In spatial domain filters like mean filter, Gaussian filter, Weiner filter, median filter, midpoint filter, unsharp filter and progressive switching median filter and combination of these filters are used for denoising and peak signal to noise ratio is used as the performance measure. Form the observations of PSNR for various filters, it is inferred that progressive switching median filter is suitable for denoising salt and pepper noise, unsharp filter is better for Gaussian and Poisson noise and the combination of Gaussian and mean filter is best for speckle noise. Weiner filter is suitable for other noises. These methods were simple and easy to apply but their effectiveness is limited since this often leads blur or smoothed out in high frequency regions. New and better approaches perform thresholding in wavelet domain of an image. The idea of wavelet thresholding relies on the assumption that the signal magnitude dominates the magnitude of the noise in wavelet representations, so that wavelet coefficients can be set to zero if their magnitudes are less than a predetermined threshold. In this paper it is proposed that VISU shrink is effective because it is not subband adaptive.

REFERENCES

[1] Zhou Wang and David Zhang 1999. " Progressive switching median filter for the removal of impulse noise from highly corrupted images", IEEE Tran circuits and systems-II: analog and digital signal processing, vol. 46, no.1.

[2] S.Grace Change, Bin Yu and M. Vattereli, 2000, "Adaptive Wavelet Thresholding for Image Denoising and Compression," IEEE Trans. Image Processing, volume 9, pp 1532- 1546.

[3] David L Donoho,1995,"Denoising by soft thresholding", IEEE Transactions on Information Theory, 41(3): 613-627.

[4] S.Sudha, G.R. Suresh, R.Sukanesh, 2007, "Wavelet based image denoising using adaptive subband thresholding" International Journal of Soft Computing ISSN: 1816-9503.

[5] Nevine Jacob and Aline Martin, 2004, "Image denosing in Wavelet domain using wiener filtering".

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