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Comparison Study on Image Denoising Through Wiener Filter

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Abstract- **Denoising is used to remove the noise from corrupted image, while retaining the edges and other detailed features as much as possible. This noise gets introduced during acquisition, transmission, reception, storage and retrieval processes. Various image restoration techniques have been developed to restore an image degraded by noise. Up to now, most of the restoration filters have been investigated.**

Image denoising is a kind of processing of image which belongs to image restoration, and the ultimate goal of restoration techniques is to improve an image in some predefined sense. So denoising is the key step of image processing and recognition. A comparative study is being taken in account for all kind of denoising techniques introduced till now, specifically using non linear filters.

Keywords- Wiener filter, wavelet transform, wavelet domain, Soft thresholding, image denoising; psnr and rmse.

I. INTRODUCTION

a) Image noise

The principal sources of noise in digital images arise during image acquisition and transmission. The performance of imaging sensors is affected by a variety of factors, such as measuring method, and by the quality of the sensing elements themselves. For image noise, it can be described by two definitions: the noise is the factor which disturbs the recognition and understanding of image; the other is defined by mathematics, The noise may be considered random variables, characterized by a probability density
function (PDF) as Eq.(1).

$$p\left(\frac{x}{\alpha}, v, \eta\right) = \frac{2b}{\Gamma(\alpha)}\left(\frac{2\alpha x}{b\eta^2}\right)^{\alpha} I_o\left(\frac{v_x}{\eta}\right) k_{\alpha-1}\left(b\frac{x}{\eta}\right) \quad (1)$$

Where $b = \sqrt{4\alpha + v2\,\eta}$, η is ratio coefficient, v describes the coherence part of the echo signal. For the visible random noise, the number of noise particle is higher and α tends to infinity. For example the PDF of Gaussian noise is

$$P(z) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(z-\mu)^2/2\sigma^2} \quad (2)$$

Where z is gray level of image, μ is the mean of average value of z, and σ is its standard deviation. The squared value of standard deviation σ^2 is variance of z. According to the noise characters, the

random noise can be divided into two groups: additive noise and multiplicative noise as in Eq. (3).

$$\dot{f} = f.\, n_m + n_a \quad (3)$$

Where f is the spatial function of image function and the noise makes the image become to $\dot{f}$. η_m is multiplicative noise, η_a is additive noise.

b) Analysis of noise

Consider an image is corrupted with additive Gaussian White noise. Then the noisy image can be modeled as:

$$y(i,j) = x(i,j) + n(i,j) \quad (4)$$

Where y (i , j) is the noisy image, x (i , j) is the original image and n (i ,j) is additive gaussian white noise. The goal of image denoising is to suppress noise from noisy image with minimum mean square error. Here, the filter minimizes the mean square error between the estimated image x' (i , j) and the original image x(i , j). This error measure can be expressed as:

$$e^2 = E[(x(i,j) - \hat{x}(i,j))^2] \quad (5)$$

The PSNR (Peak Signal-to-noise Ratio) is selected as the evaluation standard of the denoised image quality here. PSNR represents the difference between two images. For the gray image, PSNR is

$$PSNR = 10\, log_{10} \frac{M.N.255^2}{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(x(i,j)-\hat{x}(i,j))^2} \quad (6)$$

Where M, N are the number of pixels each column and row, respectively, $x(i, j)$ and $\hat{x}(i, j)$ are the gray value of original and reconstructed image at (i, j) .

II. CONVENTIONAL WIENER FILTER

a) Wiener filter is founded on considering images and noise as random processes and the objectives is to find an estimate of the uncorrupted image such that the mean square error between them is minimized, i.e. Wiener filter can be considered as a linear estimating method. For a linear system with the unit sampling response, if the input is a random signal

$x(n) = s(n) + \upsilon(n)$, the output $y(n)$ can be described as

$$y(n) = x(n) * h(n) = \sum_{M=-\infty}^{+\infty} x(m)h(n-x) \qquad (7)$$

Where $s(n)$ is signal with no noise, $\upsilon\ (n)$ with noise. The ideal result is $y(n)$ approaching to $s(n)$ by the linear system, so $y(n)$ is called the estimate value of $s(n)$, and described as $s\hat{}(n)$, and Fig.1 shows the relation between input and output.

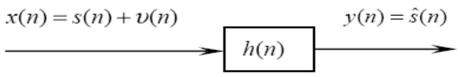

Fig.1. The principle of Wiener filter

b) The Wiener filter:- Reference from Gonzalez and Woods, book of digital image processing.

$$\frac{|H(\omega_1,\omega_2)|^2}{|H(\omega_1,\omega_2)|^2+\frac{p_n(\omega_1,\omega_2)}{p_f(\omega_1,\omega_2)}} \cdot \frac{1}{H(\omega_1,\omega_2)} \qquad (8)$$

III. COMPARITIVE STUDTY

This section describe the comparative study of various research work presented up till now.

1) A Modified Wiener Filter

FOR THE RESTORATION OF BLURRED IMAGES

a) Wiener filters give the linear least mean square estimate of the object image from the observations and have been used extensively for the restoration of noisy and blurred images.

b) The essential idea behind the Wiener filter is to make use of the information contained in the image at hand as well as in the imaging system used.

c) The conventional Wiener filters can be improved by taking the information contained in the Fourier transform of the blurring operator into account.

Explanation:- Sequential improvement using different methods:-

i) The optimal solution of the Wiener filter for the image model is determined uniquely by the power spectra p_f and p_n, and the Fourier transform H(w_f,w_z) of H. In image restoration, a number of variations of the Wiener filter have been proposed to improve its restoration performance [1]. One of the popular methods is to put

$$\frac{p_n(\omega_1,\omega_2)}{p_f(\omega_1,\omega_2)} \approx \frac{1}{SNR}$$

for all (w_1, w_2) in (8), where SNR, the signal to noise ratio is defined as

$$\text{SNR} = 10log_{10}\ \frac{variance\ \ of\ Hf}{variance\ \ of n}$$

This often gives a satisfactory result, for comparison purpose, this filter is denoted by,

$$L_1((\omega_1,\omega_2) = \frac{|H(\omega_1,\omega_2)|^2}{|H(\omega_1,\omega_2)|^2+\frac{1}{SNR}} \times \frac{1}{H(\omega_1,\omega_2)} \quad (9.a)$$

ii) In practice it is found that better results can be achieved if 1/SNR in (9.a) is modified to $\frac{\alpha}{SNR}$ with α determined by trial and error method. Where α is a regularization parameter. The resulting filter is denoted by

$$L_2(\omega_1,\omega_2) = \frac{|H(\omega_1,\omega_2)|^2}{|H(\omega_1,\omega_2)|^2+\frac{\alpha}{SNR}} \times \frac{1}{H(\omega_1,\omega_2)} \qquad (9.b)$$

iii) 'α' , Regularization techniques together with the rough substitution

$$\frac{p_n(\omega_1,\omega_2)}{p_f(\omega_1,\omega_2)} \approx \frac{1}{SNR}$$

for all $(\omega_1, \omega_2) \in D^e$ are used simultaneously to enhance the restoration capability of the Wiener filter. A modified Wiener filter:

$$L_3(\omega_1,\omega_2) = \frac{p_q(\omega_1,\omega_2) - \sigma_n^2}{p_q(\omega_1,\omega_2)} \cdot \frac{1}{|H(\omega_1,\omega_2)|}, (\omega_1,\omega_2) \in D$$

$$\frac{|H(\omega_1,\omega_2)|^2}{|H(\omega_1,\omega_2)|^2+\frac{\alpha}{SNR}} \cdot \frac{1}{H(\omega_1,\omega_2)}, (\omega_1,\omega_2) \in D^e \quad (9.c)$$

The region D and the regularization parameter α in the modified Wiener filter L3 shall be determined experimentally in order to obtain better restoration results.

Observation and suggestion:-

The denoising of an image is done by using approximation with the help of different kind of parameters which only helps to improve up to a certain level only.

Denoising must be improved at pixel level, i.e. at every pixel noise must be removed. Therefore need to divide an image in sub images so as to perform pixel level filtering.

2) Locally Adaptive Wiener Filtering In Wavelet Domain For Image Restoration

a) A Wiener filtering method in wavelet domain [2] is proposed for restoring an image corrupted by additive white noise.

b) The proposed method [3] utilizes the multiscale characteristics of wavelet transform and the local statistics of each subband. The size of a filter window for estimating the local statistics in each subband varies with each scale. The local statistics for every pixel in each wavelet subband are estimated by using only the pixels which have a similar statistical property.

c) Spatial averaging filter; a filter for combining multiple data sources, usually of the same type, by adding with weighted averages.

Merit's:- Good performance at white Gaussian noise

Demerit's:-edge blurring.

» Lee proposed [4] a spatially adaptive filter using local statistics in a window of fixed size, commonly referred to as a Lee filter.

Merit's:- This filter shows good performance in flat regions.
Demerit's:- Can't remove the noise well in edge regions which have significant information.
» Multiscale approach using wavelet analysis of signal and image is being using widely. In [5] proposed method is a locally adaptive Wiener filtering in wavelet domain which utilizes multiscale characteristics of wavelet transformed and local statistics in each sub band to suppress additive white noise in an image.

Explanation:- i) Noisy input image, converted from color to gray.
ii) Noisy input image is decomposed in to multiscale sub band by using wavelet transform.
iii) Wiener filtering applied in each sub band of wavelet domain.

Observation and Suggestion:-
since each local mean is not zero in the base band but nearly zero in wavelet sub band, the wavelet based wiener filter estimates each local mean in the baseband but does not so in wavelet sub band.
To improve accuracy, the filter must estimates the local variance in each wavelet sub band by using only that pixel which has a similar statistical property.

3) Image Denoising Via Wavelet - Domain Spatially Adaptive Fir Wiener Filtering
a) In conjunction with the coefficient-wise wavelet Shrinkage proposed by Donoho [6]. Whereas shrinkage is *as*ymptotically
minimax - optimal, in many image processing application a mean-squares solution is preferable.
b) The coefficient clustering often observed in the wavelet domain indicates that coefficients are not independent. Especially in the case of undecimated discrete wavelet transform (UDWT), both the signal and noise components are non-white, thus motivating a more powerful model.
c) Therefore proposes a simple yet powerful extension to the pixel-wise MMSE wavelet denoising. Using an exponential decay model for autocorrelations, here present a parametric solution for FIR Wiener filtering in the wavelet domain.

Explanation:- The solution takes into account the colored nature of signal and noise in UDWT, and is adaptively trained via a simple context model. The resulting Wiener filter offers impressive denoising performance at modest computational complexity. Simulation have been performed on various test images, all experiments use the 8-tap Daubcchies maximally smooth orthonormal wavelets, and the decompositions were 5 levels deep. All experiments were performed using undecimated discrete wavelet transform (UDWT).The results are compared in following three parameters which gives better denoising.
i) "sWiener" – Spatial wiener filtering[7] algorithm using matlab function wiener2 on UDWT coefficients.
ii) "HT" – It is the hard thresholding algorithm, also using UDWT.
iii) "wWiener" – It is the proposed FIR wiener filtering algorithm [8]. 'To limit infinit impulse response in undecimated wavelet transform, the FIR wiener filter has taken in account.

Observation and suggestion:-
On comparison of three techniques proposed in above method, it is clear that results are not satisfactorily improved. To improve result one can use ST (soft thrshholding) because hard thresholding exhibits spurious oscillations; soft thresholding avoids spurious oscillations. Similar to classical denoising methods (e.g., low pass filtering) there is a tradeoff between noise reduction and over smoothing of signal details.

4) Wavelet Domain Image Denoising by Thresholding and Wiener Filtering
a) The approximate analysis of the errors occuring in the empirical Wiener filtering is presented. The denoising performance of the Wiener filtering may be increased by preprocessing images with a thresholding operation.
b) The most common assumption in these models is that wavelet coefficients are conditionally independent Gaussian random variables, whose parameters are spatially varying. These parameters are estimated from the neighborhood. However, because of the limited size of the neighborhood, determined typically by a square-shaped windows of sizes 3 × 3, 5 × 5, 7 × 7, the problem of the accuracy of the estimate arises.
c) Therefore analyzing the influence of the signal power estimation error on the mean squared error (MSE) occurring in the local Wiener filter. We demonstrate that MSE may be decreased by prethresholding with an appropriate threshold.

Explanation:-
1) Applied Wiener filtering.
2) Wavelet applied on noisy image with wiener filtering. Wavelet used in it is [9] Daubechies "symmlet" with eight vanishing moments (Symmlet 8). 8-tap Daubechies is use because it is maximally-smooth. Orthonormal wavelets, and the decompositions were 5 levels deep.
3) The local wiener filtering without prethreholding. The method 'Th' wiener refers to the method proposed here with threshoding as a preprocessing step for Weiner filtering. Results from two other recently proposed denoising algorithms LAWMAP [10] and LCHMM [11], are also listed for comparison.

Observation and suggestion:-
The comparison is based on different types of algorithm and those results are compared with wavelet of single type only which is "Daubechies". The result of traditional Wiener filter depends on template selecting so much and can't fit for all noise in the image, so wavelet transform is adopted to improve the filtering result.

5) An Improved Wiener Filtering Method in Wavelet Domain

a) To improve visual quality, an improved Wiener filtering method is proposed based on wavelet transform. First, image noise is analyzed, and then the image corrupted by noise is given. The noisy image is denoised by the improved Wiener filtering method based on wavelet transform.

b) Now the main problem is to design the method which can filter most kinds of noise, so it need introduce new effective method and idea to improve the method. For the variety of noise distributing, a new multi-scale Wiener filtering method based on wavelet transform is presented.

c) Multi-scale Wiener filtering:- LL sub-image is the main part and it conclude most information of the image, while HL, LH and HH sub-images is more close to noise, so the new denoising method makes the high frequency parts as zeros, and processes the LL sub-image by Wiener filter with 3×3 template, then reconstructs image by wavelet inverse transform, and gets the denoised image.

Explanation:-

A little noise is still in the image after denoised by Wiener filter, because that the template is unchangeable and it can't fit for all noise in the image. The bigger the template is, the smoother the image is, but the more detail texture lost, while the smaller template with more noise keeps. Therefore a new denoised method is designed combined Wiener filter and wavelet transform. Wavelet transform has good localization properties both in space and frequency domains. Wavelet transform has recently emerged as promising technique for image procession, due to its flexibility in multi-scale solution representation of image signals, and high quality of the reconstructed image. The noisy image is decomposed into multi-scale representation

Merits;

1) Wavelet transform decomposed image into four sub images with different frequency characters, and make the image easy to denoise.

2) Some noise can be removed by wavelet transfom.

Demerits*;*

1) The operator quantity is reduced, because that Wiener filter just used to LL sub-image.

Observation and suggestion:-

The new method proposed in this paper will be repeated until the image should satisfy the requirements. The method is effective for noisy image especially for the image including more kinds of noise, so to have better result and to intensify the image denoised the soft thresholding method at LL frequency part can achieve batter image denoising.

6) A New Image Denoising Method Using Wavelet Transform

a) A New Image Denoising Method:-

i) This method decomposes the noisy image in order to get different sub-band image.

ii) Keeping the low-frequency wavelet coefficients unchanged, and after taking into account the relation of horizontal, vertical and diagonal high-frequency wavelet coefficients and comparing them with Donoho threshold, will make them enlarge and narrow relatively.

iii) Use [12] soft-threshold denoising method to achieve image denoising.

b) Due to the simple and effective algorithm, wavelet denoising methods based on hard-thresholding and soft-thresholding are widely used.

c) A new method of wavelet image denoising based on soft-thresholding image denoising and correlation of wavelet coefficients are proposed.

Wavelet Soft-Threshold Denoising Theory:-

Noise with the image through wavelet transforming, the wavelet coefficients which are on behalf of the original image information is larger, but the wavelet coefficients which are on behalf of the noise signal is relatively smaller [13]. By setting appropriate threshold, through removing the smaller than the absolute threshold wavelet coefficients which is regarded as noise and maintaining or shrinking the larger than the absolute threshold wavelet coefficients which is regarded as the important information of image.

Assuming no noise image is f. The image with noise is $\boldsymbol{g}$, the noise is $\mathcal{E}$, we get the image with noise model is $g = f + \mathcal{E}$ .The purpose of image denoising is to get a near image $\hat{f}$ of noise-free image f from the noising image g .The steps of wavelet threshold denoising as followed [14]:

1) Using orthogonal wavelet transform to the noising image g. Then choose appropriate wavelet and wavelet decomposition levels j to decompose the noising image. At last we get the corresponding wavelet coefficients $w_{j,k}$.

2) We use appropriate threshold to deal with the above wavelet coefficients $w_{j,k}$ and get wavelet coefficients estimated value $\widehat{w_{j,k}}$ .The soft-threshold method is:

$$\widehat{w_{j,k}} = \begin{cases} \operatorname{sign}(w_{j,k})(|w_{j,k}| - \lambda) & |w_{j,k}| > \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \quad (1)$$

In equation (1), λ is a choosing threshold.

3) Last we use inverse wavelet transform on the disposing to get the denoising image.

Explanation:-

1) Choose the single scale wavelet transform for the noisy image. Then maintain the low frequency wavelet coefficient.

2) Threshold λ set, if absolute [15] wavelet coefficients are larger than the absolute threshold, it will shrink them, or else, set them to zero.

Observation and suggestion:-

Enlarging part of the wavelet coefficients, then using traditional thresholding to denoise image. Dnoising effects are better than traditional wavelet soft thresholding image denoisng, especially in the edge and details of the image.

7) Performance Evaluation and Comparison of Modified Denoising Method and the Local Adaptive Wavelet Image Denoising Method.

a) The noisy image is denoised by modified denoising method which is based on wavelet domain and spatial domain and the local [16] adaptive wavelet domain.
b) Compared performances of modified [17] denoising method and the local adaptive wavelet image denoising method. These methods are compared with other based on PSNR (Peak Signal to Noise Ratio) between original image and noisy image and PSNR between original image and denoised image.
c) Simulation and experiment results for an image demonstrate that RMSE of the local adaptive wavelet image denoising method is least as compare to modified denoising method [18] and the PSNR of the local adaptive wavelet image denoising method is high than other method.

Explanation:-
Therefore two methods to improve the result is used:-
i) the adaptive wiener filter is employed to [19] suppress additive noise i.e, AWGN in noisy image.
ii) combination of wavelet and spatial domain adaptive wiener filtering.

Observation and suggestions:-
The performance of the local adaptive wavelet image denoising method is good compared to modified denoising method in terms of PSNR between denoised image and original image. Hence, from these results it can be concluded that the local adaptive wavelet image denoising method is more effective for suppression of noisy image with AWGN than others.

We will pursue the better expansible proportion of wavelet coefficients in order to get better denoising effects. It could be done at the 'LL' frequency component because wiener results conclude yet over the higher frequency sub images is quit got but at 'LL sub image part and, the PSNR and TMSE are not satisfactorily. So to improve that, a methodology suggested that fuzzy could be used over it, because fuzzy is a reasoning and fuzzy filters could improve results.

CONCLUSION:-

The denoising of image is initial step in image processing. The quality of the denoised image depends on the two major parts: wavelet transform for decomposition of image and adaptive wiener filtering in wavelet domain and spatial domain. Robustness and detail preservation are the two most important aspects of modern image enhancement filters. There are several methods for image denoising in spatial and transform domain. The current trends of the image denoising research are the evolution of mixed domain methods. Hence from this comparative study it can be concluded that the results are improving but need more enhancement at the tackling noise along with blurring, setting level-dependent thresholds as well as dealing with more complex corruptions. Future endeavors include better expansible proportion of wavelet coefficients in order to get better denoising effects using fuzzy filters.

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