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A Hybrid Method for Color Image De-noising

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Abstract: This paper proposes a comparison between adaptive wavelet thresholding, Non-Parametric Regression and Hybrid method based on SNR (Signal to Noise Ratio) and MSE (Mean Square Error). First method uses Wavelet Transform for de-noising of image. The proposed threshold is closed-form and simple, because it depends on data-driven estimates of the parameters so it is adaptive to each sub band. In second method, an image De-Noising procedure is proposed, based on Non-parametric estimation of a jump surface from noisy data. The third method is a hybrid of the above mentioned two methods. In this the output of adaptive wavelet thresholding method is fed as input to the Non-parametric regression method.

Keywords: Advance Adaptive Wavelet Thresholding.

Advance Adaptive Wavelet Thresholding

An image is often corrupted by noise in its transmission or acquisition. The goal of de-noising is to remove the noise while retaining the important signal features as much as possible. Traditionally, linear processing such as Wiener filtering is used to achieve this. A vast literature has emerged recently on signal using nonlinear techniques, in the setting of Additive White Gaussian Noise. The seminal work on signal denoising via wavelet thresholding or shrinkage of donoho and johnstone ([5], [6]) have shown that various Wavelet thresholding schemes for de-noising have nearoptimal properties in the minimax sense and perform well in simulation studies of onedimensional curve estimation. It has been shown to have better rates of convergence than linear methods for approximating functions in Besov spaces ([5], [6]). Thresholding is a nonlinear technique, yet it is very simple because it operates on one Wavelet coefficient at a time.

The proposed Bayesian risk minimization is sub-band dependent. Given the signal being generalized Gaussian distributed and the noise being Gaussian, via numerical calculation a nearly optimal threshold for softthresholding is found to be

$$T_B = \frac{\sigma^2}{\sigma_X}$$

Non Parametric Regression

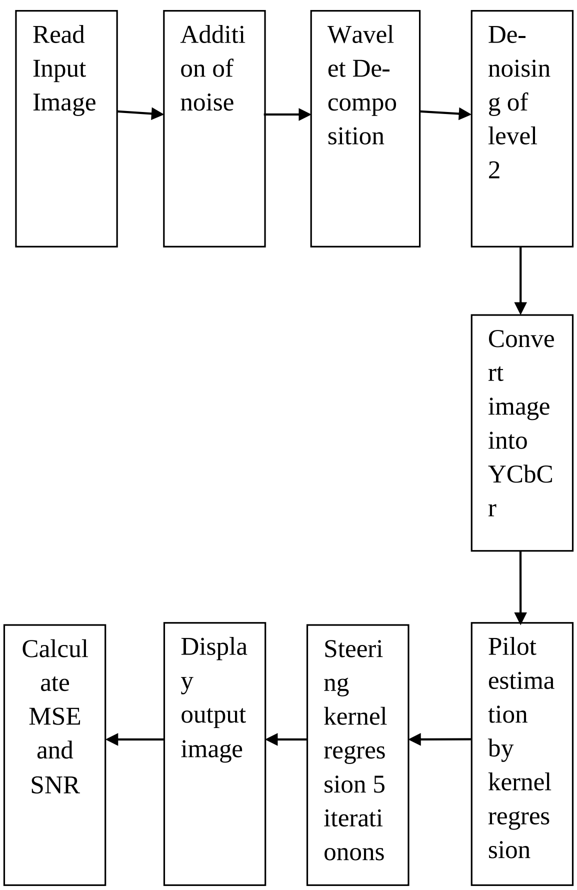
The second method to be implemented is called “Image denoising by Non Parametric Regression”.

In this method kernel regression is used. First, we estimate the gradients and compute the local covariance matrix c_i from the local gradient vectors for each pixel in the local analysis window ω_i around the position of interest. It should be noted that we compute the steering kernels $K_{Hi}(x_i - x)$ as a function of each x_i with the position of interest x held fixed. Thus, the kernel involves not only c_i at the position of interest but also its neighborhoods, and the steering kernel weights effectively take local image structures into account. Moreover, the steering weights spread wider in flat regions and spread along edges while staying small at the texture regions (for example the region around Parrot’s eye). Therefore, the pixels along the local structure are strongly smoothed by steering kernel filtering rather than across them.

Hybrid Method

The third proposed methodology is a hybrid method of the above discussed two algorithms in 4.4 and 4.5, so it is named “Hybrid method for color Image denoising”. In this method cascading of advance Adaptive Wavelet Thresholding and Non Parametric Regression is done. In this method the output of Advance Adaptive Wavelet Thresholding is fed to the Non Parametric Regression as input. The SNR (Signal to Noise Ratio) and MSE (Mean Square Error) of the methodology is calculated.

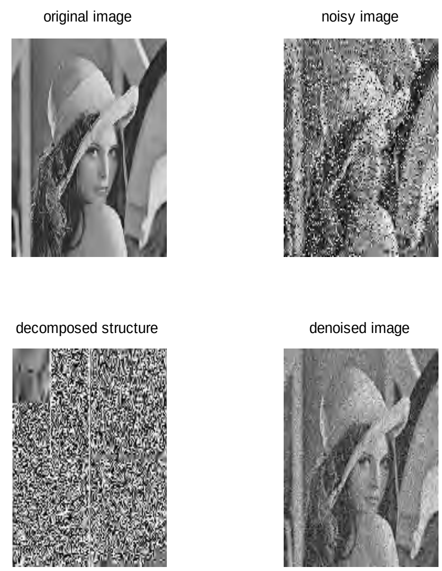
The hybrid method is a cascaded arrangement of the two methods discussed earlier. In this method the standard input image is read. This image is the original image with no noise. Noise of different types can be added to the original image to produce a noisy or corrupted form of the original image. In this work Salt and Pepper, Gaussian and Poisson noises are considered because these are the noises which are added in the process of transmission. Perform single level 2 dimensional Wavelet decomposition with respect to db2. In this work db2 family of wavelet is selected because by hit and trail it was found that this wavelet family gave the best result. Default values for de-noising are generated. In this method we are keeping the approximation coefficients after denoising process. De-noising of the image is performed. Soft thresholding type of wavelet thresholding is chosen. Perform denoising of the image obtained by Wavelet coefficient thresholding using global positive threshold. The wavelet decomposition is done in two levels. Two dimensional Fast Wavelet Transform is performed on the resultant at two levels. Display the Wavelet coefficients images. The displayed images include input image, noisy image obtained after adding noise, decomposed image in both the levels and final i=de-noised image. Convert the resultant image into YCbCr form from RGB form. Perform pilot estimation by second order classic kernel regression on luminance channel i.e. Y- channel.



Perform steering kernel regression of second order for five iterations. Display the output image. Calculate the final MSE (Mean Square Error) and SNR (Signal to Noise Ratio).

Image Outputs for Advance Adaptive Wavelet Thresholding

In this method Lena.png image is taken as the standard input (original) image shown in the top left side of Image 5.1. This Image is corrupted by Salt & Pepper noise with variance 0.2 and after addition of noise the input image looks as shown at top right side of Image 5.1. The 2- level decomposition of the noisy image is performed and can be seen in bottom left side of Image5.1. The final denoised image obtained as output is shown at the bottom right side of Image 5.1.

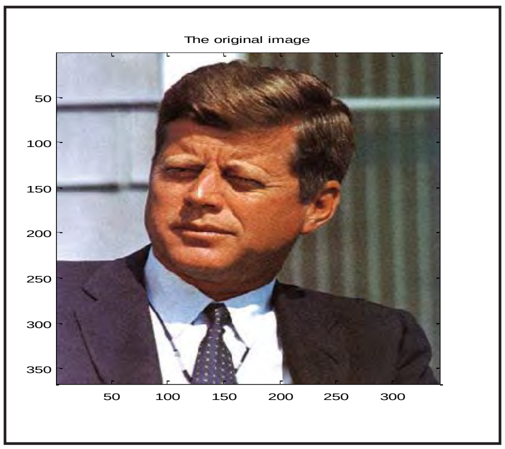


S. N o	Image	Noise	SNR	MSE
1.	Lena.png	Salt & Pepper noise, v=0.2	28.57 92	0.07 71
		Gaussian Noise, m=0,v=0 .01	35.42 28	0.04 19
		Poisson noise	39.40 17	0.03 19
2.	Boat.png	Salt & Pepper noise, v=0.2	28.30 31	0.08 42
		Gaussian Noise, m=0,v=0 .01	33.99 32	0.05 44
		Poisson noise	37.17 80	0.04 38
3.	House.png	Salt & Pepper noise, v=0.2	28.57 32	0.07 75
		Gaussian Noise, m=0,v=0 .04	34.79 21	0.04 46
		Poisson noise	38.79 21	0.03 42

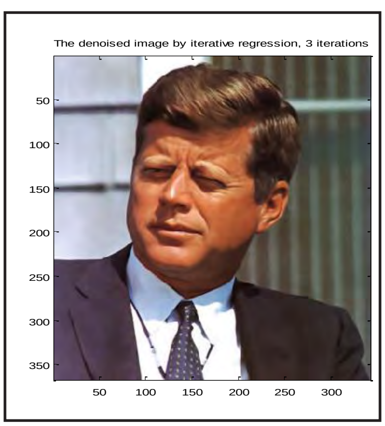
		Speckle Noise, m=0, v=0.04	34.35 71	0.04 65
4.	Cameraman .jpg	Salt & Pepper noise, v=0.2	27.01 40	0.10 48
		Gaussian Noise, m=0,v=0 .01	33.40 12	0.06 81
		Poisson noise	37.49 85	0.05 13

Image output of Non Parametric Regression

In this method kernel regression method is used. Iterative kernel regression method is used for three iterations. Image 5.5 denotes the original image given as input to this method. Image 5.6 is the output after 3 iterations and Image 5.7 shows the residual image in luminance channel.



The hybrid method is implemented on 4 images of jpg type. The following table shows the type of noise used to corrupt the image, SNR and MSE obtained.



The denoised image by iterative regression, 3 iterations

The hybrid method is implemented on 4 images of jpg type. The following table shows the type of noise used to corrupt the image, SNR and MSE obtained.

		.01		
		Poisson noise	37.20 65	144.74 31
3.	Peppers.jp g	Salt & Pepper noise, v=0.2	36.68 09	135.88 66
		Gaussia n Noise, m=0,v=0 .04	36.65 13	135.32 07
		Poisson noise	36.57 90	134.18 21
4.	Test_imag e.jpg	Salt & Pepper noise, v=0.2	36.53 97	133.99 07
		Gaussia n Noise, m=0,v=0 .01	36.48 78	132.91 35
		Poisson noise	36.55 0	133.90 62

S. N o	Image	Noise	SNR	MSE
1.	bellPepper. jpg	Salt & Pepper noise, v=0.2	39.53 97	133.99 07
		Gaussia n Noise, m=0,v=0 .01	38.89 51	175.43 6
		Poisson noise	38.96 27	176.79 47
2.	Mandrill.jp g	Salt & Pepper noise, v=0.2	37.19 41	144.54 16
		Gaussia n Noise, m=0,v=0	37.17 20	144.14 93

As observed the hybrid method for image de-noising outperforms all the other two methods. This fact is proved by the comparison tables of all the methods. The following conclusions can be drawn:

- Hybrid method performs well under Poisson noise, Salt and Pepper noise or Gaussian Noise unlike the other methods whose performance varies with type of noise.
- Best SNR values are observed in images when they are de-noised by Hybrid method.
- Use of kernel regression and Adaptive Wavelet Thresholding gives better results than the two methods individually.
- Advance Adaptive Thresholding method good SNR but its MSE can be improved.
- Non-Parametric Regression method gives visually pleasing images.

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