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NOISE REMOVAL OF DIGITAL IMAGES USING CYCLE SPINNING AND DWT

Ruhina Quazi#1, **Dr.Nidhi Tiwai**#2 Electronics & Communication Engineering, Sage University, Indore, India :[1]ruhinaquaziacet@gmail.com,[2]nidhitiwari.vlsi@gmail.com

Abstract. A wide range of techniques to collect input is through digital imaging devices such as cameras, keyboards, joystick, digitizers, scanners, radars, and many others. The majority of photos are taken using CIS (contact image sensors), CMOS sensors, and CCD (charge coupled devices). Noise is automatically introduced during image capture. Denoising algorithms, filtering, thresholding, and other techniques can be used to reduce image noise. However, this technique largely controls the image noise rather than completely eliminating it. De-noising using Wavelet includes an easy idea of calculating the threshold of a noisy signal. This research paper focuses on wavelet shrinkage combined with cycle spinning approaches for denoising. The results of the paper shows that the cycle spinning with wavelet shrinkage method produces visually clearer images.
Keywords: De-noising, Discrete Wavelet Transform (DWT), Gaussian Noise, Speckle Noise, Thresholding

1. Introductıon

Any electrical system or equipment that transmits or receives a signal always contains some level of noise. There are variety of techniques available to reduce the image noise. Some of these techniques includes denoising algorithms, filtering, thresholding, and other techniques. Though, these techniques control the image noise but don’t able to completely eliminate it. It is important to note that excessive noise reduction can result in the loss of the image's fine features and edge lines. De-noising technique using Wavelet includes an easy way of calculating the threshold of a noisy signal. The threshold is to be compared with every pixel of the given image. Usually, the wavelet coefficients having lesser value than the threshold are changed by zero and all other pixels remain the same.

There are two different types of thresholds. Namely ‘hard’ and ‘soft’ threshold. They are widely used for denoising digital images but they also have many drawbacks. Because the predicted wavelet coefficients are not having linear values at the selected thresholds, hard thresholding causes the oscillation. Although a soft threshold provides high continuity, it may result in persistent differences between the estimated and original wavelet coefficients. There is a lot more research to be done on threshold selection [1]. Techniques of Translation invariant were employed to overcome the drawbacks and allow significant improvements to the visuality of images. Thus, the term "Pseudo-Gibbs phenomenon" refers to the wave-like ripples, oscillations, and discontinuities that are caused by thresholding towards the edges [2,3,4,5,6,7,8,9,10]. The adjustments between the signal characteristics and characteristics of the wavelet basis are what cause the above phenomenon. So, generally in such conditions, the image should be shifted in places of discontinuity, apply the algorithm and then it should be shifted back. The change is dependent on the image's discontinuity [15, 21]. This research focuses on wavelet shrinkage combined with cycle spinning approaches for denoising. The resulted image is then applied inverse wavelet transform. Here, studies are first conducted for denoising using a 1-d DWT and a direct Ridgelet transform. Later, we presented a Ridgelet with a cycle-spinned 1-d DWT that can be used with or without wavelet shrinkage.

1.1 Gaussian Noise

The signal is uniformly distributed with Gaussian noise. Every pixel is constituted of the original pixel added with a random value of Gaussian type. The probability distribution function for such kind is given as,

$$F(g) = (1/ \sqrt{(2\prod\sigma^2)})\, e^{-(g-m)2/2*\sigma2} \quad \text{------ (1)}$$

The standard deviation of Gaussian Noise is as given below,

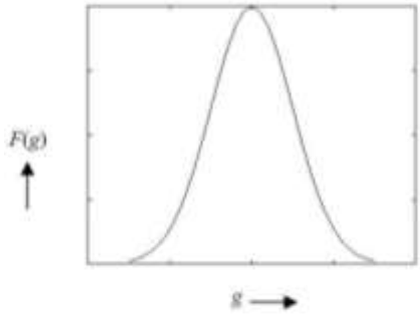


Fig. 1. Gaussian Noise Distribution

1.2 Speckle Noise

Multiplicative noise includes speckle noise. All coherent imaging techniques, including acoustic, laser, acoustic, and SAR (Synthetic Aperture Radar) pictures, are prone to this form of noise. The random interference between the coherent responses is the cause of this noise. Multiplicative noise is a feature of a fully developed speckle noise. The gamma distribution of speckle noise is given

$$F(g) = (g^{\alpha-1}/(\alpha-1)!\ a^{\alpha}) * e^{-(g/a)} \text{ ------ (2)}$$

where the grey level is g and the variance is $a^2 \alpha$.

1.3 Discrete Wavelet Transform (DWT)

The mathematical operations recognised as wavelets are used to examine data based on size or resolution. Compared to Fourier transformations, the wavelets have some advantages. They are excellent in approximating signals with sharp spikes and signals with discontinuities, for example. Music, voice, video, and non-stationary stochastic data can all be modelled using wavelets. Applications for the wavelets include predicting earthquakes, turbulence, image compression, and human eyesight. A set of orthonormal basis functions produced by translation and dilation of a scaling function and a mother wavelet ψ are referred to as “wavelets”. A discrete wavelet transform is a representation of a discrete function at a finite scale with several resolutions. The data vector's length is an integeral power of 2, and DWT is a quick linear operation on it. The individual wavelet functions are confined in frequency, just like sines and cosines. The orthonormal basis, also referred to as the wavelet basis.[19]

$$\psi_{(j,k)}(x) = 2^{j/2}\psi(2^j x - k) \text{--------------(3)}$$

Given is the scaling function

$$\phi_{(j,k)}(x) = 2^{j/2}\emptyset(2^j x - k) \text{--------------------(4)}$$

Where k and j are numerals that scale and enlarge the wavelet function ψ, respectively, and is the wavelet function. The scale index, or factor 'j' in Equations, denotes the wavelet's width and is known as the scale index. The position is given by the location index k. The wavelet function is translated by the number k and dilated by powers of two. The wavelet equation is given by the wavelet coefficientsas

$$\psi(x) = \textstyle\sum_k^{N-1} gk\sqrt{2\phi(2x - k)} \text{------------------(5)}$$

where the high pass wavelet coefficients are g0, g1, g2, etc. The following is the scaling equation in terms of scaling constants.

$$\emptyset(x) = \textstyle\sum_k^{N-1} hk\sqrt{2\emptyset(2x - k)} \text{-----------------(6)}$$

The coefficients h0, h1,... are low pass scaling coefficients, while the term φ(x) is the multiplier function. The quadrature mirror relationship, which is the relationship between the wavelet and scaling coefficients,

$$g_n = (-1)^n h_1 - n + N \text{------------------(7)}$$

N is the total number of disappearing moments.

1.4 Thresholding Using Wavelet

The process of decomposing an image's data into wavelet coefficients, comparing the detailed coefficients using a predetermined threshold value, and reducing these coefficients near to zero to eliminate the effect of noise from the data is known as wavelet thresholding. After that, the image is reconstructed using changed coefficients. The inverse discrete wavelet transform is another name for this. A wavelet coefficient is in comparison to the specified threshold in the meanwhile of thresholding and set to 0 if its magnitude is much less than the threshold; otherwise, it is maintained or adjusted in accordance with the thresholding rule. Thresholding makes a distinction between noise-related coefficients and those containing crucial signal information. An important area of interest is the choice of a threshold. De-noising frequently results in smoother images by lowering the sharpness of the image, therefore it plays a crucial part in the elimination of noise in the image. The edges of the de-noised image should be conserved with care. There are numerous wavelet thresholding techniques that depend on selecting a threshold value. Sure shrink, Visu Shrink, and Bayes Shrink are often employed techniques for image noise removal. The two general categories of thresholding must be understood. Both hard and soft thresholding fall within this category.

2. Literature Review

The Wavelet transform's success was mostly attributable to its excellent performance in both dimensions at various resolutions, albeit one at a time. The relationship between the information in the time domain and the frequency domain is preserved by the Wavelet transform. Since a two-dimensional Wavelet transform is created by taking a tensor product of a one-dimensional Wavelet, it is good at isolating discontinuities along straight or angled edges but falls short of achieving smoothness along curved edges [11]. Ridgelet transform was employed for image compression by Philippe Carre and Eric Andres [11] because it effectively handles images with linear singularities. The Ridgelet and Curvelet transformations, which are derivatives of the Wavelet transform, were introduced in [12, 13] to address the drawback of the Wavelet transform.
Radon projections serve as the foundation for the Ridgelet and Curvelet transforms [10, 13].

For improved processing of curves, “a point in the Wavelet Transform (smallest square dot) is recorded using a tiny curved line or a "Ridge" in the Ridgelet Transform. The dual tree Wavelet transform was further enhanced by S. M. E. Sahraeian and F. Marvasti” [14] to have greater orthogonality and symmetry characteristics. “A conditional application of Ridgelets on small tiles of images if the tile contains an edge was introduced by H. S. Bhadauria and Dr. M. L. Dewal and given the name Curvelet transform” [10]. Jude D. Hemanth and Daniela E. Popescu Digital Curvelet transform was introduced by Mamta Mittal and used on scanned digital grayscale images with smooth curves [15].

Ridgelet packets were calculated by G. Y. Chen and colleagues utilising tiling in the frequency and projection domain. “A family of best-basis algorithms employing anisotropic cosine packet bases, which in turn use the sparsity criterion, were proposed along with the idea that there can be a wide variety of Ridgelet packet frames (basis) for a given application. Ridgelet transform was provided in an orthonormal form by M. N. Donoho, along with a novel method of computing it using finite Radon projections”.[13]

In this field, numerous researchers have been active [4, 5, 6, 13, 15, 16, 17, 18] present digital reconstruction of multidimensional signals using projections. J. Radon's Radon transform is a ground-breaking contribution to tomographic reconstruction [13, 15, 18].

3. Research Methodology

Image denoising is a technique used to reduce the amount of key image features that are lost when additive noise is removed. Regardless of the signal's frequency content, wavelet denoising aims to keep the signal's characteristics while removing any noise that is there. Image denoising attempts to remove noise via separating it from the signal. Denoising benefits considerably from the energy compactness of the wavelet transform. When a signal is said to be "energy compact," it means that the majority of its energy is concentrated in a limited number of large wavelet coefficients as opposed to a series of smaller wavelet coefficients.

These coefficients represent the image's fine details as well as its high frequency noise. Filtering and thresholding are the conventional techniques for denoising. In essence, the Forward DWT algorithm filters and downsamples the noisy image. When an image is downscaled, every other pixel is eliminated. Filtering refers to low pass and high pass filters with the following coefficients:

- Coefficient for Low pass decomposition [1,1]
- Coefficient for High pass decomposition [1, -1]

Our up sampling and filtering operations are part of the inverse DWT method. Up sampling entails inserting zeros between each subsequent sample.

Filtering again refers to low pass and time inverted high pass filters with the following coefficients:

- Coefficient for Low pass decomposition [1,1]
- Coefficient for High pass decomposition [1, -1]

The thresholded signal is subjected to an inverse wavelet transform to get an approximation of the original signal, as shown below.

$$\hat{x}[n] = D(y[n]) = W^{-1}(w(y[n])\text{--------------------}(8)$$

Where Wand W^{-1} are the reverse and forward wavelet algorithm's representations, respectively.

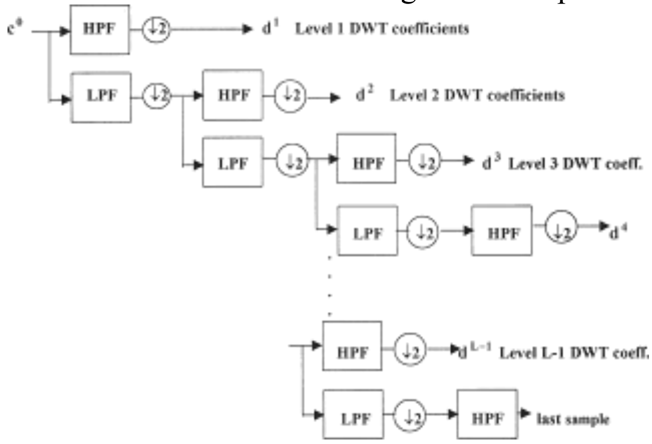


Fig. 2. Filter Bank representation of the DWT Algorithm

4. Experimental Results

The effectiveness of de-noising after cycle spinning is advanced than the overall performance earlier than cycle spinning, as may be visiblevia the results. The wavelet shrinkage (thresholding) averaging and transferring for colour images gives the suggested method a significant improvement. This is due to the fact that, as was already noted, the proposed set of rules makes use of a translation invariant technique that permits noise to be averaged out, improving denoising overall performance and creating a more aesthetically pleasing image. This illustrates the usefulness of the suggested method. Here, colour images were transformed distinctly on the R, B, and G planes, and the PSNRand MSE of each colour plane were calculated as a result.

When cycle spinning is combined with wavelet shrinkage, it has been found that colour picture reconstruction is better than when cycle spinning is not used. Table 5.1 compares the signal to noise ratio (PSNR) of different images that were recreated using the RidgeletTransform, both with and without cycle spinning and wavelet shrinkage.

Table 1. De-Noising using Speckle Noise

PSNR using Speckle Noise (σ=0.1)					
Sr. No	Images	PSNR Using Ridgelet (L1)	PSNR Using Ridgelet and Cycle Spinning (L2)	PSNR Using Ridgelet and Cycle Spinning and Shrinkage (L3)	PSNR Using Cycle SpinniedRidgelet and Shrinkage (L4)
1	Foodball.jpg	36.3093	36.3241	36.4143	36.6472
2	Peppers.png	37.2414	37.3853	37.7871	37.9405
3	Autumn.tif	35.6056	35.6604	35.8971	36.3720
4	Fabric.png	30.5990	30.7014	30.7630	31.4231
5	Saturn.png	37.3110	38.0943	38.1755	38.2584
6	Cameraman.tif	28.7587	29.0269	29.0291	29.0498

Table 2. Time Required for De-Noising Using Speckle Noise

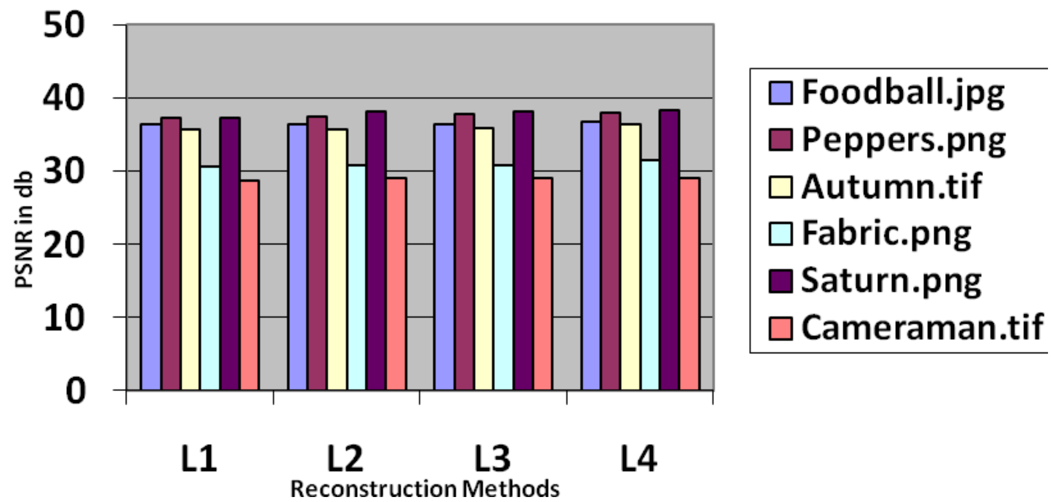
Time Required for De-Noising using Speckle Noise (σ=0.1)					
Sr. No	Images	Reconstruction Time using Ridgelet (T1)(Sec)	Reconstruction Time using Ridgelet and Cycle Spinning	Reconstruction Time using Ridgelet and Cycle Spinning and Shrinkage	Reconstruction Time using Cycle SpinniedRidgelet and
1	Foodball.jpg	15.125	27.125	40.500	58.111
2	Peppers.png	12.522	27.048	40.631	58.177
3	Autumn.tif	13.112	27.167	40.586	58.035
4	Fabric.png	21.552	66.861	86.241	58.057
5	Saturn.png	13.335	27.078	40.668	57.891
6	Cameraman. tif	7.221	12.552	18.775	21.009

Table 3. De-Noising Using Gaussian Noise (σ=0.01)

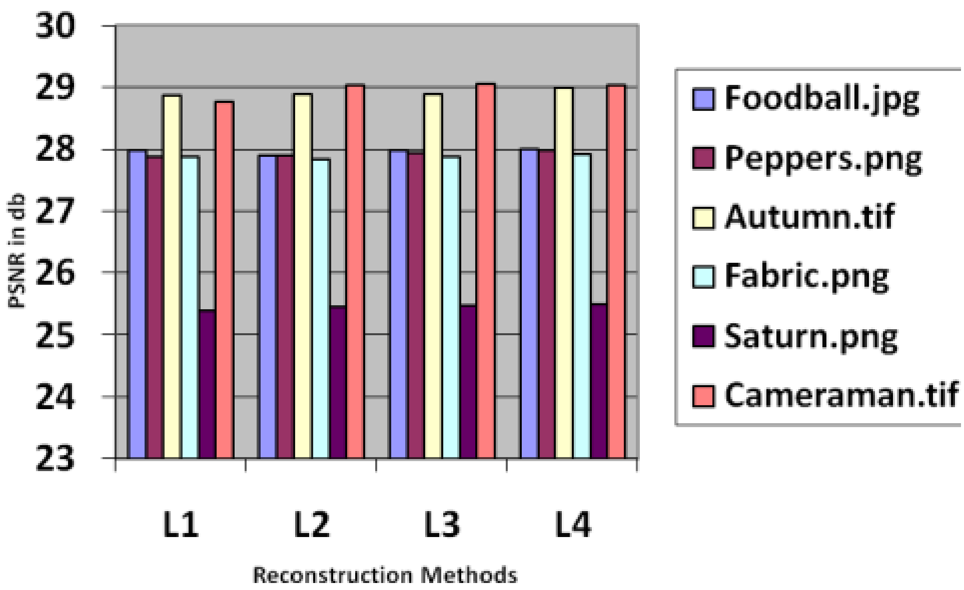
PSNR using Gaussian Noise (σ=0.01)					
Sr. No	Images	PSNR Using Ridgelet (L1)	PSNR Using Ridgelet and Cycle Spinning (L2)	PSNR Using Ridgelet and Cycle Spinning and Shrinkage (L3)	PSNR Using Cycle SpinniedRidgelet and Shrinkage
1	Foodball.jpg	34.1732	34.4293	34.3489	34.5971
2	Peppers.png	34.2355	34.3815	34.5324	35.6799
3	Autumn.tif	34.1142	34.3702	34.6251	35.8876
4	Fabric.png	29.7938	30.3046	30.8497	30.9911
5	Saturn.png	30.1799	30.3848	30.4084	30.5210
6	Cameraman.tif	29.1120	30.2012	30.5681	30.7891

Table 4. Time Required for De-Noising Using Gaussian Noise

Time Required for De-Noising using Gaussian Noise (σ=0.01)					
Sr. No	Images	Reconstruction Time using Ridgelet (T1) (Sec)	Reconstruction Time using Ridgelet and Cycle Spinning	Reconstruction Time using Ridgelet and Cycle Spinning and Shrinkage (T3) (Sec)	Reconstruction Time using Cycle SpinniedRidgelet and Shrinkage (T4)
1	Foodball.jpg	14.125	67.43	100.5	144.08
2	Peppers.png	13.522	66.94	100.48	143.43
3	Autumn.tif	15.112	66.78	100.53	143.13
4	Fabric.png	22.552	67.09	100.46	143.20
5	Saturn.png	14.335	67.32	100.99	144.07
6	Cameraman.tif	8.221	54.12	75.15	95.07



Graph 1. Comparative Analysis of PSNR Using Speckle Noise (σ=0.1)



Graph 2. Comparative Analysis of PSNR Using Gaussian Noise (σ=0.1)

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5. Conclusion

The work intends to develop Radon projection-based Ridgelet transform-based denoising methods. Denoising is accomplished by averaging the Ridgelet coefficients. In order to de-noise a variety of photos with various stages of Speckle Noiseand White Gaussian Noise (WGN), the one-dimensional Discrete Wavelet Transform (DWT1D) algorithm is used.

The work also addresses denoising utilising wavelet shrinkage and cycle spinning techniques. The original image, the noisy image, and the reconstructed image with and without the cycle spinning method are all analysed using Mean Square Error and Peak Signal to Noise Ratio. The trials demonstrate that the cycle spinning with wavelet contractionconstantly produces better results for grey and colour images, further indicating the potential for this field of study.

Research on test photos demonstrates that although the PSNR varies slightly depending on whether the cycle spinning with wavelet shrinkage or direct RidgeletTransform without cycle spinning is used, the cycle spinning with wavelet shrinkage method produces visually clearer images.

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