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Bone Marrow Cell Image De-noising using Stationary Wavelet Transform

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Abstract: The BMC image de-noising naturally corrupted by noise is a classical problem in the field of image processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by various noises like Gaussian noise using wavelet techniques are very effective because of its ability to capture the energy of a image in few energy transform values. The wavelet de-noising scheme soft and hard thresholds the wavelet coefficients arising from the standard coif and bior wavelet transform. In this paper, it is proposed to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of entropy.

Keywords: BMC Image, De-noising, wavelets, entropy.

I. INTRODUCTION

This paper investigates the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of entropy. Over the past decade, wavelet transforms have received a lot of attention from researchers in many different areas. Both discrete and continuous wavelet transforms have shown great promise in such diverse fields as image compression, image de-noising, signal processing, computer graphics, and pattern recognition to name only a few. In de-noising, single orthogonal wavelets with a single-mother wavelet function have played an important role. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. Crudely, it states that the wavelet transform yields a large number of small coefficients and a small number of large coefficients.

Simple de-noising algorithms that use the wavelet transform consist of three steps.

1. Calculate the wavelet transform of the noisy image.
2. Modify the noisy wavelet coefficients according to some rule.
3. Compute the inverse transform using the modified coefficients. One of the most well-known rules for the second step is soft thresholding. Due to its effectiveness and simplicity, it is frequently used in the literature. The main idea is to subtract the threshold value T from all wavelet coefficients larger than T, arising from the standard stationary wavelet transform and to set all other coefficients to zero. The problem of Image de-noising can be summarized as follows. Let A(i,j) be the noise-free image and B(i,j)the image corrupted with independent Gaussian noise, Poisson noise , Salt & Pepper noise ,Speckle noise(GPSPS) , Z(i, j), $B(i, j) = A(i, j) + \sigma N(i, j)$ ……(1)

where Z(i, j) has normal distribution N(0,1). The problem is to estimate the desired image as accurately as possible according to some criteria. In the wavelet domain, if an biorthogonal & coiflets wavelet transform is used, the problem can be formulated as

$Y(i, j) = W(i, j) + N(i, j)$ ……(2)

where Y(i, j) is noisy wavelet coefficient; W(i, j) is true coefficient and N(i, j) noise, which is independent GPSPS noises. . In this paper, it is proposed to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of entropy.

II. STATIONARY WAVELET TRANSFORM

The Stationary Wavelet Transform (SWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Stationary Wavelet Transform has attracted more and more nterest in image de-noising. The SWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called stationary wavelet transform and inverse stationary

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wavelet transform. An image can be decomposed into a sequence of different spatial resolution images using SWT. In case of a 2D image, an N level decomposition can be performed resulting in different coefficients namely, horizontal ,vertical , diagonal and approximation . These are also known by other names, the coefficients respectively may be called h1 called horizontal fluctuation, v1 called vertical fluctuation , d1 called the first diagonal fluctuation and a1 or the first approximation image,. The sub-image a1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by trends along columns. The next level of wavelet transform is applied to the low frequency sub image a2 only. The Gaussian noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be thresholded.

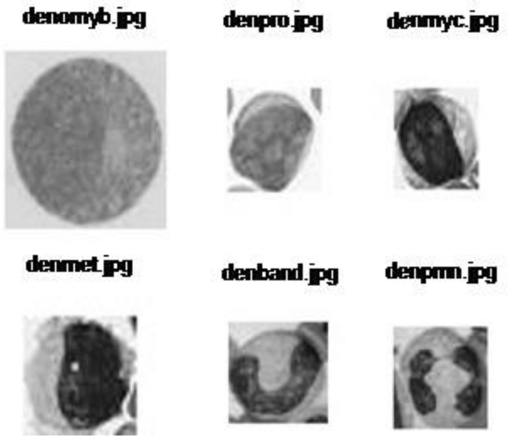

Fig1:Input Images (a)Gaussian noisy(mean=0,variance=0.01) (b)Poisson noisy(c)Salt&Pepper noisy (d)Speckle noisy(e)Gaussian noisy (m=0.3,v=0.02) (f)Gaussian noisy (m=0.05,0.02)

III. WAVELETS BASED IMAGEDE-NOISING

As shown in figure 1.All digital images contain some degree of noise. Image denoising algorithm attempts to remove this noise from the image. Ideally, the resulting de-noised image will not contain any noise or added artifacts. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. The methodology of the stationary wavelet transform based image de-noising has the following three steps:

a). Transform the noisy image into biorthogonal or coiflet or haar domain by stationary 2D wavelet transform. b). Apply hard or soft thresholding the noisy detail coefficients of the wavelet transform c). Perform inverse stationary wave let transform to obtain the de-noised image. Here, the threshold plays an important role in the denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details.Normally, hard thresholding and soft thresholding techniques are used for such de-noising process. Hard thresholding is a keep or kill rule whereas soft thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule.

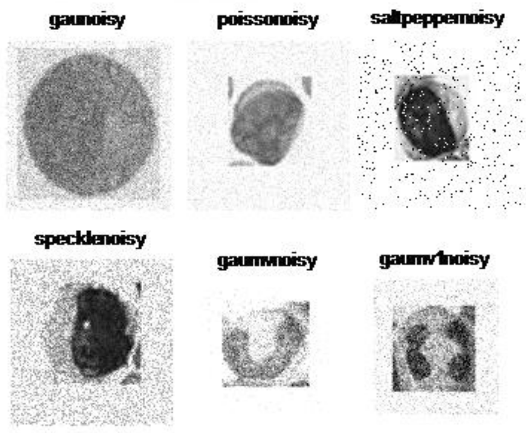

Figure2: Out put Images: Diagram of denoised bone marrow cell images .

The figure 2 shows the output images.the cell names : myeloblast , promyelocyte,, myelocyte , metamyrlocyte, band , and PMN(polymarphonucleus).

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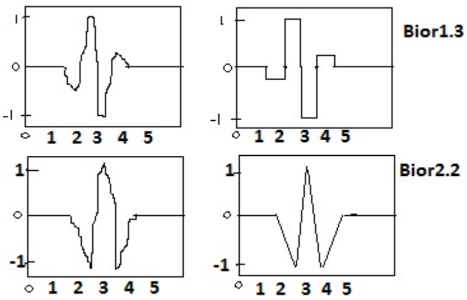
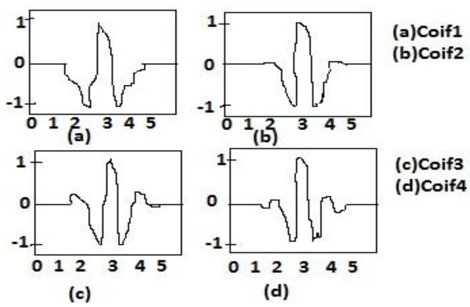
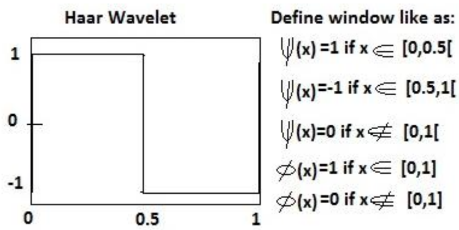


(a) Biorthogonal Transform



(b) Coiflet Transform



(c) Haar Transform

The following are the methods of threshold selection for image de-noising based on various stationary wavelet transforms.

Method 1: biorshink

This method is applied on first two images.The threshold T can be calculated using the formulae,

$T= \sigma\sqrt{2\log n2}$ …….(3)

This method performs well under a number of applications because biorthogonal wavelet transform has the compaction property of having only a small number of large coefficients. All the rest wavelet coefficients are very small. This algorithm offers the advantages of smoothness and adaptation. However, it exhibits bior artifacts.

Method 2: coif-shrink

This method is applied on second two cell images. Let c(i, j) denote the coiflet wavelet coefficients of interest and W(i, j) is a neighborhood window around c(i, j).Also let S2=Σc2(i, j) over the window W(i, j). Then the wavelet coefficient to be thresholded is shrinked according to the formulae,

c(i, j)= c(i, j)* W(i, j) ….(4)

where the shrinkage factor can be defined as W(i, j) = (1-T2/ S2(i, j))+,and

the sign + at the end of the formulae means to keep the positive value while set it to zero when it is negative

Method 3: haar-shrink

This method is applied for last two cell images.During experimentation, it was seen that when the noise content was high, the reconstructed image using haar-shrink contained mat like aberrations. These aberrations could be removed by wiener filtering the reconstructed image at the last stage of IDWT. The cost of additional filtering was slight reduction in sharpness of the reconstructed image. However, there was a slight improvement in the Entropy of the reconstructed image using wiener filtering. The de-noised image using haar-shrink sometimes unacceptably blurred and lost some details. The reason could be the suppression of too many detail wavelet coefficients. This problem will be avoided by reducing the value of threshold itself. So, the shrinkage factor is given by

W(i, j) = (1- (3/4)*T2/ S2(i, j))+ …….(5)

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IV. EVALUATION CRITERIA

The above said methods are evaluated using the quality measure Entropy which is calculated using the formulae,
h = -sum(xh(i).*log2(xh(i))) ….(6)
where, xh is the histogram between the original image and the reconstructed de-noised image. It is used to evaluate the different de-noising scheme like Wiener filter, bior-shrink, coif-shrink and Modified haar-shrink., function entropy uses find to create a vector of indices, i , into histogram xh ,which is subsequently employed to eliminate all zero valued elements from the entropy computation.

V. EXPERIMENTS

Quantitatively assessing the performance in Practical application is complicated issue because the ideal image is normally unknown at the receiver end. So this paper uses the following method for experiments. One original image is applied with GPSPS noise with different variance. The methods proposed for implementing image de-noising using wavelet transform take the following form in general. The image is transformed into the orthogonal domain by taking the wavelet transform. The detail wavelet coefficients are modified according to the shrinkage algorithm. Finally, Inverse wavelet is taken to reconstruct the denoised image. In this paper, different wavelet bases are used in all methods. For taking the wavelet transform of the image, readily available MATLAB routines are taken. In each sub-band, individual pixels of the image are shrinked based on the threshold selection. A de-noised wavelet transform is created by shrinking pixels. The inverse wavelet transform is the de-noised image.

VI. RESULTS AND DISCUSSIONS

For the above mentioned three methods, image de-noising is performed using stationary wavelets from the first level to second level decomposition and the results are shown in figure (3) and tables formulated for different noises and wavelets is as follows. It was found that haar-shrink method gave optimum results. However, first level decomposition resulted in more blurred.

Table-1 (* - e+004)

Data	Coif.1	Coif.2	Coif.3	Coif.4
mean	0.01167	0.01837	0.02186	0.02224
Std.dev.	1.373	1.427	1.45	1.472
Mean abs dev.	1.119	1.148	1.148	1.158
L1 norm.	4.98e+004	5.107*	5.101*	5.134*
L2 norm	290	301.5	306.5	311.1

Table-2

Data	Bior1.1	Bior1.3	Bior1.5	Bior2.2
mean	0.00219	0.01048	0.01384	0.01382
Std.dev.	1.303	1.237	1.222	1.502
Mean abs dev.	0.8884	0.8288	0.8301	1.213
L1 norm.	3.961*	3.678*	3.677*	5.398*
L2 norm	275.2	261.4	258.2	317.3

Table-3

Data	Haar.Thre-1	Haar.Thre-2
mean	0.002195	0.02056
Std.dev.	1.303	7.353
Mean abs dev.	0.8884	5.383
L1 norm.	3.961*	2.401*
L2 norm	275.2	1553

Table-4

Noisy images	Entropy
Gaussian	3.2079
Poisson	1.2889
Salt & Pepper	0.1139
Speckle	2.0248
Gaussianmv1	4.3593
Gaussianmv2	2.6942

Figure3: Results of various Image De-noising Methods

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VII. CONCLUSION

In this paper, the bone marrow cell images are de-noised using stationary wavelet transform, which are used for classification based on its features for analysis of disease diagnosis like cancer or leakumeia . The experiments were conducted to study the suitability of different wavelet bases and also different window sizes. Among all stationary wavelet bases, haar performs well in image de-noising. Experimental results also show that modified bior-shrink gives better result than coif-shrink,and Weiner filter .

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