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# Noise Reduction in Ultrasound Images of Upper Arm Using Wavelet

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***Abstract:*** **— Ultrasound medical images are corrupted with a prominent component of noise during its acquisition and storing. Wavelet denoising techniques are used to reduce noise component effectively. The recorded ultrasound images are cropped to uniform size and the noise component is added to understand the level of noise threshold and further, these images are denoised using Daubechie3 and Symlet3 wavelet. Further to understand the effect of denoising at a particular decomposition level the PSNR values are calculated a comparison is drawn between these two wavelets to identify the noise reduction capability.**

***Key words*****: Ultrasound images, Daubechie3 wavelet, Symlet3 wavelet, MSE, PSNR.**

## I. INTRODUCTION

Medical image processing is an emphasis on the transformation between the image and improving the visual effects of image. Noise removal is an essential element of image processing of many medical images aiming at the removal of noise. Medical images are acquired under less than ideal conditions and consequently are contaminated by significant amount of noise, there is a need for appropriate technique of refining the images so that the resultant images are of better quality free from noises as there is no unique available technique identified so far, medical image entries may be misinterpreted which lead to wrong interpretation of information contained in an image and hence leading to wrong diagnosis. Several important image processing operations work much better if random noise is absent, like contrast enhancement and edge enhancement etc. Explicit computational algorithms have been developed for generating wavelets with varying degrees of threshold and details. The basic concepts of wavelet denoising of images is by choosing a threshold that is a sufficiently large multiple of the standard deviation of the random noise, it is possible to remove most of the noise by choosing appropriate wavelet transform function and the respective decomposition level. To prove the validity of the proposed method, test medical images of different noise forms were used and the analysis was performed by self-developed programs written in MatLab platform, for comparing the results in the proposed algorithm the MSE and PSNR values are considered.

## II. THEORY

An equation must satisfy the following properties, if it is to be used as Wavelets.

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \qquad [1] \quad \text{and}$$

$$\int_{-\infty}^{+\infty} |\psi(t)|^2 dt > 0 \qquad [2]$$

This implies that, the function is oscillatory and that most of the energy $\psi(t)$ is confined to a finite duration. If f(t) is a given function then wavelet transform of f(t), w(a,b) with respect to a mother wavelet $\psi(t)$ is defined by

$$w(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\, \psi\left[\frac{(t-b)}{a}\right] dt \qquad [3]$$

Where, 'a' is the scale parameter and 'b' is the translation parameter. The magnitude of the wavelet coefficients provides the information on how close the scaled and translated wavelet is to the original signal. Transforms in image processing are two-dimensional, the original signal f(t) has one independent variable't', but the wavelets have two independent variables 'a' and 'b'. We can calculate the two dimensional separable transform by applying the corresponding one-dimensional transform to the columns first, and then to the rows.

Daubechies wavelets, are continuous time functions whose mother wavelet has a finite support width, they constitute an orthonormal basis for the functions of finite energy. Symlet wavelets are nearly symmetrical, orthogonal and biorthogonal wavelets proposed by Ingrid Daubechies as a near symmetric counterpart to Daubechies wavelet family, the properties of the two wavelet families are same. The Daubechies3 wavelet and Symlet3 wavelets at decomposition level3 are chosen for denoising ultrasound medical image. Figure1 and Figure2 are the representations of these wavelets.

 

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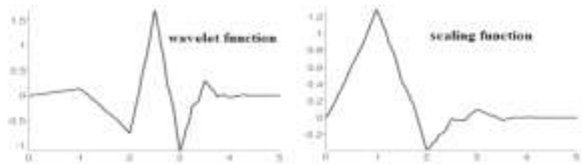



*Fig1: Daubechies3 wavelet function and the corresponding scaling function*

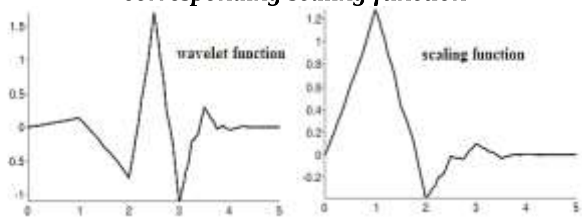



*Fig2: Symlet3 wavelet function and the corresponding scaling function*

## III. PROCEDURE

The images considered here are ultrasound images of Merkel cell carcinoma a malignant soft tissue tumor in the upper arm as characterized by the Gelderse Vallie Hospital in Ede, Netherlands the cases are collected by radiologists and ultrasound technicians of the hospital and are allowed to download for academic purpose. The images as available with ID/69099-Afbleeding1 and ID/69100-Afbleeding2 are shown in Figure3 and Figure4 respectively.

*Fig3: Ultrasound Image of Merkel cell carcinoma of the upper arm Afbleeding1*

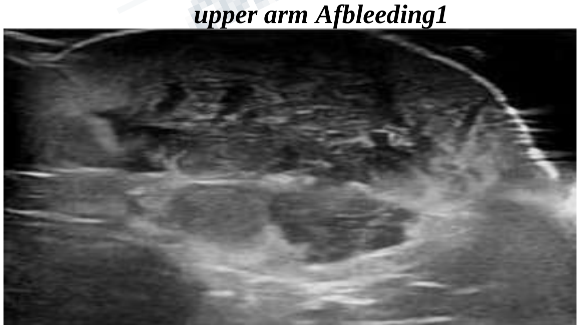


*Fig4: Ultrasound Image of Merkel cell carcinoma of the upper arm Afbleeding2*

Well known noises like Gaussian noise, Speckle noise, Salt and Pepper noise and Poissons' noise are added to the image for obtaining noisy images, these are shown in Figures5-6.

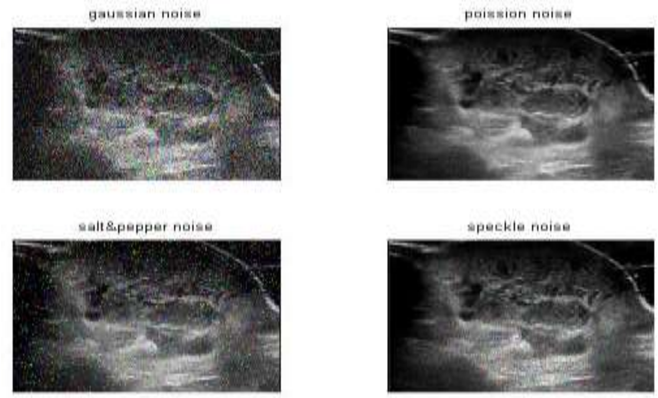



*Fig5: Noisy image of Afbleeding1*

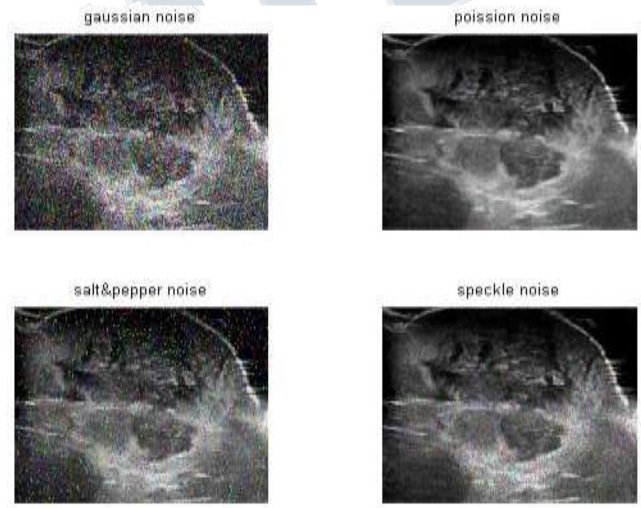



*Fig6: Noisy image of Afbleeding2*

The noisy images are generated with a noise threshold of 0.05, these images were denoised using Daubechies3 wavelet at level3 and Symlet wavelet at level3. The corresponding denoised images are used to calculate the values of MSE and PSNR.

## IV. RESULTS AND DISCUSSIONS

Intensity images recorded are stored in jpeg format, using necessary cropping algorithms these images are cropped to a uniform pixel size of 156x156; noise present in these cropped images is reduced using Daubechie3 wavelet and Symlet3 wavelet the corresponding denoised images are shown in Figure7-10.

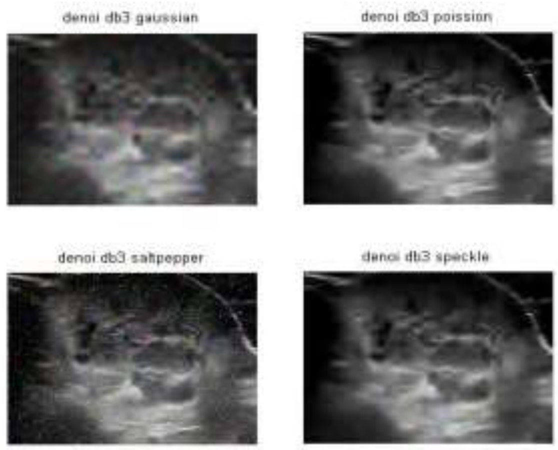
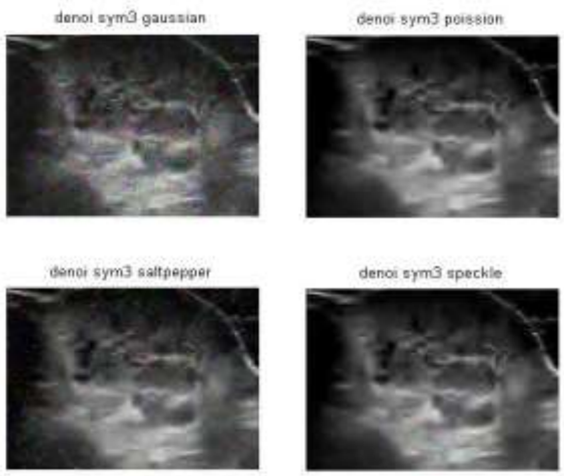



*Fig7: Denoised images obtained after cropping using Daubechie3 wavelet for Afbleeding1*




. *Fig8: Denoised images obtained after cropping using Symlet3 wavelet for Afbleeding1*

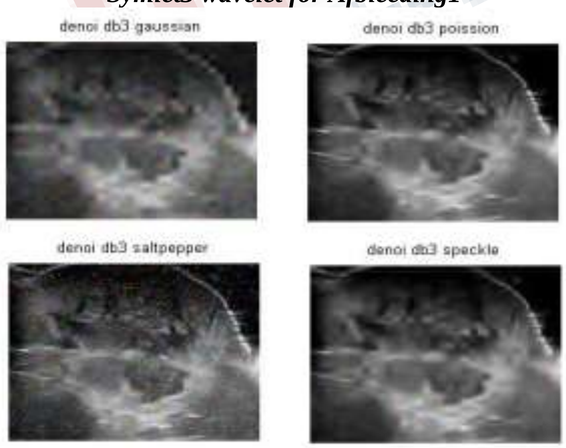



*Fig9: Denoised images obtained after cropping using Daubechie3 wavelet for Afbleeding2*

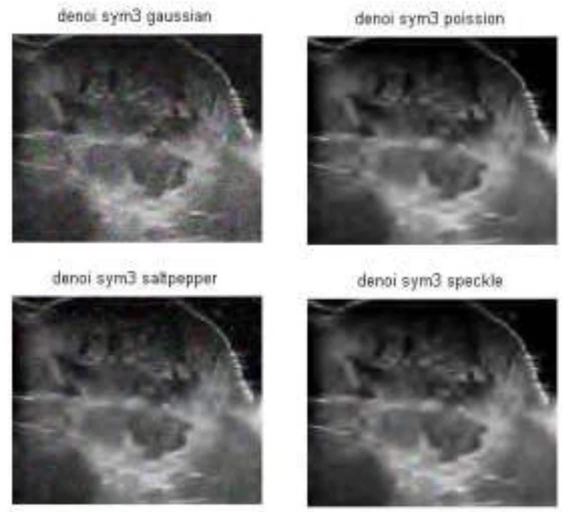



*Fig10: Denoised images obtained after cropping using Symlet3 wavelet for Afbleeding2*

For understanding the effectiveness of these wavelets in denoising original images, the values of Mean Square Error and Peak Signal to Noise Ratio was calculated that are indicated in Table1 and Table2 respectively for Afbleeding1 image and Afbleeding2 image.

*Table1: RGB components of MSE & PSNR for Afbleeding1 image*

| MSE and PSNR for Afbleeding1 image | | | | | |
|---|---|---|---|---|---|
| Gaussian noise | MSE | Sym3 | 30.03 | 29.43 | 30.08 |
| | | Db3 | 31.03 | 30.64 | 30.92 |
| | PSNR | Sym3 | 33.35 | 33.44 | 33.34 |
| | | Db3 | 33.21 | 33.26 | 33.22 |
| Poisson noise | MSE | Sym3 | 13.34 | 13.36 | 13.44 |
| | | Db3 | 12.41 | 12.40 | 12.47 |
| | PSNR | Sym3 | 36.87 | 36.87 | 36.84 |
| | | Db3 | 37.19 | 37.19 | 37.17 |
| Speckle noise | MSE | Sym3 | 17.26 | 17.24 | 17.48 |
| | | Db3 | 17.34 | 17.35 | 17.57 |
| | PSNR | Sym3 | 35.75 | 35.76 | 35.70 |
| | | Db3 | 35.73 | 35.73 | 35.68 |
| Salt and Pepper noise | MSE | Sym3 | 21.29 | 19.72 | 21.83 |
| | | Db3 | 20.25 | 18.79 | 20.67 |
| | PSNR | Sym3 | 34.84 | 35.18 | 34.73 |
| | | Db3 | 35.06 | 35.39 | 34.97 |

*Table2: RGB components of MSE & PSNR for Afbleeding2 image*

| MSE and PSNR for Afbleeding2 image | | | | | |
|---|---|---|---|---|---|
| Gaussian noise | MSE | Sym3 | 30.48 | 30.15 | 30.80 |

| | | | | | |
|---|---|---|---|---|---|
| | | Db3 | 31.53 | 31.57 | 31.81 |
| | PSNR | Sym3 | 33.29 | 33.33 | 33.24 |
| | | Db3 | 33.14 | 33.13 | 33.10 |
| Poisson noise | MSE | Sym3 | 14.48 | 14.34 | 14.54 |
| | | Db3 | 13.76 | 13.66 | 13.91 |
| | PSNR | Sym3 | 36.52 | 36.56 | 36.50 |
| | | Db3 | 36.74 | 36.77 | 36.69 |
| Speckle noise noise | MSE | Sym3 | 19.59 | 19.56 | 19.52 |
| | | Db3 | 20.02 | 19.93 | 19.99 |
| | PSNR | Sym3 | 35.20 | 35.22 | 35.22 |
| | | Db3 | 35.11 | 35.13 | 35.12 |
| Salt and Pepper noise | MSE | Sym3 | 21.57 | 20.41 | 22.11 |
| | | Db3 | 20.67 | 19.34 | 20.83 |
| | PSNR | Sym3 | 34.79 | 35.03 | 34.68 |
| | | Db3 | 34.97 | 35.26 | 34.94 |

## V. CONCLUSIONS

Our study shows that noise is prominent in the recorded medical images and denoising using wavelet Daubechie3 and Symlet3 wavelets successfully reduced noise content present in the image. The two types of wavelets considered were however showing the same PSNR with little difference hence both can be used for denoising. However, the importance of symmetry of the mother wavelet in terms of the edge smoothening and contrast retaining mechanism of the image is clearly evident from the Figures 7-10. For speckle noise which is one of the most widely observed noise in the medical image the effectiveness of symmetric mother wavlet like Symlet3 in denoising showed higher PSNR value as compared to asymmetric mother wavlet like Daubechie3.

## VI. ACKNOWLEDGEMENTS

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