Analysis of Medical Image De-Noising using DWT and UDWT in Presence of Different Noises

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Abstract— The progress in computerized automatic systems are all possible due to the image processing. The computer assisted medical image reconstruction and other associated analysis in medical diagnosis are only possible due to image processing. Image processing includes image enhancement, segmentation and restoration. The field of medical image processing is not new still research is going on to find new and more efficient ways of imaging. The area of health information such as medical imaging are more unique, medical images requires more understanding of images, techniques and also higher resolution images are processed than ordinary texture images. The most important part is to ensure the reliability of image processing technique for clinical applications. In this paper two methods in wavelet domain DWT and UDWT are analyzed to check the de-noising efficiency of these two methods in presence of different noises on different types of medical imagesteristics.

Key words: DWT, Medical Image De-Noising, UDWT

I. Introduction

Various de-noising techniques are proposed and implemented in literature. As far as the process of de-noising is concerned it can be assumed that no single technique or method can be fixed to perform optimally for all images. In general there are many transforms available like the Fourier transform, Wavelet transform and Hilbert transform [2,9]. The goal however, is to adjust the parameters of the de-nosing algorithm to process the image properly. The de-noising scheme used in wavelet domain has been extended to the direction let domain to make the image features to concentrate on fewer coefficients so that more effective thresholding is possible [3]. Another techniques using neighbouring wavelet coefficients is the adaptive thresholding method [4]. Research papers show how different methods are implemented to deal with different types of images [5]. Literature compares different methods on basis of reconstructed image and other statistical parameters. In [1] the author implements a modified Un-decimated wavelets and compares its performance with discrete wavelet transform for de-noising mammographic images. A generalized tree based scheme is also present to represent images more efficiently than the common 1D and separable 2D wavelet transforms [6]. There are many advanced methods of image processing involving techniques that include the traditional Fourier transform and the wavelet transform [8]. To benchmark the de-noising process for medical images a set of images corrupted with artificial noise are used. Gaussian, speckle noise and salt and paper noise is added to MRI, ultrasound and X-Ray images respectively. Salt and pepper noise [7] is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. In this paper the aim is to compare the results of discrete wavelet transform and un-decimated wavelet transforms for different types of medical images like MRI, X-ray and ultrasound.

II. Methodology

The decomposition and type of wavelet has an important role in the de-noising of images. If wavelet type and decomposition level is properly selected and optimized, image texture can be preserved up to large extent. In proposed algorithm the two de-noising methods using DWT and UDWT are implemented and evaluated. In the beginning discrete wavelet transform is used to de-noise a set of images artificially corrupted by noise of known type. Iterations are done by varying the type and level of decomposition. Second examination is performed by implementing the un-decimated discrete wavelet transform (UDWT), similarly varying wavelet type and decomposition level. The results obtained from applying these two are compared on the basis of MSE and PSNR. Visual inspection is finally done to figure out any anomaly in the reconstructed image. The two wavelets are extensively checked and benchmarked for their performance in de-noising the medical images of different types.

Algorithm for de-noising using Wavelets

- Step-1: Take an original image.
- Step-2: Add noise with original image.
- Step-3: Set type and level of decomposition
- Step-4: Apply Decomposition
- Step-5: Perform de-noising operation.
- Step-6: Save the restored image.
- Step-7: Compare the restored image that obtained in step 6 with input image and calculate MSE and PSNR.
- Step-8: Repeat the previous steps unless desired level of PSNR and image details are not obtained in visual inspection.

To evaluate the de-noising algorithm DWT is first implemented. The noisy medical image is input to the DWT de-noising algorithm. In beginning haar wavelet and decomposition level-1 is selected. After decomposition of image, de-noising is performed. The reconstructed de-noised image is stored. MSE and PSNR of the input image and the de-noised image is calculated and tabulated. In second iteration the decomposition level is set to level-2 and again the image is de-noised. This process is continued until the decomposition level of 5 is reached.

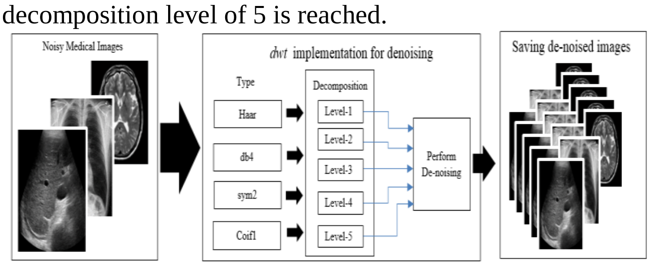


Fig. 1: De-noising process using the DWT wavelet implementation

This process is repeated with another wavelet types like haar, db4, sym2 and Coif1 wavelet types. This process is represented in Fig-1.

The de-noising process is represented by the flowchart in Fig-2. The flowchart also represents the computation of evaluation parameters i.e. MSE and PSNR. The wavelet filter type and decomposition levels are varied and output de-noised image is saved for each iteration performed. At the end of each iteration performed the image is visually inspected in detail for texture and other anomaly occurred by virtue of de-noising process

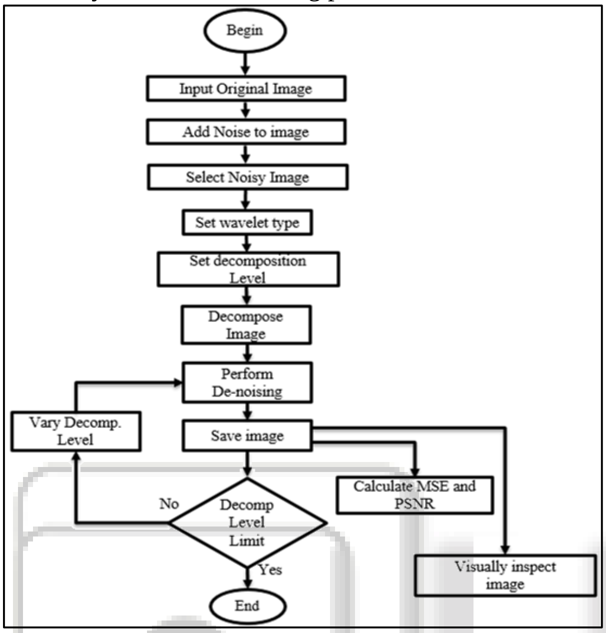


Fig. 2: Flow chart for de-noising process

To implement the denosing algorithm a MATLAB GUI is developed. This interface enables easy adjustment of variables used in the evaluation process. The wavelet filter and level of decompostion can be selected from the dropdown list provided in the developed GUI. This GUI also writes the denoised image on the memory for post examination. This graphical user interface also has a theshold control setting these values are prefixed in our case. Fig-3 shows the controls available on the developed GUI.

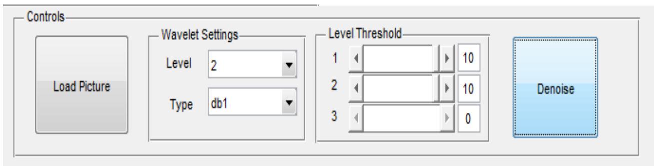


Fig. 3: Control options in devloped GUI for denoising using DWT

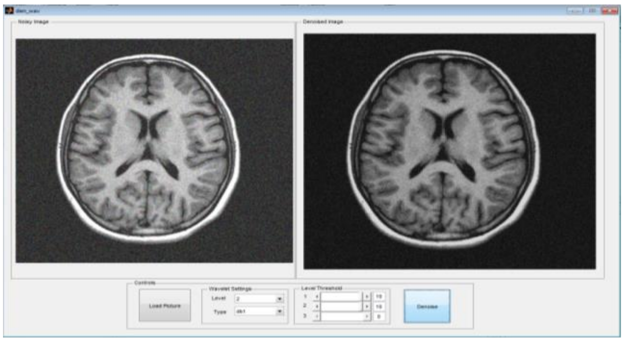


Fig. 4: MATLAB GUI developed for Image De-noising using DWT

This process is repeated using the UDWT transform and set of de-noised images formed. It is first processed with discrete wavelet transform varying type of wavelet and at different levels of decomposition. In second step the same image is processed with the un-decimated wavelet transform or stationary wavelet transform. The resolved image is compared on the basis of PSNR and MSE.

A. *Measurement of MSE*

The mean-squared error (MSE) between two images g(x, y) and $\hat{g}(x,y)$ is:

$$MSE = \frac{1}{MN}\sum_{n=1}^{M}\sum_{m=1}^{N}[g(n,m) - \hat{g}(n,m)]^2 \quad (1.1)$$

One problem with mean-squared error is that it depends strongly on the image intensity scaling. It means that MSE is dependent on resolution of the image. If resolution of image is high a specific value of MSE may have negligible effect when compared with a low resolution image. For example, a mean-squared error of 100.0 for an 8-bit image (with pixel values in the range 0-255) seems terrible; but a MSE of 100.0 for a higher say 10-bit image (1023 pixel) is hardly visible. This situation is solved using another parameter called Peak Signal-to-Noise Ratio (PSNR).

B. *Measurement of PSNR*

PSNR handles this problem by scaling the MSE according to the image range:

$$PSNR = -10\log_{10}\frac{e_{MSE}}{S^2} \quad (1.2)$$

Where, S is the maximum pixel value. PSNR is measured in decibels (dB).

C. *Visual Inspection*

Final performance check is done by a visual inspection of the recovered or de-noised image. The de-noised image is analyzed for getting the texture related details and other anomaly occurred due to decomposition or wavelet transform implementation.

III. RESULTS

When implementing DWT transform (*haar*) at level four it is observed in Fig-5a and 5b, that the de-noised image is affected by blocking effect whereas the output of UDWT at same level of decomposition doesn't have any such effect and looking more natural. Edges in image Fig-5a are more continuous than the edges in Fig-5b.

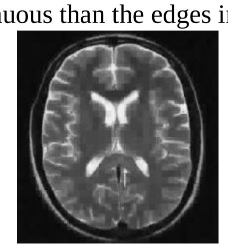


Fig. 5(a): DWT_Haar_l4,

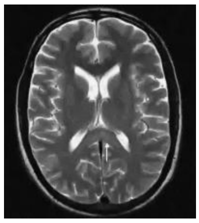
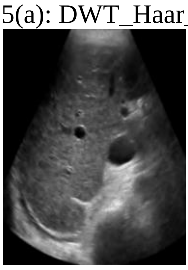


Fig. 5(b): UDWT_Haar_l4



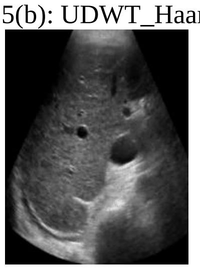


Fig. 6(a): DWT_sym2_l3 Fig. 6(b): UDWT_sym2_l3

Ultrasound images when processed with two de-noising algorithms the results obtained are noticeable due to the smoothing effect of wavelets the details in the ultrasound image are the not so visible, Fig-6a in case of discrete wavelet transform but on the other hand the un-decimated discrete wavelet transform yielded very good results the de-noised image is visually more acceptable as more details are visible in this image Fig-6b. Further visually inspecting the de-noised images it is also observed that in some cases due to the smoothing effect of wavelet operation at higher levels of decomposition over smoothing of images occurs due to which the detail of texture is lost in some images. Therefore it is preferable that the inspector must control the decomposition levels up to the extent of texture details required for the diagnosis purpose. The MSE an PSNR results are presented in Table-1 to Table-4.

Fig. 7(a): DWT_coif1_l5 Fig. 7(b): UDWT_coif_l5

Level	Type			
	Haar	db4	sym2	Coif1
1	20.9277	21.1399	21.0891	21.0868
2	19.6242	19.8902	19.8303	19.8246
3	19.1808	19.4428	19.3748	19.3747
4	19.0108	19.2618	19.1962	19.2026
5	18.9507	19.2024	19.1342	19.1423

Table 1: PSNR after de-noising using discrete wavelet transform

Level	Type			
	Haar	db4	sym2	Coif1
1	525.1791	500.1396	506.0187	506.2909
2	709.0165	666.9024	676.1604	677.0558
3	785.2276	739.2623	750.9281	750.9475
4	816.5822	770.7316	782.4611	781.3094
5	827.9606	781.332	793.7159	792.2292

Table 2: MSE after de-noising using discrete wavelet transform

Level	Type			
	Haar	db4	sym2	Coif1
1	21.6849	21.4862	21.5918	21.586
2	20.0448	20.0112	20.0318	20.0294
3	19.5397	19.5393	19.5471	19.5456
4	19.3395	19.3528	19.3578	19.3582
5	19.2588	19.2943	19.2927	19.2949

Table 3: PSNR after de-noising using un-decimated wavelet transform

Level	Type			
	Haar	db4	sym2	Coif1
1	441.1508	461.810	450.716	451.320
2	643.5709	648.575	645.510	645.864
3	722.9563	723.019	721.724	721.967
4	757.0671	754.739	753.878	753.814
5	771.2574	764.983	765.261	764.870

Table 4: MSE after de-noising using un-decimated wavelet transform

Implementing wavelet de-noising on medical images produce acceptable results. As medical images are perceptible to different types of noises, the un-decimated wavelet has shown remarkable PSNR and MSE values compared to discrete wavelet transform.

IV. Conclusion

Experimenting with different medical images using the wavelet domain is efficient and fast. In this simulation work the two wavelet methods are implemented and compared on the basis of the reconstructed image. Thus a comparison between the qualities and performance of various wavelet functions were deduced using these criteria. From Statistical and visual results it can be concluded that for different noise types, the un-decimated transform is efficient in reconstructing image.

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