An Improved Denoising Of Medical Images Based On Hybrid Filter Approach And Assess Quality Metrics

Mopidevi Suneetha , Mopidevi Subbarao

Abstract: Degradation of images and segmentation are the two most demanding fields for medical image processing, particularly when explicitly applied. The involvement of noise not only deteriorates the visual quality but also the precision of the segmentation which is vital to the medical diagnosis process of development. The complicated and monotonous main task is to manually denoise medical images such as CT, ultrasound and large numbers of clinical routine MRI images. The medical image must be denoised automatically. The proposed approach is associated with less complexity, this follows from the fact that, the design of system and time for optimization. Results show their efficacy for noise removal in medical ultrasound and MRI images .The final results of the proposed scheme in terms of noise reduction and structural preservation are excellent. However the proposed scheme is compared with existing methods and the performance of the proposed method in terms of visual quality, image quality index, peak SNR and PSNR is shown to be superior to existing methods.

Index Terms: Denoising, MRI, CT, Non-local means filter, wavelet domain, medical image, Noise

1 INTRODUCTION

In today's world, a great deal of digital data consists of images. They are often corrupted by noises in the acquisition or transmission of images. Noise decrease is, for several purposes, a very challenging and complicated issue. First, the nature and features of the noise differ greatly from one application to other, and changesaccording to time.Secondly, the objective of a noise reduction scheme is very much based on the specific circumstance and framework. Denoising images is an important aspect of digital image processing, focusing on the elimination of noise while still maintaining useful features. Medical imaging seeks to encapsulate human body abnormalities like tumor, cancer, fibroid, cyst, etc. The measurements were taken by different platforms with significantly different modalities, such as Magnetic Resonance Imagery (MRI), X-ray, CT, Ultrasound, Electrocardiogram (ECG) and Positron Emission Tomography (PET). There are, however, many useful methods for dealing with this problem, such as the median filter, the Wiener filter, the bilateral filter, the variation methods [1–5], the sparse representation-based methods [6], the wavelet-based methods [7] and the convolution neural network-based methods [8–10]. Wavelets are currently one of the best approaches used for denoising. A noisy image s', represented as sum of original signal s and added noise b, is subjected to a wavelet transform (WT). But, in wavelet thresholding the problem experienced is generally smoothening of edges. Assessment of the quality of medical images such as radiographs, ultra-sound images, MRI images, etc. Compared to general / natural photographic images, this is a crucial task. In the case of X-ray images, edge information must be given a high preference when determining the quality of those images.

- *Mopidevi Suneetha , Assistant professor, Dept. of Electronics and Communication Engineering, GRIET, Hyderabad , Telangana, India. E-mail: suneetha645@gmail.com*
- *Mopidevi Subbarao, Assistant professor, Dept. of Electrical and Electronics Engineering, VFSTR(Deemed to be University), Vadlamudi, Guntur, India.. E-mail: subbarao.mopidevi@gmail.com.*

This paper proposes a dramatically improved image denoising strategy and an appropriate quality measurement for X-ray, MRI and ultra-sound medical images.The main aims of the work in view of the above are: (1). Acquire a hybrid filter by hybridizing wavelet thresholds and improved non-local means filters and maybe even adjust the different filter parameters to optimize the filter's overall performance to detect different types of images. 2). To adjust both wavelet-based filter and non-local means filter parameters to optimize their performance to filter the same image types as in step (i). (3). Trying to equate the performance of the filters acquired in step (i) with those acquired in step (ii) in different image types.

2 MATERIALS AND METHODS

2.1 Wiener filter

Wiener filters seem to be a class of optimal linear filters that require linear measurement from a certain connected sequence of the required signal sequence. The primary objective of the wiener filter is to reduce the level of noise present in an image compared to the estimate of the intended noiseless image. The Wiener filter's objective is to remove noise that has damaged a signal thereby the strategy is based on statistics. Typical modern filters are designed to respond to the desired frequency, among them, the Wiener filter moves from a different angle towards filtering. Moreover the Wiener filters are often used to filter the noise from the corrupted signal to produce

2.2 Improved Non-local Means (Algorithm1)

The patch foveation is proposed here to get some space and frequency selectivity, especially in comparison with classical windows that are really spatially selective to relieve sharp details and soft regions. In fact, shifted patches comprise patch translations from fine-scale to gross-scale and non-adaptive filters select this space/frequency. The Nonlocal mean algorithm (NL-medium) is thus a simple prototype for the elimination of additive white Gaussian noise and it derives from an explicit construct of its corresponding foveation operator, usually resulting in the Foveated NL-medium algorithm. The Foveated NL-means[17], which optimizes the classical NL-denoising approaches[17] by calibrating average weights totally from the faveted patch-distance instead of just the standard windowed patch based, inevitably results in consistent rise in the quality of the preserved images, in fact quite the opposite due to unbiased and visual criteria. Something that we actually reproduce here by means of PSFs for an anisotropic generalization of most foveation operators. The negative quality of isotropic foveation operators would be further decreased.

Step1:Acquire Original medical Image from datafolder

Step 2:Artificially generate noisy observation with additive white Gaussian noise with different levels of noise standard deviationStep 3: Look for PSNR_in and SSIM_in from the the given data

Step 4: Call Anistropic Foveated NL-means function and tune the parameters accordingly as radius of search window, radius of patch, disables foveation and enables self-map as well sets elongation and orientation of the blur kernels
Step 5:For Anisotropy calculation based on the following conditions

i. theta is the angle between the first axis of the elliptical pdf (main axis if rho>1) and the radial (meridian) line between the blur kernel center and the center of the patch
ii. if theta=0, this is the tangent-radial ratio: set to 1 for circular-symmetric blur kernel, >1 for radially elongated elliptical blur kernels, <1 for tangentially elongated elliptical blur kernels.
iii. By leaving search_radius and U_radius empty, their values are chosen automatically based on the value of sigma (the signal is assumed to be in the standard [0,255] range)search-neighborhood and patch radiuses.

Step 6: Patching and construction of the Fdenotes to windowing kernel kcan be constructed in such a way to satisfy the four essentials

i. Accordingly foveation operator is specifically to be linear w.r.t input image
ii. Correspondigly foveation operator maps a treated images to regular patches
iii. Foveation operator is considered to be clear in the center of the patch
iv. The foveated distance FOV could be utilised completely replace the windowed distance d calculated from k, without any kind of alteration or tuning parameters.

Step 7: The renovation of F foveation Operator which fulfills the above requirements is equivalent to the adaptation of the scaling and propagation of the blurred PSFs to the extent that somehow their standard and square standards are congruent to the commensurate values of the kernel k window.
Step 8: As mentioned the Isotropic at this moment because all blurred PSFs are circular symmetrical and considerably decrease image features regardless of their orientation.

2.3 Wavelet domain transform(Algorithm2)

However, one of the profitable strategies for removing noises from images is wavelet transformation based denoising. The literature shows that, although frequency content variations [12], using wavelets successfully eliminates noise without ever influencing signal characteristics.

2.4 Proposed system

Possibly the target of the problem is to guess the signal s from noisyassumptions s' in order to preserve the characteristics of interest. Medical images are usually corrupted by two noise types, additive and multiple noise. The noise additive primarily corrupted image $S^1(x, y)$ is modeled as:

$$S^1(x, y) = S(x, y) + n(x, y) \tag{1}$$

In the same way, the multiplicative noise corrupted image $S^1(x, y)$ is demonstrated as:

$$\begin{aligned} S^1(x, y) &= S(x, y) + n(x, y)S(x, y) \\ &= S(x, y)\{1 + n(x, y)\} \end{aligned} \tag{2}$$

At this point $n(x, y)$ is noise function which returns random value with arbitrary distribution.It was shown that the suggested denoising system is displayed in Fig.1, where the reference medical images are associated where the various noise variances are artificially corrupted. Mostly in the particular case of non-local medium filter, noise will affect the precision of the similarity weight. This often outcomes even in the similar change that bilateral filtering in medical images, in particular the tissue region of the image and brain grooves, can be weakened by noise. When transforming domain methods such as wavelet thresholding (WT) is performed, the retention of edges and texture information becomes very efficient. Taking into account the results, the WT as a preprocessing step retains the edge parts.

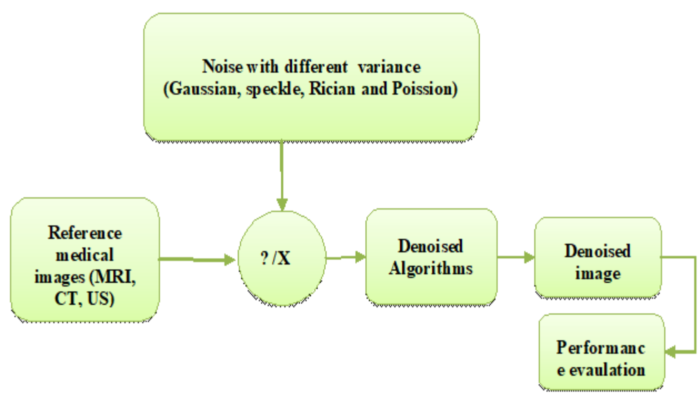


Fig. 1: *Procedural flow diagram for image denoising.*

3 FOR APPLICATION OF MRI IMAGES

It is well known that signal interpretations is present both on true and imaginary channels, with AWGN affecting each of the two orthogonal channels. Since there is a square root of the sums of two separate Gaussian factors, the size of the MRI signal is followed by the Rician curve.

TABLE 1

QUALITY METRICS ASSESSMENT WITH WEINER-FILTER FOR MRI BRAIN IMAGE CORRUPTED BY GAUSSIAN NOISE

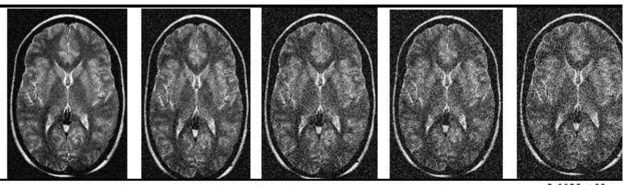
Quality metric	0.02	0.04	0.06	0.08	0.1
Image					
MSE	762.38	1.2923e+02	1.7884e+03	2.2424e+03	2.6685e+03
PSNR	19.30	16.99	15.60	14.62	13.86
NK	0.89	0.8337	0.79	0.75	0.73
AD	-0.05	-0.01	0.01	0.05	0.08
SC	1.14	1.24	1.32	1.39	1.44
MD	128	195	204	224	236
NAE	0.31	0.39	0.46	0.50	0.53

TABLE 2

QUALITY METRICS ASSESSMENT WITH OUR APPROACH AND WAVELET+NLM FOR MRI BRAIN IMAGE CORRUPTED BY ADDITIVE GAUSSIAN NOISE FOR DIFFERENT LEVELS OF NOISE STANDARD DEVIATION

Sigma	*20*	*30*	*40*	*50*	*60*
MRI	*MRI*	*MRI*	*MRI*	*MRI*	*MRI*
PSNR_out (Our approach)	*31.27*	*29.41*	*27.99*	*14.62*	*13.86*
PSNR_out (Wavelet+NLM)	*25.73*	*25.39*	*22.71*	*19.75*	*17.50*

4 FOR APPLICATION OF ULTRASOUND IMAGES

Because of developments in ultrasound imaging technology, commercially accessible ultrasound technologies now have spatial and temporal resolution for precise images. Doctors from time to time prefer a noisy image to a soft image to determine the value of ultrasonic images.Popular noise prototypes have indeed been chosen for performance testing and to equate the overall performance of certain filters. Noise can be of any kind totally unpredictable [11],thereafter for evaluating the operations several denoising methods, different forms of noises were reflected. As demonstrated in this document, the numbering for sections upper case Arabic numerals, then upper case Arabic numerals, separated by periods. Initial paragraphs after the section title are not indented. Only the initial, introductory paragraph has a drop cap.

4 CONCLUSION

In this paper, NLM and wavelet-based filtering were analyzed for different images contaminated with different noises. A hybrid denoising model is developed by hybridization and its performance is tested on various types of noisy images. Finally, the restored image is attained by incorporating the outcomes of the two deletion mechanisms. Perhaps this mechanism aims at eliminating Gaussian noise and restoring its texture. The denoising simulations show the overall efficiency of the hybrid system by constantly comparing it to state-of-the-art methodologies of denoising. The proposed strategy therefore enhances PSNR quality and maintains fine image structures.

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