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Medical Image De-noising using Non Local means Filtering

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Abstract: Due to the exponential advancement of information technology, computer, storage systems and networking technology, medical devices and clinical diagnosis has acquired tremendous popularity in the last two decades. Mostly in medical field including biomedical science, the effect of such advances is becoming apparent, allowing the detection and diagnosis in a much more vivid way. The significant hurdle in the diagnostic imaging study is to select an image without any substantial details being lost. It is extremely likely that throughout the course of retrieval or again subsequent processing phases, the data captured can be distorted by noises or artifacts. Noise is defined as the initial pixel value being modified at random. Noise lowers the clarity of the image which is particularly important whenever the structures are scanned are smaller and even have comparatively poor intensity. De-noising of image data is thus important, and in medical diagnostics it has always been a necessary pre-processing level. An analysis of several significant research in the field of image de-noising is discussed in this article. Since images were quite essential in any area, image de-noising is indeed a valuable pre-process prior towards more image analysis, such as segmentation, extraction of features, texture analysis, etc. This research intended to perform the comprehensive study of various de-noising strategies for medical imaging that involves MRI, CT and Retinal fundus images. A comparison study with many existing methods approaches focused on resemblance tests, reveals that the proposed approach is superior in image consistency to them.

Keyword: Filtering, MRI, CT Scan, Retinal, SSIM.

Introduction

In medical imaging frameworks and predominantly in pre-processing phases, image de-noising serves a very significant role. Numerous filters are developed to process the images, presuming a particular distribution of noise to obtain noise free images from various modalities of diagnostic imaging systems [1, 2]. Hence de-noising becoming crucial step in pre-processing phase of image processing. The central aim of de-noising the image is to recreate the original image as faithfully as possible while retaining essential detailed features [3-5].

In medical imaging, it is important for the accurate study of diseases de-noising medical images such as CT scan [6-8], X-Ray [9-10], MR Imaging [11-13] and PE Tomography [14-17] because a small loss of a specific region in these images will result in a huge, death-like disaster. One of the unavoidable limitations of images is noise, which directly impacts the image analysis process. Images are eventually polluted by noise during acquiring, processing, and transmitting due to the effect of the background, transmission medium, and other variables, contributing to interference and degradation of image content.

In image processing and computer vision context, image de-noising has been thoroughly researched and proposed multiple de-noising strategies to minimize those risks during the last few decades. Various strategies has its implications, merits and shortcomings. A comprehensive investigation on different image de-noising methods and their outcome on medical images was carried out in this research work which specifically focusing on biomedical images.

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Related Work

As shown in figure 1 there are two basic approaches to image de-noising, spatial filtering methods and transform domain filtering methods. A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters. With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible. In recent years, a variety of nonlinear median type filters such as weighted median [18], rank conditioned rank selection [19], and relaxed median [20] have been developed to overcome this drawback.

A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise. The wiener filtering [21] method requires the information about the spectra of the noise and the original signal and it works well only if the underlying signal is smooth.

Wiener method implements spatial smoothing and its model complexity control correspond to choosing the window size. To overcome the weakness of the Wiener filtering, Donoho and Johnstone proposed the wavelet based de-noising scheme in [22, 23].The transform domain filtering methods can be subdivided according to the choice of the basis functions. The basis functions can be further classified as data adaptive and non-adaptive.

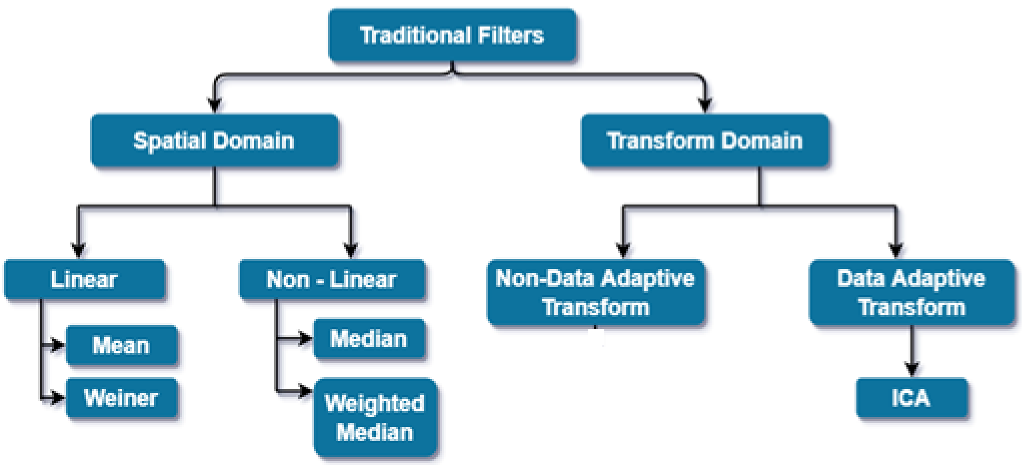

Fig 1 Classification of Filtering Approaches

Method

The pre-processing phase is the main step in the preservation of critical data. It will take a substantial period of data processing to filter and prepare the image. Pre-processing of images requires cleaning normalization, adjustment, retrieval and collection of features, etc. The raw image is pre-processed to increase the accuracy of the image so as to enhance its reliability as well as convenience of such data processing. Pre-processing has a huge effect on the efficiency of the extracting the features on the significant performance of image processing. In pre-processing, a

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database has both a useful function iterator form which correlates with computational convergence. The process is depicted in figure 2.

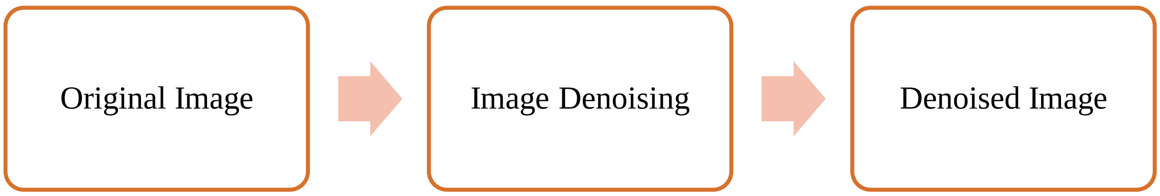

Figure 2: Flow of Medical Image De-noising Process

Non-Local Means Filtering

Non-local means is an algorithm in image processing for image de-noising. Unlike "local mean" filters, which take the mean value of a group of pixels surrounding a target pixel to smooth the image, non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. This results in much greater post-filtering clarity, and less loss of detail in the image compared with local mean algorithms [24].

If compared with other well-known de-noising techniques, non-local means adds "method noise" (i.e. error in the de-noising process) which looks more like white noise, which is desirable because it is typically less disturbing in the denoised product. Recently non-local means has been extended to other image processing applications such as de-interlacing, view interpolation, and depth maps regularization [25,26].

Result:

Simulation Results using NLM Filtering

Input image CT	MRI	Retinal Fundus	Preprocessed Images using NLM

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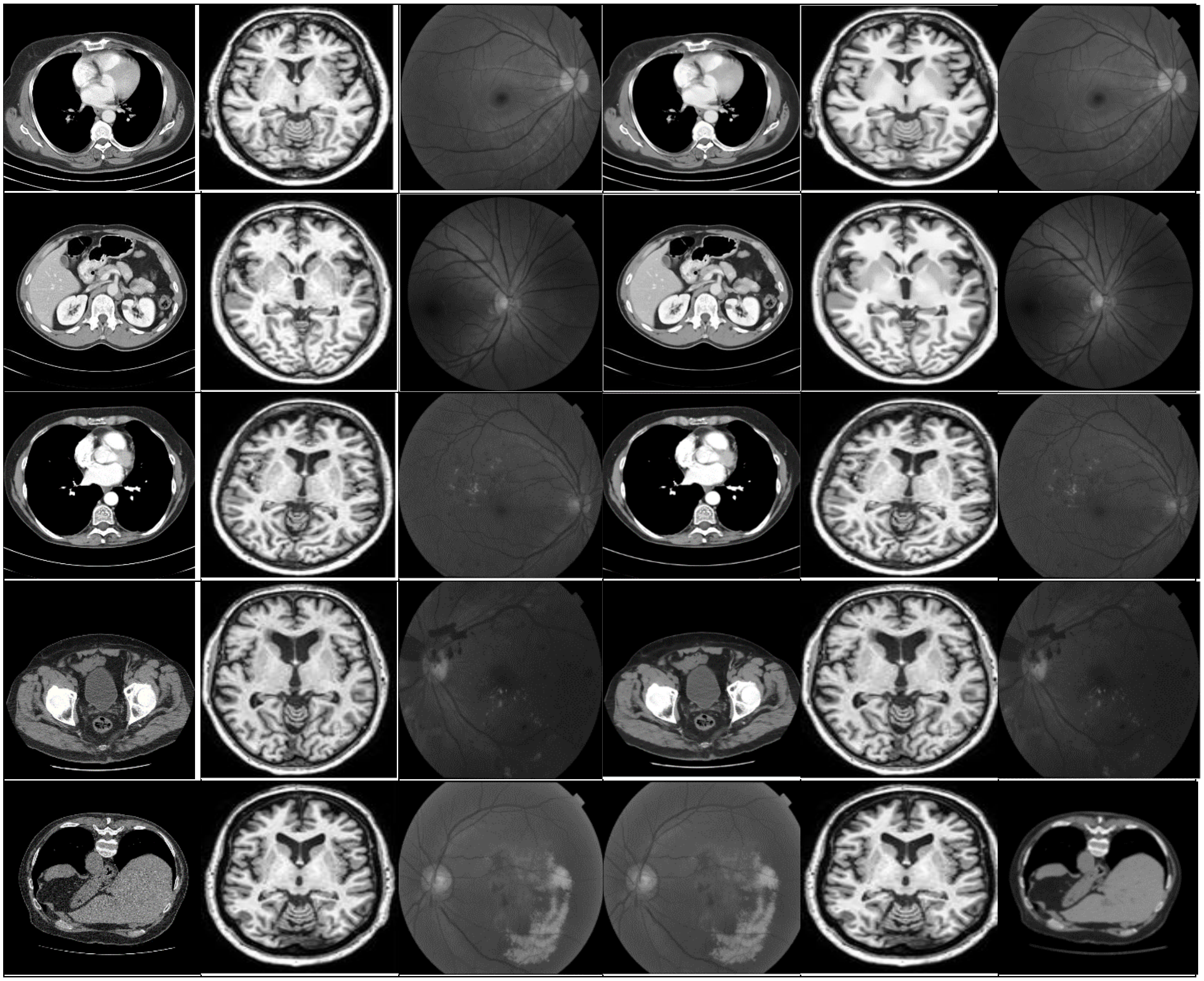

Performance Parameters

The performance parameters achieved for Non Local Means filtering for CT, Retinal fundus and MR images are presented in Table 1, 2, and 3 respectively.

Table 1 : Performance Matrix for CT Images using Non Local Means Filtering

Image	MSE	PSNR	RMSE	MSSSIM	PSNR	PSNR (blocking	RMSE	REF_SAM	SSIM	UQI	VIFP

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						effect)					
Library used	Scikit			Sewar							
CT1	0.04	302.33	0.06	71.15	0.96	312.69	16.81	0.06	0.96	0.95	0.97
CT2	0.05	318.51	0.04	66.87	0.97	315.63	15.46	0.07	0.95	0.96	0.98
CT3	0.04	320.29	0.05	67.84	0.96	321.58	16.46	0.06	0.96	0.97	0.97
CT4	0.04	316.73	0.06	68.48	0.98	310.79	16.46	0.06	0.97	0.98	0.97
CT5	0.04	318.58	0.05	87.25	0.96	326.26	nan	0.07	0.96	0.97	0.97
Ideal	0	INF	0	0	1+0j	INF	0	0	1	1	1

Table 2: Performance Matrix for Retinal Fundus Images using Non Local Means Filtering

Image	**MSE**	**PSNR**	**RMSE**	**MSSSIM**	**PSNR**	**PSNR (blocking effect)**	**RMSE**	**REF_SAM**	**SSIM**	**UQI**	**VIFP**
Library used	Scikit			Sewar							
Retina1	0.05	322.47	0.07	75.12	0.95	322.69	19.28	0.08	0.95	0.95	0.97
Retina2	0.07	306.27	0.08	76.26	0.96	305.63	21.63	0.08	0.95	0.96	0.96
Retina3	0.05	326.70	0.07	77.22	0.95	311.90	24.46	0.08	0.95	0.96	0.97
Retina4	0.05	345.54	0.09	78.76	0.96	308.99	26.63	0.07	0.97	0.96	0.96
Retina5	0.05	349.24	0.05	89.46	0.95	306.69	nan	0.07	0.96	0.96	0.97

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Ideal	0	INF	0	0	1+0j	INF	0	0	1	1	1

Table 3: Performance Matrix for MRI Images using Non Local Means Filtering

Image	**MSE**	**PSNR**	**RMSE**	**MSSSIM**	**PSNR**	**PSNR (blocking effect)**	**RMSE**	**REF_SAM**	**SSIM**	**UQI**	**VIFP**
Library used	Scikit			Sewar							
MRI1	0.03	370.47	0.05	55.51	0.98	352.56	10.81	0.04	0.99	0.98	0.99
MRI 2	0.04	368.13	0.04	53.73	0.99	355.79	9.46	0.05	0.98	0.98	0.98
MRI 3	0.03	370.99	0.05	52.42	0.98	378.58	8.56	0.03	0.99	0.99	0.99
MRI 4	0.04	386.54	0.04	56.76	0.98	355.80	6.56	0.03	0.99	0.98	0.99
MRI 5	0.03	378.58	0.04	50.46	0.99	356.57	nan	0.04	0.98	0.97	0.99
Ideal	0	INF	0	0	1+0j	INF	0	0	1	1	1

Conclusion

The increasing number of patient data in medical images imposes a research challenge for the scientific treatment for diagnosing, detecting and prediction of the diseases. Now-a-days, the interests of the radiologists are attracted towards the medical data mining for patience care. Medical data mining and image de-noising is the state of art challenge for researchers. The rapid growth is an outcome of the requirement for cost-effective, accurate, fast and persistent treatment. The detection and prediction of imaging is getting easier by the advancement in the technology. The quick development is an outcome of the requirement for more fast, precise and less intrusive treatment. Advanced technology in radiologic imaging gear has additionally energized the use of imaging.

Noise is inherently presents in digital images during image acquisition, coding, transmission, and processing steps. It is very difficult to remove noise from the digital images without the prior knowledge of filtering techniques. From thorough analysis it is perceived that the medical image de-noising is an emergent research area and has received great attention among the researchers from image and signal processing in recent years. As such, a broad review of the significant researches and techniques that exist for medical image de-noising is presented. The proposed NLM filtering outperforms as compared to existing method.

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