A Novel Medical Image de-Noising Algorithm for Efficient Diagnosis in Smart Health Environment

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Abstract— ***Smart healthcare is defined by the technology that leads to better diagnostic tools, better treatment for patients, and devices that improve the quality of life for anyone and everyone.***
Medical images have significant to facilitate that smart health environment. However, the medical images frequently get noisy in the acquisition process, which engages many different physical mechanisms. Most of the de-noising algorithms conceive the additive white Gaussian noise (AWGN). However, among the popular medical image modalities, several are degraded by some type of non-Gaussian noise, such as Poisson noise. Poisson noise is mainly associated with many imaging modalities like single-photon emission computerized tomography (SPECT), (positron emission tomography) PET, and fluorescent confocal microscopy imaging. Because of the signal-dependent nature of Poisson noise, the various de-noising filters proposed in the literature, including the Non-Local Mean (NL-Mean) filter. In literature, NL-Mean is mostly applied for Gaussian noise extraction and very rarely used for Poisson noise removal. In this work, notable efforts are put to modified NL-Mean filter, and high order NL-Mean Methods are proposed. These novel high order algorithms de-noise images by prominent the signals and noise because it takes the high order odd moment of the medical image. The visual quality of the de-noised medical image (PET) and correlation graph determines that the proposed algorithms outperform the conventional denoising filter. This study's findings will significantly contribute to the development of a more accurate and robust image analysis model, which is the need of todays modern age of digitization.

Keywords— Smart Health, Poisson Noise removal, Medical Images De-noising, Poisson Noise in medical images, De-noise Poisson noise-contaminated images, Improve medical images visual quality

I. INTRODUCTION

During the medical image acquisition process, the noise is contaminated into it and degrade the visual quality. Further, this noise contamination also affects the image segmentation and registration processes [1, 2]. The noise may have the Gaussian distribution model [3] or non-Gaussian distribution model like a Poisson distribution model [4, 5]. The Poisson noise exhibits signal dependence [6, 7]; therefore, the de-noising process needs special efforts for optimizing the image from degraded images. The various de-noising methods deployed for the suppression of Gaussian distributed noise. However, measures have been taken to suppress the Poisson noise; further efficient algorithms need to be developed to retain the fine details in the de-noised image. R-L algorithm is an iteration based non-quadratic log-likelihood function with multiplicative corrections is considered a first de-noising algorithm presented for Poisson noise removal [8]. The R-L combined with total variation (TV) for visual quality enhancement of degraded Confocal. Laser Scanning Microscopy Images with Poisson Noise [9]. The TV is also used to reduces the Poisson noise from the tomographic imaging [10, 11]. The wavelet-based methods get attention for de-noising the Poisson noise-contaminated medical images. These wavelet-based work with the shrinkage and with the thresholding. The selection of suitable thresholding and shrinkage plays a crucial role in the successful de-noising of these images [12, 13]. The several thresholding approaches developed that work combined with Discrete wavelet transform for medical image visuality improvement [14, 15]. Several other hybrid algorithms were proposed for noise removal from different medical images modalities [16, 17].

Generally, it is considered that original images are comprised of low frequencies, whereas the noisy images are comprised of both high and low frequencies [18]. Therefore, the noisy image has a non-smooth structure. The conventional Wiener, Median, and Gaussian filters remove only the high frequencies and make the image smooth by leaving behind the low frequencies. However, some original image structures also have fine details and information in high frequencies [18], which also requires several hyperparameter and model architecture tunning [19]. Therefore, de-noising this type of image with a conventional de-noising filter leads to the loss of fine details and blur the resultant image. NL-Mean filter eliminates this loss factor and prevents the image from getting blurred. Instead of removing the high frequencies as conventional do, this filter adopts the neighbouring pixel similarity concept. The modification is done in the Yaroslavsky filter [20] to get the NL-Mean filter [21], which averages the local same intensity pixels. The NL-Mean filter exploits the pixels similarity intensity at the region level but not at the local level pixel comparison. Therefore, it effectively de-noise the images and preserves the fine details. The NLM filter in literature is mostly presented for Gaussian noise removal from medical images.

Let the image is U, the NLM filtered value at point $\dot{\imath}$ calculated with the weighted average of neighbouring pixels $\aleph_{\dot{\imath}}$ of an image. The NL-Mean is mathematically represented as (1)

$$\begin{cases} NL(U(\dot{\imath})) = \sum_{\hat{\jmath}\epsilon\aleph_{\dot{\imath}}} w(\dot{\imath},\hat{\jmath})U(\hat{\jmath}) & 0 \le w(\dot{\imath},\hat{\jmath}) \ge 1 \\ & \sum_{j\epsilon\aleph_i} w(\dot{\imath},\hat{\jmath}) = 1 \end{cases} \quad (1)$$

Where weight $w(\dot{\imath},\hat{\jmath})$ calculated by

$$w(\dot{\imath},\hat{\jmath}) = \frac{1}{\sum_{\hat{\jmath}\epsilon S} \exp(\,{}^{-d(\dot{\imath},\hat{\jmath})}/_{h^2})} \exp(\,{}^{-d(\dot{\imath},\hat{\jmath})}/_{h^2}) \quad (2)$$

In the given weight calculation formula, the h and $d(\dot{\imath},\hat{\jmath})$ determine the filtering parameter and Gaussian weighted Euclidean distance [22]. The filter parameter controls exponential expression decay in the weighting scheme. The noise is not entirely eliminated with a very small size of filtering parameter. Contrary to this large filter parameter size smoothen the image. So, the smoothening degree of the filtered image is dependent on filtering parameter size. Where the $d(\dot{\imath},\hat{\jmath})$ mathematically represented as (3)

$$d(\dot{\imath},\hat{\jmath}) = \left\| v(\aleph_{\dot{\imath}}) - v(\aleph_{\hat{\jmath}}) \right\|^2 \quad (3)$$

At the pixel points $\dot{\imath}$ and $\hat{\jmath}$, the neighbourhood window indices can be represented by $\aleph_{\dot{\imath}}$ and $\aleph_{\hat{\jmath}}$ respectively. Therefore, the $v(\aleph_{\dot{\imath}})$ and $v(\aleph_{\hat{\jmath}})$ windows centred at points $\dot{\imath}$ and $\hat{\jmath}$, respectively. Interestingly, this issue becomes more severe when dealing in real-time analysis, hence requiring more robust solutions [23, 24].

Several modifications are done in the original NLM to get the high performing version out of it. The proposed NL-Means methods for de-nosing of PET image is presented in section 2. The simulation results are presented in section 3. The future research direction discussed in section 4 and section 5 is comprised of a conclusion.

II. Proposed NLM De-Noising Algorithm

In this work, the modified high order NL-Means models are proposed. The steps followed to deploy these proposed approaches for de-noising medical images are shown in figure 1. Three NL-Mean methods are proposed for medical image de-noising, which are contaminated with Poisson noise. The actual NL-Mean is defined by equation (1), where the three proposed methods can be understood by equations 4,5 and 7. For high order NL-Means Method I, the Poisson corrupted image's cubic is taken in order to make the pixel more intense while keeping the original sign. After that, NL-Means has implemented to de-noise this noisy cube image. The mathematical model is represented in (4).

$$NL - Means(\text{N}^3(\dot{\imath})) = \sum_{\hat{\jmath}\epsilon\aleph_{\dot{\imath}^3}} w^3(\dot{\imath},\hat{\jmath})\text{N}^3(\hat{\jmath}) \quad (4)$$

The NL-Means Method II is dependent on the result of NL-Means Method I. The noise variance ($\tilde{\sigma}^2$) of the actual noisy image is estimated first and then subtracted from the de-noised image of NL-Means Method I. Later on, the square root of the resultant image is taken. This further eliminated the remaining noise. Mathematically it is defined in (5).

$$NL - Means\ Method\ II = \sqrt{\sum_{\hat{\jmath}\epsilon\aleph_{\dot{\imath}^3}} w^3(\dot{\imath},\hat{\jmath})\text{N}^3(\hat{\jmath}) - \tilde{\sigma}^2} \quad (5)$$

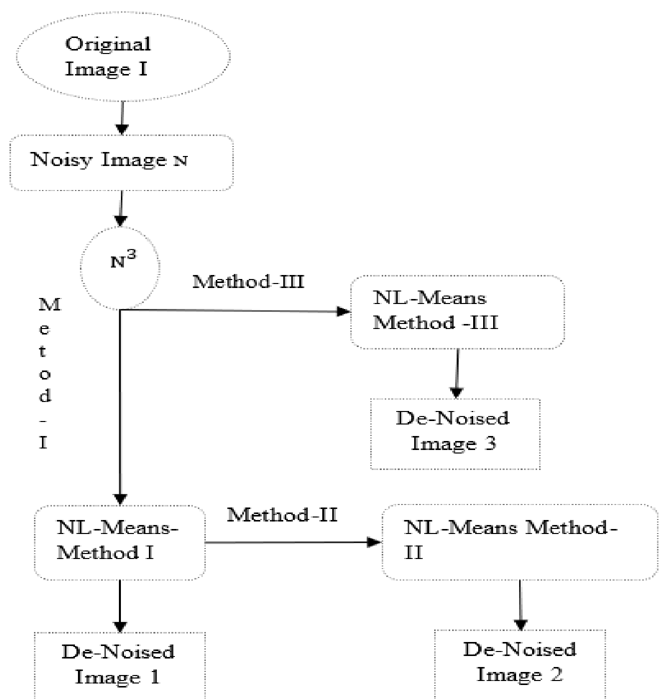

Fig. 1. Steps Followed to Deploy the Proposed High-Order NL-Means Models for Medical Image De-noising

Where the NL-Means Method III first estimate the noise variance ($\tilde{\sigma}^2$) and it subtracted from the noisy cubic image N^3.

On the resultant image, the NL-Means filter applied to get the de-noised image.

$$Resultent\ Image\ \acute{R} = \sqrt{N^3 - \tilde{\sigma}^2} \quad (6)$$

Therefore, mathematically the NL-Means Method III is represented as

$$NL - Means(\acute{R}) = NL(\sqrt{N^3 - \tilde{\sigma}^2}) \quad (7)$$

III. Results and Discussion

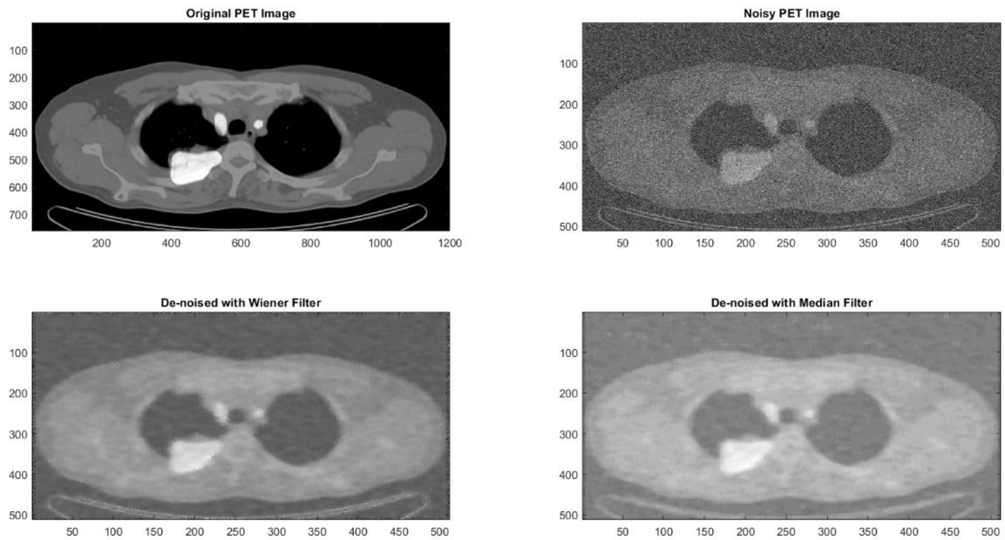

Fig. 2. De-noise Performance Results of Conventional De-noising Filters for PET Image

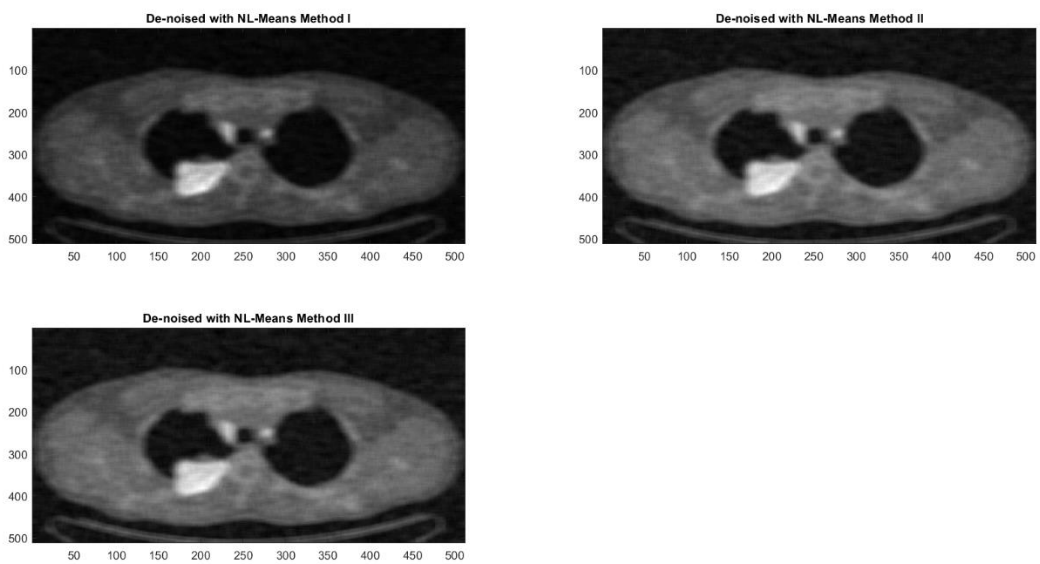

Fig. 3. De-noising Performance Results of Proposed De-noising Methods for PET Image

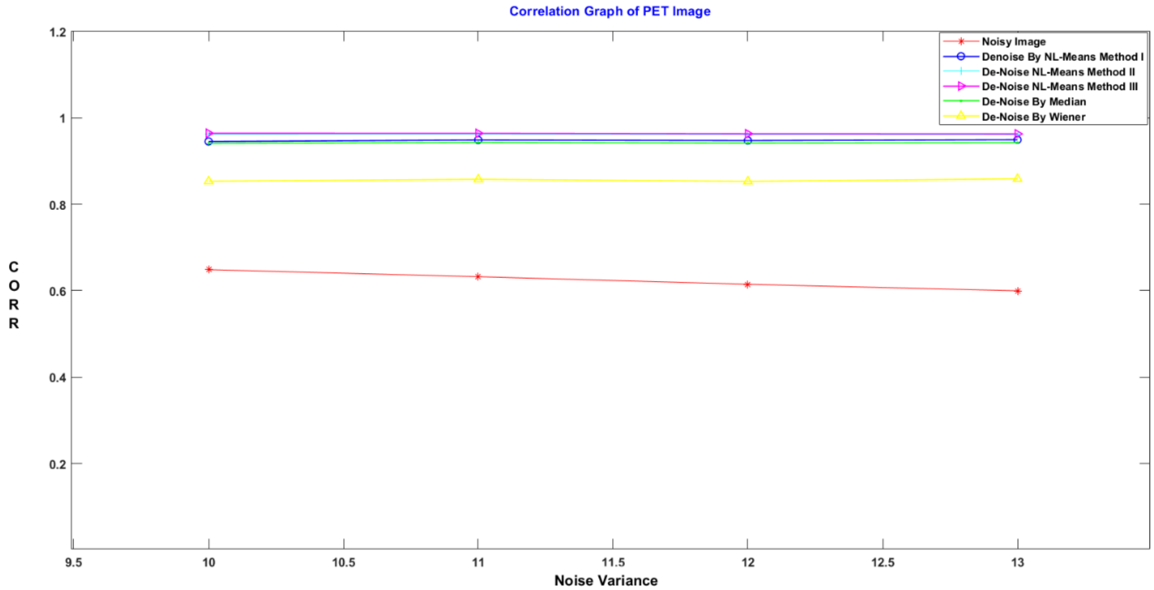

Fig. 4. Correlation Performance Analysis Graph of Conventional and Proposed NL-Means De-noising Methods for PET Image

Table 1. Correlation - A Performance Analysis of De-noising Filters for PET Image

	Correlation of PET					
	Noisy Image	De-noised by NL-Means Method I	De-noised by NL-Means Method II	De-noised by NL-Means Method III	De-noised by Wiener Filter	De-noised By Median Filter
Correlation value (dB)	0.59	0.951	0.962	0.961	0.954	0.942

The simulation is carried out on positron emission tomography (PET) images in order to measure the performance of de-noising filters. Figure 2 shows the visual output of conventional filters like Median filter and Wiener filter deployed to extract the image from the Poisson noise-contaminated images. Where figure 3 shows the visual performance results of proposed de-noising methods. The results of conventional filters are blurry because the image's fine details are removed during the de-noising process. Even these conventional filters do not fully remove the imposed noise from the PET image. In contrast, the proposed methods perform better than the conventional ones. Proposed filters completely remove the noise while retaining the fine details of the PET image. The de-noising performance of conventional and intended methods is analyzed with correlation comparison.

Fig. 4 shows the correlation graph of the PET image de-noised with a different filter. The correlation results indicate a slightly better performance of the proposed methods. On the other hand, the correlation of PET image de-noised with conventional filters is a little less than the proposed ones.

The correlation is found by correlating the original with noisy and with a de-noised image obtained by de-noising algorithms. Table 1 is comprised of the correlation values of a noisy image and de-noised with different filters. The results define that the proposed methods are outperforming the Median filter results. However, the de-noised by NL-Means I lack very slightly in performance when compared with the Wiener filter. The other proposed methods have comparatively good performance from both conventional filters.

IV. Future Work and Research Direction

The visual performance of the intended methods is better than the conventional filter. The correlation performance measure of Intend methods is better than that of the conventional ones. Moreover, in current methods, the variance is measured manually, so future work can be in the direction to develop some adaptive algorithm for measuring the noise variance of noisy images, which bring out the practical implementation of this approach. The Weight calculation in the NL-Means filter plays a vital role in de-noising corrupted images while holding the fine details in the retained image. The efficient measure can improve the performance of the NL-Means filter. Therefore, it open ways for future work in this direction. The proposed NL-Means Methods can be tested for other medical image modalities like X-Rays, SPECT etc.

V. Conclusion

Medical images frequently get noisy in the acquisition process, which engages the physical mechanisms. Among the popular medical image modalities, several are degraded by some type of non-Gaussian noise, such as Poisson noise. The various de-noising filters proposed in the literature, including the NLM filter for this noise removal. In this work, notable efforts are put to modified NL-Mean filters, and high order NLM algorithms are proposed. The visual results of intended filters are far better than the results of conventional filters. The correlation graph also determines the effective performance of the proposed methods.

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