

Probabilistic Nonlocal Means Image De-noising in Tele-radiology

J.SaiKrishna^{1*} M.Venkatanaresh² P.V.S.R Bharadwaja³ N.Dushyanth⁴

¹Assistant Professor/ECE, S.V Engineering college for Women, Tirupati, Andhra Pradesh., ²Assistant Professor/ECE, Sree Vidyanikethan Engineering College, Tirupati, Andhra Pradesh, ³Assistant Professor/ECE, Sree Vidyanikethan Engineering College, Tirupati, Andhra Pradesh, ⁴Assistant Professor/ECE, S.V Engineering college for Women, Tirupati, Andhra Pradesh.

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Abstract

Tele-radiology is one among the digital medical diagnosis systems, where the transmission and maintenance of diagnosed Medical reports like X-Ray, C.T Scan and MRI, are accessed through internet. While transmitting such medical reports in the channel it may be affected by Noise at different sources. Restoring the original image from noisy image is a critical issue, where Nonlocal means is one of Spatial de-noising techniques. In this technique, de-noising is initiated from the center patch by using weighted versions of all patches in search neighborhood. Process of Searching neighborhood includes some dissimilar patches. We use hard thresholding based on distribution of distances of similar patches that eliminates the dissimilar patches. Probabilistic Non Local Means P-NLM denoted by Elimination of Dissimilar Patches in Nonlocal Means (NLM-EDP). This NLM-EDP method improve PSNR and SSIM of the retrieved image in comparison with nonlocal means.

Index Terms

Tele-radiology, Image denoising, hard thresholding, Probabilistic nonlocal means.

I. INTRODUCTION

Tele-radiology comes under the stream of electronic health care, where monitoring and diagnosing of patients is done through internet. It is more concern about paperless, wireless accessing of medical reports like MRI, C.T. Scan. Transmitting medical reports through wireless channels may be effected by noise, where restoring the original image from noisy image is a critical issue. From few decades we use to some denoising techniques by using mean, median, Gaussian, and bilateral filters. The conventional nonlocal means Method denoises the center patch, but we use weighted version for all patches in a search of neighborhood. In NLM there exists many variants for performance Improvement One Such de-noising variant is probabilistic nonlocal means (PNLM), we use a new weight function based on the distribution of distances of patches. This weight function out performs the weights used in conventional NLM. But in probabilistic approach of early termination is used to reduce dissimilar Patches through applying hard thresholding based on regardless of the weights. However, performance of P-NLM is not optimum than conventional NLM because some similar patches are also eliminated. we propose a pre-processing hard thresholding algorithm that is based on distribution of distances of similar patches. This hard thresholding algorithm

eliminates those dissimilar patches. Our simulation results more superior compared to the conventional NLM.

II. PROPOSED IMPLEMENTATION

Consider a 2D Image and add an additive random noise with zero-mean and unknown variance σ^2 Which is given as

$$y_i = x_i + n_i \quad \forall i: n_i \sim (0, \sigma^2) \dots \dots \dots (1)$$

Where y_i =noisy Image,

x_i =clean pixel and n_i =noise pixel

To remove the noise from the noisy image we use conventional NLM method and we estimates pixel, \hat{x}_i which is a weighted average of remaining pixels in a search neighborhood S_i

$$\hat{x}_i = \frac{\sum w_{i,j} y_j \quad j \in S_i}{\sum w_{i,j} \quad j \in S_i} \dots \dots \dots (2)$$

Where $w_{i,j}$ weight between square patches centered at pixels i, j .

$$w_{i,j} = e^{-d_{i,j}/h} \dots \dots \dots (3)$$

The Euclidean distance of two local patches P_i and P_j with centers at pixels i and j which is given as

$$d_{i,j} = \|P_i - P_j\|_2^2 \dots \dots \dots (4)$$

Where h is the decaying parameter and is generally set to 10σ [3].

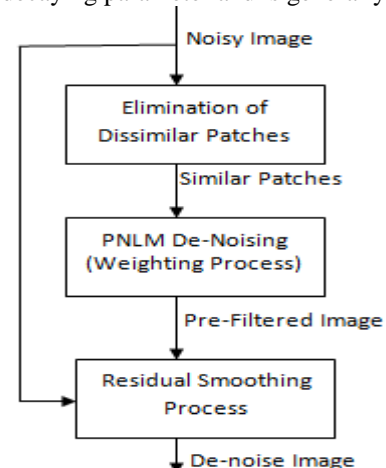


Fig1. Elimination of dissimilar patches in nonlocal means

Proposed implementation is done by elimination of dissimilar patches in nonlocal means image de-noising .as shown in Figure.1

A. Elimination of Dissimilar Patches

Using conventional NLM, distance is calculated from reference to patches in search neighborhood S_i .

If two patches are similar then their distance is due to only additive white Gaussian noise as nature of distance has a chi-squared distribution x given as

$$\chi_k^2(x) = \frac{x^{\frac{k}{2}-1} e^{-x/2}}{2^{\frac{k}{2}} \Gamma(\frac{k}{2})} \dots\dots\dots (5)$$

Where Γ the gamma function and k is the degree of freedom.

By using hard thresholding algorithm it eliminates more dissimilar patches compared with conventional NLM. For i^{th} center patch in an image, we calculate $d_{i,j}$ s in a search neighbourhood S_i . In hard thresholding similar patches with $d_{i,j}$ s fall within the probabilistic boundaries that are pre-calculated based on chi-square distribution. These probabilistic boundaries are example of hard thresholding algorithm. In a search neighborhood we will find three cases flat, edge and pattern. Probabilistic boundaries are fixed for flat, edge, pattern cases. These probabilistic boundaries are only function of σ and size of search neighbourhood S_i

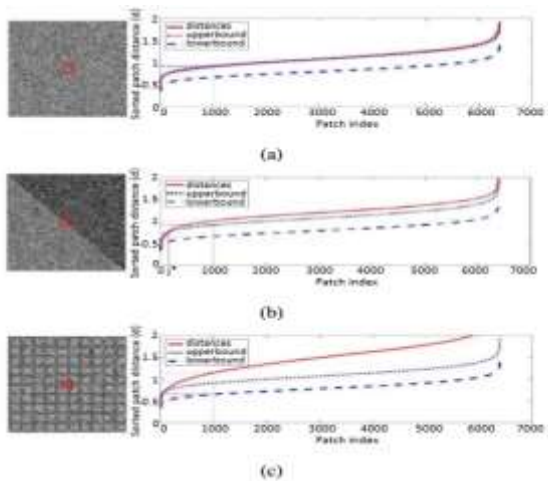


Fig2. Three cases in search neighborhood S_i :
(a) Flat (b) edge (c) pattern.

B. Weighting process

After hard thresholding remaining similar patches are passed through weighting stage (De-noising). In this stage probabilistic weights are calculated based on chi-square distribution given as

$$w_{i,j} = \chi_{\eta_{i,j}}^2 \left(\frac{d_{i,j}^2}{\gamma_{i,j}} \right) \dots\dots\dots (6)$$

Where $w_{i,j}$ is the probabilistic weight function

$$\gamma_{i,j} = (2|P_i| + |O_{i,j}|) / 2|P_i| \dots\dots\dots (7)$$

$$\eta_{i,j} = |P_i| / \gamma_{i,j} \dots\dots\dots (8)$$

Where $|P_i|$ is the number of pixels in reference patch P_i and $|O_{i,j}|$ is the number of overlapping pixels between square patches P_i and P_j . The Process of Weighting Process can be claimed as soft thresholding

C. RESIDUAL SMOOTHING PROCESS

In this stage we use the smoothing filter (Median Filter) [8]

$$\hat{x}_i^{new} = \hat{x}_i + \lambda D(y_i - \hat{x}_i) \dots\dots\dots (9)$$

Where D is the residual smoothing de-noising function and λ is percentage of smoothing residuals.

A median filtering is used over smoothed residuals, $y_i - \hat{x}_i$. For each pixel of residual image is the median value of pixels in a 3×3 neighbourhood is calculated to replace the center pixel value and chosen $\lambda = 10\%$.

III. RESULTS AND DISCUSSIONS

The Input Bio-medical image is loaded to system for processing as shown in the figure. 3



Fig.3 Input Image-1

The loaded Bio-Medical image is corrupted by the additive random noise as shown in the Figure 4.

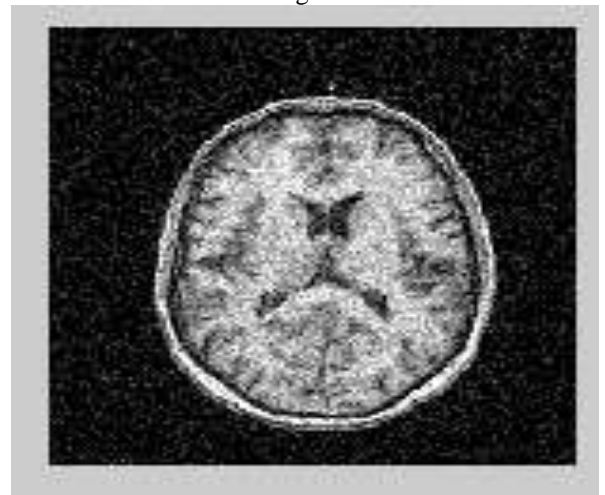


Fig.4 Noisy Image

The noisy image is de-noised in two steps i.e. hard thresholding and PNLM (weighting Process). The resultant pre-filtered image is as shown in the Figure 5.



Fig 5. Pre Filtered Image

By applying the residual Smoothing between noisy image and pre-filtered image yield the de-noised image as shown in the figure 5.

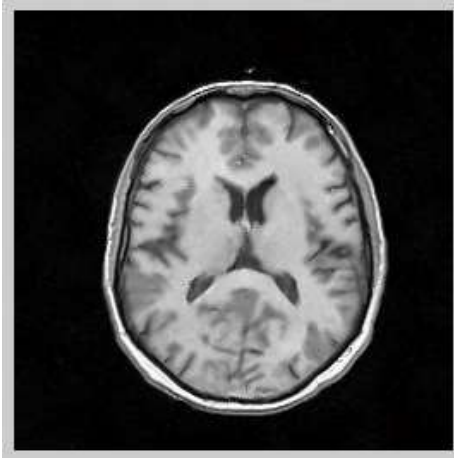


Fig 6. De-noised Image

The above Implementation is done for following testimonial bio-medical images to validate the accuracy of the proposed implementation.



Fig 7. Input Image-2



Fig 8. Input Image-3

The proposed method compared with NLM and PNLM [4]. Our propose method patch size used as 5×5 and serch neighbourhood of size 21×21 .

TABLE I Performance comparison for $\sigma=30$

Fig.NO	NLM		PNLM		Hard Thresholding + PNLM	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
3	25.90	68.36	28.56	72.94	28.76	73.58
7	25.28	67.27	27.89	70.19	27.98	71.28
8	26.24	70.12	27.69	72.03	28.10	73.25

Table 1 shows Performance comparison of NLM, PNLM and Hard Thresholding + PNLM with deviation is equal to 30.

IV. CONCLUSION

De-noising the Bio-medical images through additional pre-processing hard thresholding before PNLM is implemented on noisy images and observed de-noised images. The same de-noising is replicated with conventional de-noising schemes NLM, PNLM, but significant improvement in all metrics like PSNR, SSIM and quality of de-noised image is significantly improved in the proposed implementation. As hard thresholding algorithm eliminates dissimilar patches before PNLM de-noising the elimination of dissimilar patches more for neighborhoods with more details and less for flat neighborhoods. Further de-noising scheme can be extended to any of adaptive weighting process which may yield far better results and improved performance than proposed implementation.

REFERENCES

- [1] C. Tomasi and R. Mantachic, "Bilateral filtering for gray and color images," in Computer Vision, 1998.Sixth International Conference on. IEEE, 1998, pp. 839–846.
- [2] A. Buades, B. Coll, and J.-M.Morel, "A review of image denoising algorithms, with a new one," Multiscale Modeling & Simulation, vol. 4, no. 2, pp. 490–530, 2005.
- [3] "A non-local algorithm for image denoising," in Computer Vision and Pattern Recognition, 2005. CVPR 2005.IEEE Computer Society Conference on, vol. 2. IEEE, 2005, pp. 60–65.
- [4] Y. Wu, B. Tracey, P. Natarajan, and J. P. Noonan, "Probabilistic non-local means," Signal Processing Letters, IEEE, vol. 20, no. 8, pp. 763–766, 2013.
- [5] R. Vignesh, B. T. Oh, and C.-C.Kuo, "Fast non-local means (nlm) computation with probabilistic early termination," Signal Processing Letters, IEEE, vol. 17, no. 3, pp. 277–280, 2010.
- [6] C.-A. Deledalle, V. Duval, and J. Salmon, "Non-local methods with shape-adaptive patches (nlm-sap)," Journal of Mathematical Imaging and Vision, vol. 43, no. 2, pp. 103–120, 2012.
- [7] S. Beheshti, M. Hashemi, X.-P. Zhang, and N. Nikvand, "Noise invalidation denoising," Signal Processing, IEEE Transactions on, vol. 58, no. 12, pp. 6007–6016, 2010.
- [8] D. Brunet, E. R. Vrscay, and Z. Wang, "The use of residuals in image denoising," in Image Analysis and Recognition. Springer, 2009, pp. 1–12.

Vidyanikethan Engineering college,
Tirupati.

BIOGRAPHIES:



J.SAIKRISHNA completed his B.Tech in Electronics and Communication Engineering at Sri Venkatesa Perumal College of Engineering and Technology, JNTU-A, Puttur, India in 2010 and completed his M.Tech degree with specialization of Signal Processing at Sri Venkateswara University college of Engineering (SVUCE), S.V. University, Tirupathi, India. At present he is working as Assistant Professor in the Dept. of ECE, at S.V. Engineering College for Women, Tirupathi.



M.VENKATANARESH completed his B.Tech in Electronics and Communication Engineering at Sri Vidyanikethan Engineering college , Tirupati, India in 2011 and completed his M.Tech degree with specialization of Communication Systems at Sri Venkatesawara University college of Engineering (SVUCE), S.V. University, Tirupathi, India. At present he is working as Assistant Professor in the Dept. of ECE, at Sri