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A New Statistical Approach for Elimination of Dissimilar Patches in Nonlocal Means Image Denoising

[1]P. Sudhakar Reddy, [2] Prof.G.Sreenivasulu
[1]M.tech Student [SP], Dept. Of ECE SVUCE, Tirupati, Andhra Pradesh, India
[2]Professor and HOD, Dept. Of ECE SVUCE, Tirupati, Andhra Pradesh, India

Abstract:- **Nonlocal means is one of the well-known image denoising technique. In this nonlocal means technique to denoise the center patch by using weighted version of all patches in search neighbourhood.Some dissimilar patches also include in this search neighbourhood.We propose hard thresholding algorithm based on distribution of distances of similar patches. We use hard thresholding algorithm that eliminates those dissimilar patches. The method denoted by Elimination of Dissimilar Patches in Nonlocal Means (NLM-EDP).This NLM-EDP method improves PSNR and SSIM of the retrieved image in comparison with nonlocal means.**

Index Terms— **Image denoising, hard thresholding, nonlocal means.**

I. INTRODUCTION

In image processing image denoising is a main problem. It is defined as to recover original clean image from its observed noisy image. Removing noise is an important pre-processing step in the image processing techniques such as medical image analysis, image segmentation, or it can be also used improves visual quality of image. In past decades use some denoising methods are mean, median, Gaussian, and bilateral filters [1].There are methods that transform pixels into coefficients for the denoising purpose such as wavelets [2].In these paper concentrate nonlocal means (NLM) methods. Nonlocal means algorithm proposed by Buades based on Self-Similarity concept [3].In conventional nonlocal means to denoise the center patch by using weighted version of all patches in a search neighbourhood. In NLM many variations are proposed to improve performance. For example probabilistic nonlocal means (PNLM) [4], create a new weight function based on distribution of distances of patches. This weight function outperforms the weights used in conventional NLM.In probabilistic early termination (NLM-PET) [5] to reduce dissimilar patches by using pre-processing hard thresholding based on regardless of the weights. However, performance of NLM-PET worse than conventional NLM because of some similar patches also eliminated. Nonlocal means with shape adaptive patches (NLM-SAP) explained in [6], in this method use shapes pie or quarter pie. Advantage of NLM-SAP is reduce noise produced in high contrast edges. Motivated issue of dissimilar patches unnecessary, we propose a pre-processing hard thresholding algorithm 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 and its variations of NLM method.

II. PROBLEM FORMULATION

We consider a 2D clean image corrupted with additive white Gaussian noise with zero-mean and unknown variance σ^2,i.e

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

Where y_i =noisy observation, x_i=clean pixel
n_i=noise pixel
Our aim is to recover noise free image from the noise observation. In conventional NLM estimated pixel $\hat{x}_i$ is a weighted average of remaining pixels in a search neighborhood S_i

$$\hat{x}_i = \frac{\Sigma_{j\epsilon\, s_i} w_{i,j}\, y_j}{\Sigma_{j\epsilon\, s_i} w_{i,j}} \qquad (2)$$

Where$w_{i,j}$ weight between square patches centered at pixels i and j.The weight is a function of squared value of

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Euclidean distance of two local patches P_i and P_j with centers at pixels i and j

$$d_{i,j} = \| P_i - P_j \|_2^2 \qquad (3)$$

$$w_{i,j} = e^{-d_{i,j}/h} \qquad (4)$$

Where h is the decaying parameter and is generally set to 10σ[3].This weight used as Gaussian kernel weight in conventional NLM.

PROPOSEDMETHOD

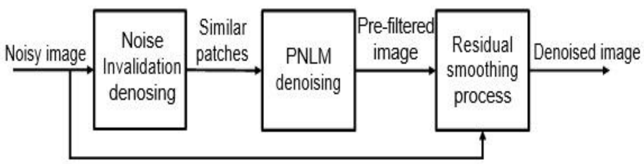

Fig1. Elimination of dissimilar patches in nonlocal means (NLM-EDP)

Our proposed method denoted by elimination of dissimilar patches in nonlocal means image denoising(NLM-EDP).NLM-EDP consists three steps as shown in the Figure 1.In the following three steps are explained given below

Elimination of Dissimilar Patches

Using fundamentals of conventional NLM, distance calculated from reference to patches in search neighborhoodS_i.If two patches are similar their distance due to only additive white Gaussian noise.Due to nature of distance has a chi-squared distribution *x* is defined as

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

Where Γ the gamma function and *k* is the degree of freedom. Our goal is by using hard thresholding algorithm eliminates as many as dissimilar patches. The fallowing procedure given below:

For any reference *i*th center patch we first calculate sort all $d_{i,j}s$ in a search neighbourhoodS_i.In this method similar patches with $d_{i,j}s$fall within the probabilistic boundaries that are pre-calculated based on chi-square distribution. Details of calculation of probabilistic boundaries shown in Appendix. These probabilistic boundaries are example of hard thresholding algorithm that is also explain in Appendix .In a search neighbourhood consists three cases flat ,edge, 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

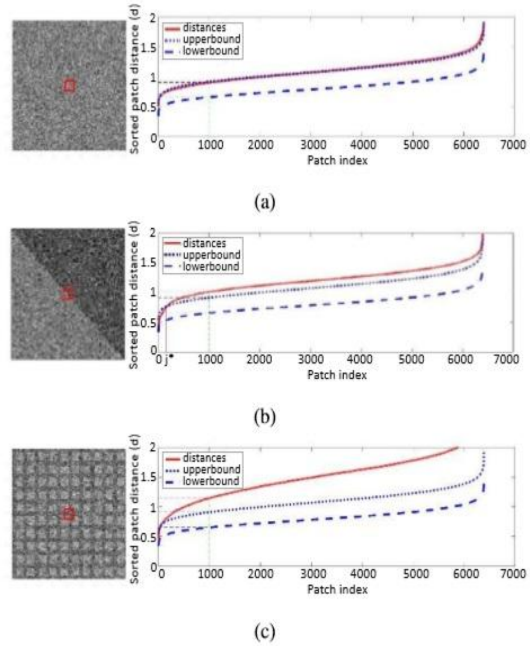

Fig2. Three cases in search neighborhood S_i: (a) Flat, (b) edge, (c) pattern. Little red square is reference patch P_i.Right column: sorted distance of patches and pre-calculated probabilistic boundaries(18).

By using Figure2 after sorting the patch distances consider any *j*th patch with patch distance$d_{i,j}$ out of this boundey .It consider as a dissimilar patch with respect to ithpatch. After sorting patches distances we consider patch index *j*=1000 the probabilistic upper bound and lower bound are 0.9110 and 0.6541(with probability 99.7%,3σ is probabilistic confidence).The figure shows for flat case,$d_{i,j}$ at patch index *j*=1000 is 0.8960, which falls within the probabilistic boundaries. However this value 1.0114 for edge case and 1.1480 for pattern case, which falls out of the probabilistic boundaries. Therefore patch index *j*=1000 with $d_{i,j}$ passed through the weighting process in flat case and $d_{i,j}$ will be discarded or set to zero in edge and pattern case.

B. Weighting process

After elimination of dissimilar patches by using hard thresholding algorithm remaining similar patches are passing through weighting stage .For this stage probabilistic weights are calculated based on chi-square distribution[4] as fallows given below by using given formula

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$$w_{i,j} = \chi^2_{\eta_{i,j}}(d^n_{i,j}/\gamma_{i,j}) \qquad (6)$$

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

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

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

And $|P_i|$ 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 .
This step can be considered soft thresholding after the hard thresholding algorithm

Advantages of hard thresholding before weighting stage

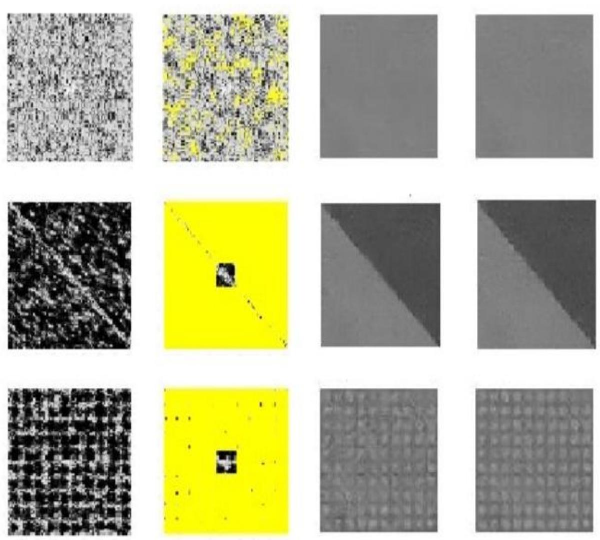


Fig3.In a search neighbourhood S_i ,First column: PNLM weights, second column: weights of hard thresholding + PNLM, third and fourth columns: denoised images by PNLM and hard thresholding +PNLM.

Figure3 first column shows weights of PNLM and second column shows weights of hard thresholding+PNLM. In second column additional zero weights are shown in yellow. Comparing these two columns, the additional hard thresholding set to zero weights to many dissimilar patches and remaining patches are very similar to the center patch. The third and fourth columns shows denoised version of noisy images. As these two columns elimination of dissimilar patches using hard thresholding algorithm shows better denoised image more specially for the cases of edge and pattern cases. In edge and pattern case more dissimilar patches are eliminated compared to the flat case.

C. Residual smoothing process

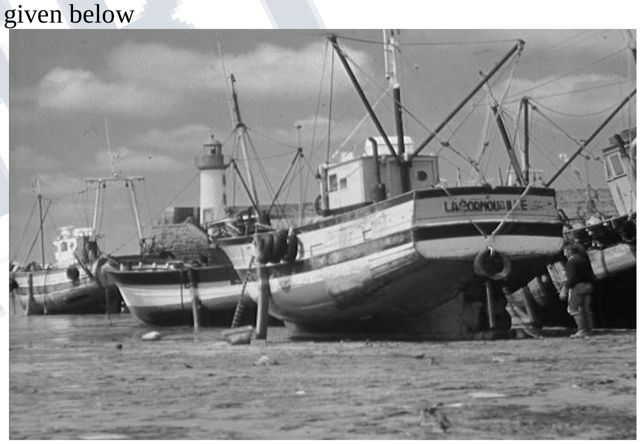
In this stage we use the smoothing filter [8]

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

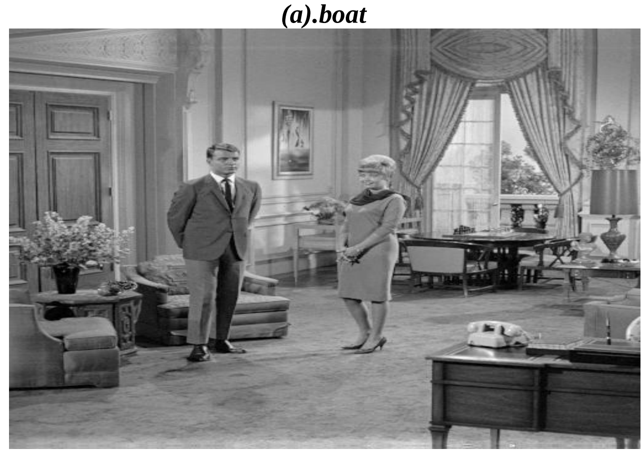
Where D is the residual smoothing denoising function and λ is the percentage added to the smoothing residuals.A median filtering is applied over smoothed residuals,y_i-$\hat{x}_i$. For each pixel of residual image is the median value of pixels in a 3$\times$3 neighbourhood is calculated to replace the center pixel value and take λ=10%.

III. SIMULATION RESULTS

Our test images are boat, man, couple as shown given below



(a).boat



(b).couple

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(c).man

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

Performance comparison for σ=30(PSNR/SSIM)

Images	Boat	Couple	Man
Noisy	18.58/28.98	18.58/31.27	18.58/27.34
NLM	25.90/67.94	25.28/66.16	26.24/69.59
PNLM	27.46/70.94	26.76/69.73	27.59/72.03
ht+ PNLM	27.64/71.46	27.08/71.01	27.82/72.26
NLM-EDP	27.78/72.03	27.25/71.84	27.97/72.91

Table shows the results for man, couple, boat over noise standard deviation is equal to 30.Table shows NLM-EDP better denoised results compared with NLM and PNLM [4] because of additional pre-processing hard thresholding algorithm.

IV. CONCLUSION

By adding additional pre-processing hard thresholding algorithm before PNLM denoising improve the performance of conventional NLM .This hard thresholding algorithm eliminates dissimilar patches before PNLM denoising. Elimination of dissimilar patches more for neighborhoods with more details and less for flat neighbourhoods.Our proposed method simulation results better compared with conventional NLM and PNLM.

APPENDIX
CALCULATION OF PROBABILISTIC BOUNDARIES FOR ELIMINATION OF DISSIMILAR PATCHES.

By using noise invalidation denoising [7] dissimilar patches are eliminated. For reference patchP_i and search neighbourhood size $S_i$we denote non overlapping patches in search neighborhood by$\bar{S_i}$ .If P_i and P_j are similar patches both are corrupted only due to additive white Gaussian noise and denote their distance $d_{i,j}^n$ .The set of all $d_{i,j}^n$ in $\bar{S_i}$ by $\{d_{i,j}^n\}$ .Define noise signature function at any given z:

$$g(z, d_{i,j}^n) = \begin{cases} 1 & \text{if} \quad d_{i,j}^n < z \\ 0 & \text{if} \quad d_{i,j}^n \geq z \end{cases}$$

(10)

The mean value of random variable is

$$E\left(g(z, D_{i,j}^n)\right) = 1\times Pr(\ D_{i,j}^n \leq z) + 0\times Pr(\ D_{i,j}^n \leq z)$$
$$= Pr(\ D_{i,j}^n \leq z) \quad = \quad F \quad (z)$$

(11)

$d_{i,j}^n$ is sample of the random variable$D_{i,j}^n$

where F is the chi-square distribution function with degrees of freedom$|P_i|$

The variance of random variable is

$$Var\left(g(z, D_{i,j}^n)\right) = E\left(g(z, D_{i,j}^n)^2\right) - E\left(g(z, D_{i,j}^n)\right)^2$$
$$= F\ (z)\ (1 - F\ (z)) \qquad (12)$$

where

$$E\left(g(z, D_{i,j}^n)^2\right) = 1\times Pr(\ D_{i,j}^n \leq z) + 0\times Pr(\ D_{i,j}^n \leq z)$$
$$= \quad Pr(\ D_{i,j}^n \leq z) \quad = \quad F \quad (z)$$

(13)

Calculates number of pixels with patches distance less than z and their sorting$d_{i,j}^n$s, if m number of pixels less than or equal to z: then

$$\bar{g}(z, \{d_{i,j}^n\}) = \frac{1}{|\bar{s_i}|} \Sigma_{j\epsilon\, \bar{s_i}} \quad g(z, d_{i,j}^n) \qquad (14)$$

$$E\left(\bar{g}(z, \{D_{i,j}^n\})\right) = E\left(g(z, D_{i,j}^n)\right) = F \quad (z)$$

(15)

$$Var\left(\bar{g}(z, \{D_{i,j}^n\})\right) = \frac{1}{|\bar{s_i}|} Var\left(g(z, D_{i,j}^n)\right)$$
$$= \frac{1}{|\bar{s_i}|}\ F \quad (z) \quad (1- \quad F \quad (z))$$

(16)

$|\bar{S_i}|$Consider large number because of this variance of $\bar{g}$(z,$\{d_{i,j}^n\}$) less than its mean.By using Central Limit Theorem estimate this random variable with Gaussian

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distribution .The fallowing probabilistic boundaries hold for $d_{i,j}$:

$$Pr\left(L(i) < \bar{g}\left(d_{i,j}^{n}, \{D_{i,j}^{n}\}\right) < U(i)\right) \approx erf(\lambda/\sqrt{2}) \quad (17)$$

Where L (i) and U (i) are

$$E(\bar{g}(d_{i,j}^{n}, \{D_{i,j}^{n}\})) \pm \lambda \sqrt{Var(\bar{g}(d_{i,j}^{n}, \{D_{i,j}^{n}\}))} \quad (18)$$

We use λ three times of the standard deviation rule that results in a confidence probability of 99.7% .To implement this this pre-calculate upper bound and lower bound as function of λ.

REFERENCES

[1] C. Tomasi and R. Mantachie, "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.

