ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 9, September 2016

Elimination of Dissimilar Patches in Nonlocal Means by Using Noise Invalidation Denoising

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ABSTRACT: Nonlocal means is one of the well known technique and used in image denoising . The nonlocal means method uses weighted version of all patches in a search neighbourhood to denoise the center patch. This search neighbourhood can also include some dissimilar patches. We propose a pre-processing hard thresholding algorithm based on distribution of distances of similar noisy patches that eliminates those dissimilar patches. This hard thresholding improves the performance of nonlocal means . The method denoted by Elimination of Dissimilar Patches in Nonlocal Means(EDP-NLM).This method shows improvement in terms of PSNR and SSIM of the retrieved image in comparison with nonlocal means and variations of nonlocal means.

KEYWORDS: Image denoising, Nonlocal means, Noise invalidation, Hard thresholding

I. INTRODUCTION

In digital image processing image denoising techniques are more advanced. Removing additive noise is an essential pre-processing step in the image processing techniques , or it can be used to improve image visual quality. Some of the previous methods of denoising are averaging filters such as mean, median, Gaussian filters, and bilateral filters [1]. Nonlocal means(NLM) method proposed by Buades based on self-similarities in the search neighbourhood . In this NLM method by using weighted version of all patches in search neighbourhood to denoise the center patch.Many variations of NLM was proposed to improve the SSIM and PSNR. For example, NLM with shape adaptive patches (NLM-SAP) [5] was proposed to reduce the noise produced in the high contrast edges by using pie and quarter pie shapes. Another method, probabilistic nonlocal means (PNLM) [3], implements a new weight function based on the distribution of the distances of patches. This weighting scheme outperforms the Gaussian kernel weights in NLM. The method probabilistic early termination (NLM-PET) [4] implemented performance of NLM-PET worse than NLM because some similar patches are also eliminated in the preprocessing step . We propose a new hard thresholding pre-processing algorithm based on distribution of distances of similar patches to eliminate those dissimilar patches before the weighting process. Our proposed method is more superior to the probabilistic distribution of the distance of similar patches. Our simulation results superiority of this approach compared to the NLM and the variations of this NLM method.

II. PROBLEM FORMULATION

We consider an digital image corrupted with an additive white Gaussian noise (AWGN) with zero mean and variance σ^2
where ith noisy pixel value is y_i and ith true pixel value is x_i.

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

The gole is to recover true image from the true image corrupted with additive white gaussion noise .In the NLM method each estimated pixel $\hat{x}_i$ calculated by using weighted average of all other pixels in the search neighbourhood S_i

$$\hat{x}_i = \frac{\sum w_{i,j} y_{j}{}_{j \in S_i}}{\sum w_{i,j}{}_{j \in S_i}} \tag{2}$$

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Where $w_{i,j}$ weight between square patches centered at *i*th and *j*th pixels .This weight function is squared value of Euclidean distance between two local patches P_i and P_j .

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

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

This weight function used in the NLM named as Gaussian kernel weight ,where *h* is decaying parameter and it is set to 10σ[2].

III. PROPOSED ALGORITHM

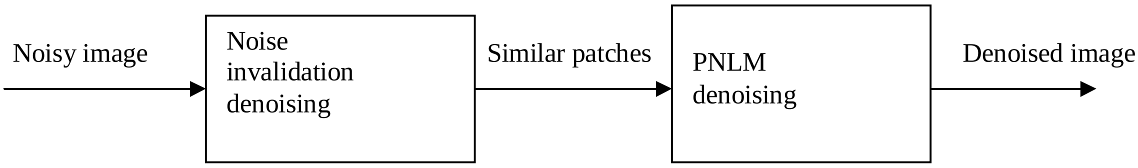

Fig1.Elimination of dissimilar patches in nonlocal means (EDP-NLM)

A. *ELIMINATION OF DISSIMILAR PATCHES*

Using fundamentals of NLM, from the reference patch the distance is calculated the patches in search neighbourhood S_i is first calculated. The goal is to keep similar patches further weighting process .If two patches are considered similar if their distance is only due to additive noise. Due to the nature of the distance, $d_{i,j}$ has a chi-squared distribution where the distribution for *x* is defined as:

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

where Γ denotes the Gamma function and *k* is the degree of freedom. Our goal by using hard threshold to eliminates dissimilar patches . By using the given procedure: For any *i*th center patch, we first calculate distance and sort all the $d_{i,j}s$ in the search neighborhood S_i. In this similar patches with $d_{i,j}s$ following Chi-squared distribution fall within a probabilistic boundaries .These probabilistic bounderies are pre-calculated based on that Chi-squared distribution. Details of calculation of these boundaries are shows in the Appendix . These probabilistic boundaries are example of the hard thresholding, that can also explained in Appendix , Figure 2 shows the probabilistic boundries and sorted $d_{i,j}s$ for the three cases of a flat, an edge and a pattern in a search neighbourhood . Red square is the reference patch P_i .These probabilistic boundaries are fixed for all three cases and as a function of the σ and the size of search neighbourhood S_i. The hard thresholding process considers any *j*th patch with its $d_{i,j}s$ out of this boundaries as a dissimilar patch to the *i*th reference patch. For example, after sorting the patch distances, at index j = 1000 the probabilistic upperbound and lowerbound with probability 99.8% (3σ probabilistic confidence) are 0.9114 and 0.6546. As the figure shows for the flat scenario, $d_{i,j}$ at index j = 1000 is 0.8962, which falls within the boundaries. This value is 1.0116 and 1.1483 for edge and pattern cases respectively that are outside boundaries. Therefore, 1000th sorted pixel is passed to step 2 in flat case, and set to zero for the edge,pattern cases.

B. *WEIGHTING PROCESS*

After elimination of dissimilar patches by using the hard thresholding, the remaining similar patches are processed through weighting stage. For this stage probabilistic weights are calculated given below

$$w_{i,j}=\chi^2_{\eta_{i,j}}\left(\frac{d^n_{i,j}}{\gamma_{i,j}}\right) \tag{6}$$

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

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

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

and $|P_i|$ is the number of pixels in P_i and $|O_{i,j}|$ is the number of overlapping pixels between P_i and P_j. This step can be considered as a soft thresholding after a hard thresholding .

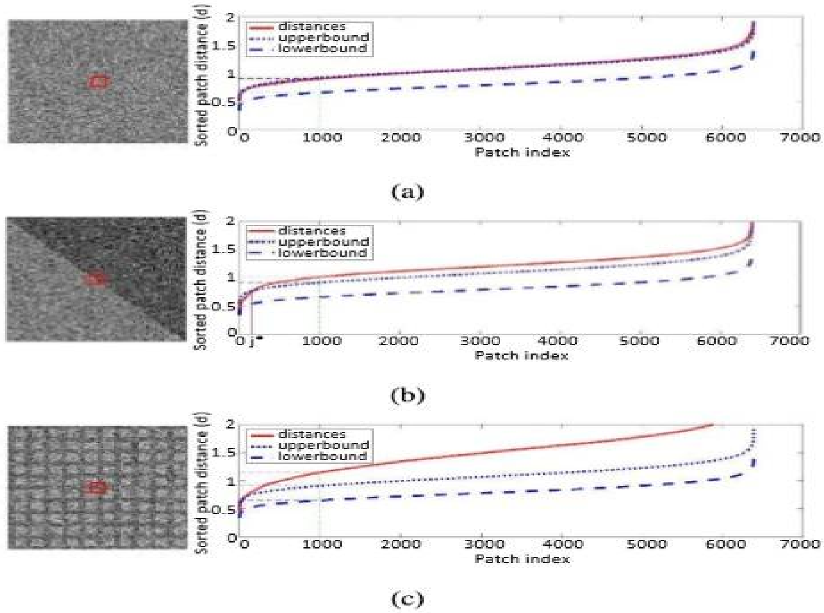

Fig. 2. Three cases of search neighbourhood S_i: (a) flat, (b) edge, (c) pattern . red square in the reference patch P_i. Right column: sorted distances and probabilistic boundaries(16) .

Advantages of hard thresholding before weighting process

Figure 3 shows advantages of hard thresholding before the existing soft thresholding (PNLM) for the same cases as in Figure 2. The first column shows the weights of PNLM while the second column shows the weights of hard thresholding+PNLM. The additional zero weights are shown in yellow in the second column. Comparing these two columns, the additional hard thresholding give zero weights to many dissimilar patches . The remaining patches are very similar to the reference patch. The third and forth columns are shows the denoised results. These two columns show elimination of the dissimilar patches using hard thresholding resulted better denoised image, for the more specially edge and pattern structure because more dissimilar patches are eliminated.

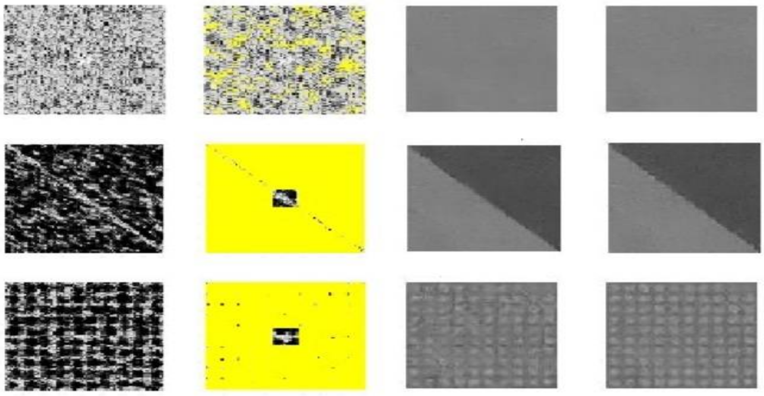

Fig. 3. First column: PNLM weights, second column: hard thresholding+PNLM weights, third and fourth columns: denoised images by PNLM and hard thresholding+PNLM respectively**.**

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IV. SIMULATION RESULTS

Our test images are boat ,man,couple,hill(512× 512) as shown below


(a).Boat


(b).Man


(c).Couple


(d).Hill

The proposed method compared with the NLM and PNLM. Our propose method patch size as 5× 5 and search neighbourhood size as 21×21

TABLE
Performance comparison for σ=30 (PSNR/SSIM)

Image	Noisy	NLM	PNLM	EDP-NLM
Boat	18.58/28.98	25.90/67.94	27.46/70.94	27.64/71.46
Man	18.58/27.34	26.24/69.59	27.59/72.03	27.82/72.26
Couple	18.58/31.27	25.28/66.16	26.76/69.73	27.08/71.01
Hill	18.58/26.70	26.95/66.83	27.56/67.43	27.85/68.50

V. CONCLUSION

By adding pre-processing hard thresholding process before PNLM denoising to improve the performance of NLM.This pre-processing hard thresholding eliminates dissimilar patches . E limination of dissimilar patches more in neighbourhoods with more details and less for neighbourhood with less details.Our proposed method give better simulation results compared with NLM and PNLM.

APPENDIX

CALCULATION OF PROBABILISTIC BOUNDARIES FOR ELIMINATION OF DISSIMILAR PATCHES.

By using noise invalidation[6] dissimilar patches are eliminated. For reference patch P_i and search neighbourhood size $S_i$we denote non overlapping patches in search neighborhood by $\overline{S_\iota}$ .If P_i and P_j are similar patches both are corrupted only due to additive white Gaussian noise and denote their distance $d^n_{i,j}$ .The set of all $d^n_{i,j}$ in $\overline{S_\iota}$ by $\{d^n_{i,j}\}$ .Define noise signature function at any given z:

$$g(z,d^n_{i,j})=1 \text{ if } \quad d^n_{i,j} \leq z \tag{9}$$

$$g(z,d^n_{i,j})=0 \text{ if } \quad d^n_{i,j} > z \tag{10}$$

The mean value of random variable is

$$E(g(z,D^n_{i,j}))=Pr(\, D^n_{i,j} \leq z)=F\,(z) \tag{11}$$

$d^n_{i,j}$ sample of the random variable $D^n_{i,j}$

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

The variance of random variable is

$$Var(g(z,D^n_{i,j}))=F\,(z)(1\text{-}F\,(z)) \tag{12}$$

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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,$\{d_{i,j}^{n}\}$) =m/$|\bar{S}_{\iota}|$

$$E\ (\bar{g}(z,\{D_{i,j}^{n}\})) = E\ (g\ (z,D_{i,j}^{n})) = F\ (z) \tag{13}$$

$$Var\ (\bar{g}(z,\{D_{i,j}^{n}\})) = F\ (z)\ (1-F\ (z))\ /|\bar{S}_{\iota}| \tag{14}$$

$|\bar{S}_{\iota}|$Consider large number because of these variance of $\bar{g}$(z,$\{d_{i,j}^{n}\}$) less than its mean.By using Central Limit Theorem estimate this random variable with Gaussian distribution .The fallowing probabilistic boundaries hold for$d_{i,j}$:

$$Pr(L\ (i) < \bar{g}(d_{i,j}^{n},\{D_{i,j}^{n}\}) < U\ (i)) \approx erf\ (\lambda/\sqrt{2}) \tag{15}$$

Where L (i) and U (i) are

$$E(\bar{g}(d_{i,j}^{n},\{D_{i,j}^{n}\})) \pm \lambda \sqrt{Var(\bar{g}(d_{i,j}^{n},\{D_{i,j}^{n}\}))} \tag{16}$$

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.

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