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Robust Estimation Approach for Nonlocal-means Denoising Based On Structurally Similar Patches

Dinesh peter. J, Govindan. V. K, Abraham T. Mathew

Department of Computer Science and Engineering,
National Institute of Technology Calicut, Calicut - 673601,
India. email: dineshpeterson@gmail.com
Department of Computer Science and Engineering,
National Institute of Technology Calicut, Calicut - 673601,
India. email: vkg@nitc.ac.in
Department of Electrical Engineering,
National Institute of Technology Calicut, Calicut - 673601,
India. email: atm@nitc.ac.in

Abstract

Edge preserved smoothing techniques has gained importance for the purpose of image denoising. A good edge preserved filtering is given by nonlocal-means filter than any linear model based approaches.The contributions are in two fold. First, this paper explores a refined approach of nonlocal-means filter by using robust estimation function rather than the usual exponential function for its weight calculation. Here the filter output at each pixel is the weighted average of pixels with the surrounding neighborhoods using the chosen robust estimation function. Second, in order to speed up the computation, a new patch classification method is followed to eliminate the uncorrelated patches from the weighted averaging process. This patch classification approach compares favorably to existing techniques in respect of quality versus computational time. Validations using various test images have been analyzed and the results were compared with other known recent methods. There is reason to believe that this refined algorithm has some interesting and notable points.

Keywords: *Image processing, Image Denoising, Nonlocal-means filter, Robust Statistics, Robust M-estimators*

1 Introduction

Denoising is the technique of removing noise from an image. Most of the denoising techniques seem to be very similar regardless of the image being processed. All denoising algorithms are based on the noise framework and the relative smoothing framework. Due to the fixed estimations of smoothing methods on the original image, fine structures are smoothed out since they act like noise. So the effectuation of these techniques must be greatly contingent on the type of images and the analytic knowledge of the characteristics of an output image.

A linear Gaussian smoothing function[1] reduces noise in piecewise constant area but blurs edges. Nonlinear models handle edges much better than any other linear models. Total variation filter [2], among many nonlinear models gives good edge preserving smoothing scheme but tends to generate mask effect in flat regions on the output image. Variational methods have shown impressive results to tackle the problem of edge preserved smoothing by involving automatic adjustment of global weights. Bilateral filter is another nonlinear filter proposed by many researchers [3-6]to smooth images while preserving edges. The k-svd (k-singular value decomposition) method is used for denoising by means of a sparsity prior on all fixed-sized overlapped patches in an image [36]. This work has been extended to color images, with state-of-the-art results in denoising [42], video denoising [43] and providing a framework for learning multiscale and sparse image representation in [38]. The extended work of BM3D filter, sparse 3D transform domain proposed by Dabov *et al* [37], gives state-of-the-art denoising results that outperform all other existing recent denoising results. Takeda *et al* [44] proposed a novel data adaptive generalized kernel regression technique for image denoising.

Buades *et al* [8] pointed out that nonlocal-means filter is a special case of bilateral filter which gives better edge preserved denoising results. The output of the filter at each pixel is replaced by the weighted average of pixels with surrounding neighborhoods. This method gives good results but it is too slow to be manageable. Various fast approaches of nonlocal-means algorithm was already proposed in [9-11]. In [9], the selection of relevant patches is based on the similarity of the mean intensities, and on the average gradient orientation over the patches. Moreover gradient orientation is sensitive to noise and thus it requires robust estimation technique [9]. In [10], the patches are classified using mean and variance. An efficient patch classification can be made by applying svd to eliminate pixel pairs that are dissimilar [11]. A block matching approach is used for finding similar patches in nonlocal-means filter is found in [7]. In [28,39-41], the weights are not based on the similarities between patches but similarities between the point-wise estimate in a local neighborhood. In [30], the library of natural image patches have been worked out for denoising

application. This paper extended the work in [10] for the better classification of patches thereby reducing the effect of uncorrelated patches for the weight calculation. The details are given in section 2.3.1.
A more realistic image model assumes that images are made of smooth regions, separated by sharp edges and contains more number of duplicated structures. On averaging the duplicated structures, noise is impressively reduced when compared with the averaging of pixels in the same structure, so the computation of nonlocal neighborhoods gives better results than the local neighborhood computation. The proposed paper gives a refined approach in which it says that the reconstructed pixel value is obtained by the weighted average of all pixel values in an image using robust estimation function from robust statistics.
The rest of this paper deals about the following. In section 2, the methodology followed to refine the classical nonlocal-means algorithm is introduced. In this, the inside information of various robust functions are examined and the selection of best robust function for the weight calculation in nonlocal-means algorithm has been exercised. In order to automate and speedup the weight calculation process, various improvements have also been proposed. In section 3, the results are compared with other latest restoration techniques and its details are discussed briefly. We have compared our results with the recent wavelet based methods [27,29] also. Section 4 concludes the paper.

2 Methodology

2.1 A Statistical perspective

Our aim is to develop a statistical interpretation of the nonlocal-means algorithm. In particular, we assume that a given input image is a piecewise constant function that has been corrupted by white gaussian noise. Consider the patch intensity difference $|s(x)-s(y)|$, within the piecewise constant search region $\mathcal{N}(x)$, this difference is small, zero-mean, and normally distributed. For the search region that includes intensity discontinuity, the difference of pixel values between two patches are drawn from two different population. So the square of the pixel difference is increased. This will skew the original estimate. Thus within a search region, the pixel difference can be viewed as an *outlier*. The dealing of outliers can be handled by robust functions from the area of robust statistics.

2.2 Robust estimation and Nonlocal-means filter

Estimation function is the function of intensities of an image. The properties that will satisfy the estimation function for edge preservation have been defined from various papers. Geman et al. [12] recommends functions having a finite asymptotic behavior for the edge preserving regularization. In [13-16], authors prefer using convex potentials in order to ensure the uniqueness of the solution. The problem of estimating a smooth image from a noisy image can be explained from the area of robust statistics [17] and the review of applications of robust statistics in computer vision can be seen in [18]. Robust approaches for local image smoothing can be seen in [19]. A suitable *robust function* permits us to minimize the consequence of the outliers, and the derivative of the robust function examines its behavior. Black *et al.* [21] has compared some robust functions for the purpose of robust anisotropic diffusion and he suggested Tukey's biweight function since it contributes larger potential to outliers. But here, one needs to determine a best robust function which will be suited for nonlocal-means filter. The classical nonlocal-means filter uses the exponential function as a weight function for its weight calculation i.e., $w(x,y) = e^{-\frac{||s(x)-s(y)||^2_{2,\sigma}}{h^2}}$. Since this function has a wide symmetric bell-shaped probability density function, the influence function of this (see in Fig.4) symbolizes that this is rather robust to outliers. Leclerc *et al*[20] pointed out that the exponential function can be viewed in the robust statistical framework by converting this into related robust object function. In [22], the authors have adopted the weight function $\vartheta_h = \frac{1}{1+\frac{x^2}{h^2}}$ instead of the usual exponential function for nonlocal-means filter which leads to a more efficient implementation. This function is actually a robust weight function that have been already used by [23],[24]. Consider this robust error norm plotted in Fig.1.

$$\rho_{hl}(x,\sigma) = \begin{cases} \log[1+\frac{x^2}{\sigma^2}] & |x| \leq \sigma, \\ 0, & \text{otherwise} \end{cases}$$

$$\psi_{hl}(x,\sigma) = \begin{cases} \frac{x}{1+\frac{x^2}{\sigma^2}} & |x| \leq \sigma, \\ 0, & \text{otherwise} \end{cases}$$

$$g_{hl}(x,\sigma) = \begin{cases} \frac{1}{1+\frac{x^2}{\sigma^2}} & |x| \leq \sigma, \\ 0, & \text{otherwise} \end{cases}$$

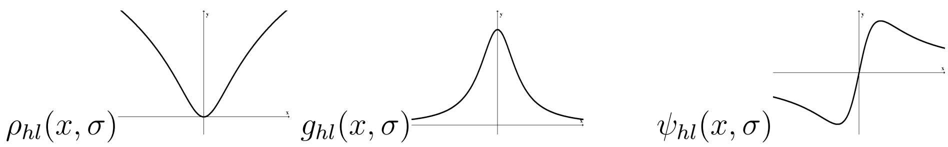


Figure 1: Hebert-Leahy error norm

Examination of its ψ_{hl}-function reveals that, for the nonlocal-means filter, when the distance $\|s(x) - s(y)\|^2_{2,\sigma}$ increases beyond a fixed point determined

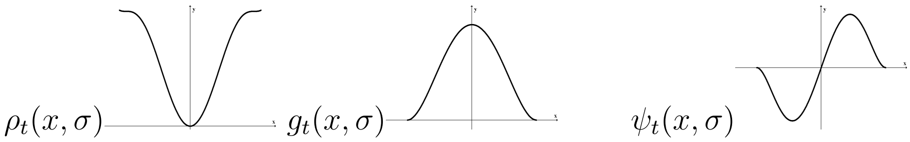


Figure 2: Tukey's biweight error norm

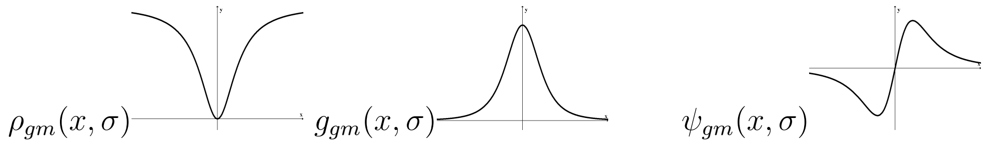


Figure 3: Geman-McClure error norm

by the decay parameter h, its influence is reduced. So this can be generally referred as a *redescending* influence function. If a particular local difference has a large magnitude then the value of $w(x, y)$ will be small and therefore that measurement will have little effect on the output image. Though this function is robust, its influence function does not descend to all the way to zero. Thus it is called as *Soft redescending* norm. We can choose a more robust norm from the robust statistics which does descend to zero e.g. *Hard redescending* norm. Tukey's biweight norm, is plotted along with its influence function in Fig.2.

$$\rho_t(x,\sigma) = \begin{cases} \frac{x^2}{\sigma^2} - \frac{x^4}{\sigma^4} + \frac{x^6}{3\sigma^6} & |x| \le \sigma, \\ \frac{1}{3} & \text{otherwise} \end{cases}$$

$$\psi_t(x,\sigma) = \begin{cases} x[1-(\frac{x}{\sigma})^2]^2 & |x| \le \sigma, \\ 0 & \text{otherwise} \end{cases}$$

$$g_t(x,\sigma) = \begin{cases} \frac{1}{2}[1-(\frac{x}{\sigma})^2]^2 & |x| \le \sigma, \\ 0 & \text{otherwise} \end{cases}$$

Another error norm from the robust statistics literature, Geman-McClure norm is plotted along with its influence function in Fig.3.

$$\rho_{gm}(x,\sigma) = \begin{cases} \frac{x^2}{\sigma+x^2} & |x| \le \sigma, \\ 0 & \text{otherwise} \end{cases}$$

$$\psi_{gm}(x,\sigma) = \begin{cases} \frac{2x\sigma}{(\sigma+x^2)^2} & |x| \le \sigma, \\ 0 & \text{otherwise} \end{cases}$$

$$g_{gm}(x,\sigma) = \begin{cases} \frac{2\sigma}{(\sigma+x^2)^2} & |x| \le \sigma, \\ 0 & \text{otherwise} \end{cases}$$

This function is also a *hard redescending* norm. It gives a optimized redescending behavior than the function used in [22] i.e., Hebert-Leahy norm and Tukey's

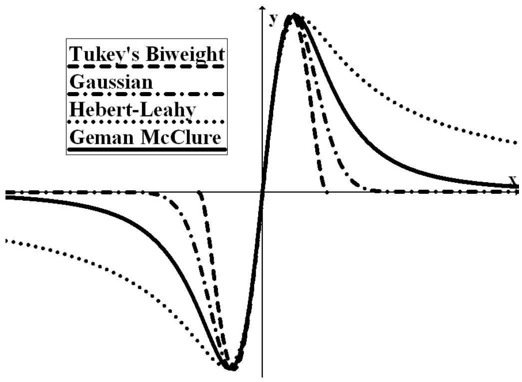


Figure 4: Robust influence functions aligned and scaled

biweight norm. Due to the fast decay of the exponential and Tukey's biweight influence function, euclidean distances outside the fixed point lead to zero weights immediately, so smoothing may not behave properly but the edges are preserved. Hence, we need a function that compromises the effect of smoothness as well as edge preservation. For the weight calculation $w(x, y)$ in nonlocal-means filter, weight function ϑ_h is strictly relying on the similarity of the patches i.e., similar patches give larger weights and dissimilar patches give smaller weights. Our method uses Geman-McClure function for the weight calculation in nonlocal-means filter and the results show that it has more stable characters for calculating the weights.

2.2.1 Robust Nonlocal-means filter

Let s be the noisy image $s = \{s(x)|x \in \Omega\}$ defined over a discrete domain $\Omega \subset \mathbb{R}^2$ and $s(x) \in \mathbb{R}_+$ is the intensity of noisy observed pixel $x \in \Omega$. The estimated value of $NL\{s(x)\}$ is computed as the weighted average of all pixels in an image s,

$$NL\{s(x)\} = \frac{\sum_{y \in \mathcal{N}(x)} w(x, y)s(y)}{\sum_{y \in \mathcal{N}(x)} w(x, y)} \tag{1}$$

where $w(\cdot, \cdot)$ are positive weights and $\mathcal{N}(x)$ corresponds to a set of neighboring pixels of x which is otherwise called as searching window [8]. The weight $w(x, y)$ measures the similarity between two square patches of the pixels centered on x and y and it is defined as

$$w(x, y) = \vartheta_h\Big(\sum_{t \in \Xi} G_\sigma(t)(s(x + t) - s(y + t))^2\Big) := \vartheta_h\Big(\|s(x) - s(y)\|^2_{2,\sigma}\Big) \tag{2}$$

where G_σ is gaussian kernel of variance σ^2 is used to take into account the distance between the center pixel and other pixels in the patch, ϑ_h is a continuous decreasing function with $\vartheta_h(0) = 1$ and $\vartheta_h(+\infty) = 0$, and Ξ represents the discrete patch region containing the neighboring pixels t. The parameter h is used to control the amount of filtering. Typical examples of ϑ_h are already discussed. Here Geman-McClure function is used as ϑ_h-function where the exponential function is used in [8]. The robust nonlocal-means filter NL_r, we will then consider, is defined as

$$NL_r\{s(x)\} = \frac{1}{C(x)} \sum_{y \in \mathcal{N}(x)} \frac{s(y)}{\left(1 + \frac{\|s(x)-s(y)\|^2_{2,\sigma}}{h^2}\right)^2} \tag{3}$$

where $\|\cdot\|$ is the usual l^2-norm. $C(x)$ is normalizing constant such that for any pixel x we have $C(x) = \sum_{y \in \mathcal{N}(x)} \frac{1}{\left(1+\frac{\|s(x)-s(y)\|^2_{2,\sigma}}{h^2}\right)^2}$. The usage of Geman-McClure function for the weight calculation of nonlocal-means filter enhances the image much better than the usual exponential function. Because whenever the algorithm faces dissimilar patches, this will not leave the weight to zero value instantly. This is the major reward of using Geman-McClure function and the experimental results depicted this distinctly.
In this algorithm, assume the search windows $\mathcal{N}(\cdot)$ and patches Ξ have uniform cardinalities of, respectively, $(2P+1)^n$ and $(2Q+1)^n$ with $\mathcal{N} = [-P, P]^n$ and $\Xi = [-Q, Q]^n$. Then the time complexity is $O(|\Omega|P^nQ^n)$. This is exponential with respect to dimension n but it is polynomial with respect to $|\Omega|$. When the dimensions are fixed and low, the algorithm remains polynomial. However, this paper proposes a new acceleration technique in the next section to speed up the weight computation process.

2.3 Other meliorations in Nonlocal-means filter

2.3.1 Patch classification in the search space

Many recently proposed methods from [9-11,25,35,40,31], deals with the computational burden of nonlocal-means filter. In [9-10], the methods used low-order statistics called "mean" for preselecting the patches. But it is easy to show that this simplistic pre-filtering method can lead to sub-optimal results[31]. Fig.5 shows the example involving three 7×7 binary patches. The mean intensity of the patch centered on x is 0.4286. The two other patches centered on y and z have mean intensities 0.4286 and 0.5714 respectively, therefore favoring the weight computation process for the patches centered on y over z. However, the sample correlation coefficients $Corr(x, y) = -0.75$ while $Corr(x, z) = 0.75$, suggesting that z matches x much better than y does. Among those, we select a method to preselect a subset of the most relevant patches in a search space to avoid unnecessary weight computations. We suggest a single measure that is more enough to classify the patches in a search space. It is called as structural information that can be calculated from the mean and standard deviation. The structural information of each patch centered on x in a search space is calculated as $\frac{x_i-\mu_x}{\sigma_x}|x_i \in X$ where μ_x is the mean and σ_x is the the standard deviation of a patch X. The patch is normalized by its own standard deviation so that the two patches being compared have unit standard deviation. A circular-symmetric gaussian weighting function $W = \{w_i|i = 1, 2, \cdots, |\Xi|\}$ with unit sum $(\sum_{i=1}^{|\Xi|} w_i = 1)$ is adopted in order to reduce the effect of noise. The estimates of the low-order statistics for the patch X, μ_x,σ_x are then modified according as $\mu_x = \sum_{i=1}^{X} w_i x_i$ and $\sigma_x = (\sum_{i=1}^{X} w_i(x_i - \mu_x)^2)^{\frac{1}{2}}$ as described in [45]. The correlation (inner product) between any two patches, say X,Y, is a simple and effective measure to quantify the structural similarity. The correlation between $\frac{x_i-\mu_x}{\sigma_x}$ and $\frac{y_i-\mu_y}{\sigma_y}$ is equivalent to the correlation coefficient between the patches centered on x and y respectively. The structural comparison $\zeta(X, Y)$ is conducted on these normalized patches as $\zeta(X, Y) = \zeta(\frac{x_i-\mu_x}{\sigma_x}, \frac{y_i-\mu_y}{\sigma_y})|x_i \in X, y_i \in Y$. Indeed, the mean structural map $\overline{\zeta}$ between the patches in a search space are pre-computed in order to avoid unnecessary weight calculations. And the classification can be carried out well for necessary weight calculation by putting the condition

$$w(x, y) = \begin{cases} \frac{1}{C(x)} \sum_{y \in \mathcal{N}(x)} \frac{1}{(1+(\frac{\|s(x)-s(y)\|}{h})^2)^2} & \overline{\zeta} \geq \eta \\ 0 & otherwise. \end{cases} \tag{4}$$

where η is a predefined value. But this kind of patch classification leads to the nonlocal-means filter rather reducing the effect of denoising in the flat regions while preserving the detailed regions as well.

2.3.2 Automatic adjustment of the decay parameter h

The decay parameter h quantifies how fast the weights decay with increasing dissimilarity of respective patches that depends on σ of the noise and also $|\Xi|$, where Ξ is the discrete patch region containing the neighboring pixels. The statistical reasoning in [32], allows us to determine h automatically. A functional relationship for automatically finding h is defined as $h^2 = f(\widehat{\sigma}^2, |\Xi|, \kappa)$, where κ is a constant. For low levels of noise, κ is set to 0.5 and for higher levels of noise, it is 1 [25]. Here, κ allows to adjust the automatic estimation of h. The optimal smoothing parameter h can be estimated by calculating the pseudo-residuals ε_i as described in [25,40]. If we choose P is six-neighborhood system, pseudo-residuals are compactly represented by $\varepsilon_i = \sqrt{\frac{6}{7}}(s(x) - \frac{1}{6}\sum_{y \in P} s(y))$, where the constant $\sqrt{\frac{6}{7}}$ is introduced to insure that $\mathbb{E}[\varepsilon_i^2] = \widehat{\sigma}^2$. Given the residuals ε_i, we can then robustly estimate the noise variance $\widehat{\sigma}^2$ by $\widehat{\sigma} = 1.4826\, med_i(|\varepsilon_i - med_j|\varepsilon_j||)$. Finally, h can be automatically calculated as $h = 2\kappa\widehat{\sigma}^2|\Xi|$. Therefore the weight is calculated

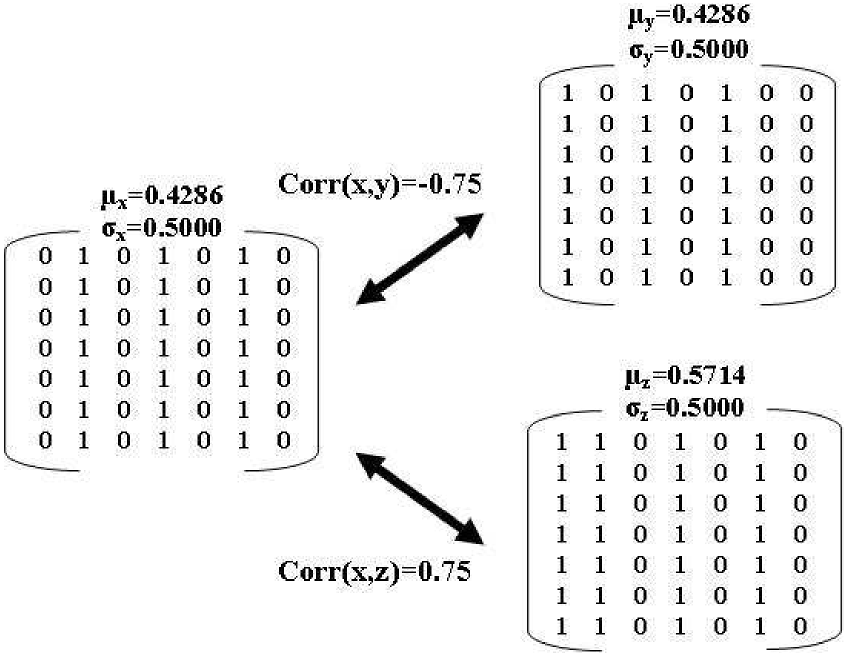


Figure 5: A case where the similarity between patches using mean is sub-optimal

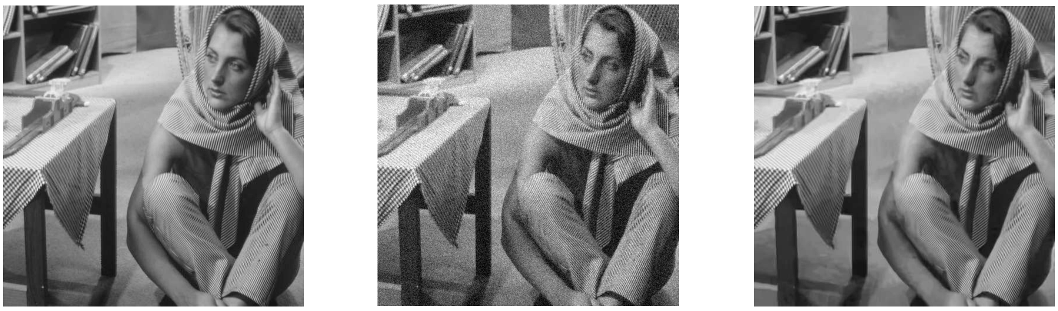
automatically as $w(x,y) = \frac{1}{\left(1+\frac{\|s(x)-s(y)\|^2_{2,\sigma}}{2\kappa\widehat{\sigma^2}|\Xi|}\right)^2}$. The estimation of the standard deviation of the noise is correctly performed by pseudo-residuals.

2.4 Implementation details

In practice, for a classical nonlocal-means filter, it is required to set the patch size Ξ, search space (or search window) $\mathcal{N}(x)$ and the decay parameter h. In section 2.3.2, automatic adjustment of h has been studied. The pixel intensities of a square patch Ξ are taken and reordered lexicographically to form a n-dimensional vector $s(x) = (s(x_k), x_k \in \Xi) \in \mathbb{R}^n$. Here we use 7×7 patches that are able to take care of the local structures (geometry and texture) around the pixels in consideration [8]. Note that pixels outside $\mathcal{N}(x)$ do not contribute to the value of $NL_r\{s(x)\}$. To make averaging more robust, the search window $\mathcal{N}(\cdot)$ in the nonlocal-means algorithm can be as large as possible and in the limit extend it to the entire image. And it is necessary to reduce the total number of weights for each pixel. This can be achieved by selecting the patches Ξ corresponding to a search window $\mathcal{N}(x)$ of 21×21 pixels. We follow the patch classification approach as explained in section 2.3.1. The parameter $\eta = 0.7$ here. For the mean structural map $\overline{\zeta}$ less than η, the weight is set to 0. Otherwise, the weight will be calculated using equation (4).

3 Experimental results and discussion

In this section, the proposed refined approach of nonlocal-means filter is applied on various test images to demonstrate its superior performance in noise reduction without noticeable loss of overall structures. Performances are also compared with several other recent denoising techniques in the literature. Our results were measured by the peak signal-to-noise ratio (PSNR) in decibels (dB) as $PSNR = 10log_{10}\frac{255^2}{MSE}$ where MSE is Mean Square Error. The potential of the estimation method is mainly illustrated with the 512×512 barbara image [Fig.6(a)] corrupted by an additive white gaussian noise (WGN) [Fig.6(b)], PSNR=22.18dB, $\sigma = 20$. In Fig.6(c), our approach is applied with 21×21 search window. The noise is well reduced and the structures are recovered (PSNR=30.61dB).



(a) (b) (c)

Figure 6: (a) 512x512 Barbara test image (b) Added with WGN of $\sigma = 20$ (c) Denoised image using our approach

We have compared the performance of our method to several recent competitive methods. Table.1 lists the PSNR values of various recent denoising algorithms applied to various test images. Our results compare favorably with previous approaches. For the noise variance $\sigma = 20$, our approach produces good PSNR values when compared to the first set of denoising algorithms. And the recent denoising algorithms in the second set, outperform our approach. The other denoising results were adopted from [39] and also from the respective publications.

In order to identify the performance of our denoising results for various levels of noise, we compare our result with the recent state-of-the-art denoising algorithms in Table 2. Even though the very sophisticated state-of-the-art filtering methods can achieve higher PSNR values, there is a reason to believe that our approach can also compete with them. Table 3 shows that the proposed robust nonolocal-means filter without patch classification gives better

(a) (b)

Figure 7: (a) Noisy input image ($400 \times 400 \quad hamiltonfaceimage$)(b) restored image (estimated $\hat{\sigma} = 8.91$)

PSNR values than the same with the proposed patch classification technique. In general, the patch classification approach to speedup the nonlocal-means algorithm works poor in detailed regions of an image, e.g., the 512×512 barbara test image contains several fine textural details. Less number of similar pixels in the detailed region are used for weight computation process when compared to flat region. Our result outperforms the classical nonlocal-means filter and the recent cluster tree based patch classification approach. The results of the recent fast bayesian nonlocal-means approach [40] outperform our result. Table 4 shows the computation times of several fast nonlocal means implementations depending on the search window size. The methods were run with the 512×512 barbara test image. For growing window sizes, the cluster tree based approach outperforms our faster approach. In [40], for 15×15 search window and 7×7 patches, the algorithm works in 21.2 seconds. intuitively, it is seen from the Table.4 that our patch classification method is faster than the new statistical distance measure based patch classification in [40]. Several iterative versions of nonlocal-means algorithm are also presented in Table.1 [32-35]. Since we are interested only on pre-selection based patch classification technique to speed up the weight computation process in nonlocal-means filter, the computational times for the iterated versions of nonlocal means filters are not given in Table.4. Finally, the proposed robust nonlocal means algorithm has been used to restore hamilton's face image which has more textural patterns as shown in Fig.7(a). In that case, the noise variance $\hat{\sigma}^2$ is automatically estimated from image data using the approach explored in section 2.3.2. In

Table 1: Performances of Denoising algorithms when applied to various test noisy(WGN) images at $\sigma = 20$

Image $\sigma/PSNR$	Lena 20/22.13	Barbara 20/22.18	Boats 20/22.17	House 20/22.11
Our approach	32.36	30.61	30.07	33.14
Kervrann et al.[41]	30.54	26.50	28.01	30.70
Buades et al. [8]	31.78	30.31	29.34	32.49
Ghazel et al. [26]	28.50	25.64	26.34	-
Pizurica et al. [27]	32.20	29.53	29.93	-
Polzehl et al. [28]	29.74	26.05	27.74	30.31
Portilla et al. [29]	32.66	30.32	30.38	32.39
Roth et al. [30]	31.92	28.32	29.85	32.17
Rudin et al. [2]	31.40	27.05	29.40	31.47
Tomasi et al. [5]	30.26	27.02	28.41	30.01
Awate et al. [32]	31.79	30.14	29.54	32.59
Gilboa et al. [33]	31.95	30.20	29.89	32.55
Gilboa et al. [34]	31.39	29.43	29.53	32.17
Brox et al. [35]	32.08	30.33	29.69	32.74
Elad et al. [36]	32.38	30.83	30.36	33.20
Dabov et al. [37]	33.05	31.78	30.88	33.79
Mairal et al. [38]	32.88	31.53	30.82	33.75
Kervrann et al. [39]	32.64	30.37	30.12	32.90
Kervrann et al. [40]	32.63	30.88	30.16	33.24

Table 2: Quantitative comparison of state-of-the-art denoising algorithms when applied to 512×512 Lena image with various levels of noise $\sigma = 15, 25, 50$

$\sigma/PSNR$	15/24.61	25/20.17	50/14.15
Our approach	33.36	31.12	27.13
Buades et al. [8]	32.40	29.59	25.55
Elad et al. [36]	33.70	31.32	27.79
Dabov et al. [37]	34.27	32.06	28.86
Mairal et al. [38]	34.14	31.92	28.80
Kervrann et al. [39]	33.71	31.73	28.46
Takeda et al. [44]	33.69	31.70	28.28

Fig.7(b), the coherence of lines in the image is enhanced well and the blurring effect is optimal.

Table 3: Performances of some faster implementation of NL-means when applied to 512 × 512 barbara test noisy(WGN) image

$\sigma/PSNR$	20/22.18
Classical NL-means	30.31
Robust NL-means (Without Patch classification)	30.64
Robust NL-means (With Patch classification)	30.61
Patch classification by mean and variance	29.80
Cluster trees ($\omega = 10$)	30.26
Fast Bayesian NL-means	30.71

Table 4: Computation time of various fast implementation of NL-means filters depending on the size of the search window

Search Window	17×17	21×21	33×33	65×65	129×129	no window
Classical NL-means	27s	42s	106s	410s	1539s	16107s
Patch classification-by mean and variance	13s	17s	34s	88s	221s	1529s
Robust NL-means (With proposed-Patch classification)	12s	15s	29s	59s	135s	798s
Cluster tree ($\omega = 0$)	12s	14s	14s	14s	14s	14s

4 Conclusion and Open Problem

We have described a refined approach of nonlocal-means filter. This proposed method suggests the use of Geman-McClure robust estimation function as ϑ_h. And to speed up this algorithm, the classification of patches using structural map ζ is presented. This method allows for the efficient pre-selection of similar patches. By doing this so, some features of an image are well preserved even better than the classical nonlocal-means filter. The two contributions of this paper can be combined well to produce good results. The comparisons made for the denoised images from various recent denoising techniques are presented. As shown by the experimental evaluation, the proposed one preserves the contrast of textural structures much better. The performance of our algorithm is very close, and in some cases even outperforms, to that of existing state-of-the-art denoising results. This new proposal considerably increases the power of denoising and one can say that the proposed approach achieved the worthy level of pertinency.
There is a scope to tune this proposed method in order to outperform all the state-of-the-art denoising techniques by considering the issue like patch classi-

fication. Many research works are going on for the patch classification method to speedup the weight calculation process in nonlocal-means filter. Since the sample correlation coefficient is not robust to the outliers, the classification using this may not work properly for the images contain outliers.

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