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An improved non-local means filter for color image denoising

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Abstract

Non-local means filter is a special case of non-linear filter. It performs well for filtering Gaussian noise while preserving edges and details of the original images. In this paper, we propose an improved filter for color image denoising based on combining the advantages of non-local means filter and bilateral filter. To compare the similarity of patches, a new weight value is computed by adding texture information into weights. The experimental results of color image filtering show that the proposed method has a better performance for reducing Gaussian noise and mixture noise.

Key words: non-local means; bilateral filter; Gaussian noise; color image denoising

1 Introduction

Color images are widely used but are often corrupted by noises that come from the image acquisition process, transmission or storage. The types of image noise are mainly Gaussian noise, impulse noise and mixed noise. For impulse noise, vector median filter (VFM) [1], vector directional filter (VDF) [2], and directional distance filter (DDF) [3] are well-known classical non-linear filters that have been widely used. However, these filters are spatially invariant operators that make no distinctions between noisy and noise-free pixels. To avoid damaging clean pixels in color images, adaptive vector median filter (AVMF) [4,5], fast peer group filter (FPGF) [6,7] and vector lower-upper-middle smoother (VLUM) [8] are widely used by certain switching schemes. Moreover, These filters are computationally efficient and perform reasonably well in removing noise. Following the success of switching filtering schemes in general imaging, several studies have been conducted to remove the random-valued impulse noise [9–12], but all these median methods aim to remove the impulse noise. When confronting with Gaussian noise, the performances of those methods would be dramatically dropped.

Unlike the local means filter, a non-local means (NLM) filter operates on a non-local area by using a dissimilarity measure between patches. It works well for removing Gaussian noise [13]. Many algorithms based on the NLM technique have been proposed to trade off detail preservation against noise reduction. Li and Suen [14] analyzed the structure similarity by grey relation of coefficients, and set similar weight function accordingly. Zheng et al. [15] proposed a non-local selection scheme of regularization parameters, which is based on a content-aware function through discriminating image contents. Chen et al. [16] proposed incorporating circulant similarity into a weighted average filter and choosing an appropriate kernel as weight function. To avoid the damage of edge pixels, Bhujle and Chaudhuri [17] proposed matching of both intensity and edge patches, and edge maps were extracted for the neighborhoods. Torres et al. [18] selected homogeneous pixels in the filtering area through statistical tests between distributions, and the weights of the location-variant linear filter are function of p-values of the tests. Sun et al. [19] established a general non-local denoising model based on multi-kernel-induced measures (GNLMKIM). The solutions based on NLM can remove Gaussian noise effectively, but the computational time is longer, and the cost is larger. Meanwhile, blurring still exists and blocking artifacts are also produced. To solve these problems, Wang et al. [20] uses fuzzy membership value to describe the property of pixels and pixels are defined between noises and noise-free, and combined the advantages of fuzzy decision filter (FDF) and NLM filter for noise suppression and edge preservation (FDNLM). Liu et al. [21] propose a NLM filter based on quaternion representation of color images. In addition, the papers [22, 23] efficiently remove noise by using a faster NLM filter and show superior denoising performance for clinical images. In addition, to solve over-smoothing of the image or inadequate noise removal, Verma et al. [24] select an optimal size of search window that vary from region to region based on the characteristics of the search region. In addition, the methods [25, 26] based on sparse and redundant representations also applied to NLM. And the computationally scalable algorithms can achieve better denoising performance

for Gaussian noise.

The bilateral filter (BILF) [27] is another non-linear filter that smooths images while preserves edges. Its application can be found in many image processing systems. Pinto et al. [28] introduced a robust bilateral and temporal filter (RBLT) using the spatial and temporal evolution of sequences to guide the filtering process. Shao et al. [29] presented an adaptive fast bilateral filter (AFBF) to reduce the speckle noise. In [30], through the filtering operation of the joint three-dimensional histogram, the target image is processed by jointing bilateral band filter. In [31], a rough set theory based approach is used to derive pixel level edge map and class labels which in turn are used to improve the performance of BILF. The main principle based on BILF extends the concept of Gaussian filter and combines spatial and intensity similarities.

Above all, the weights of the related NLM are all calculated by only using pixel information to measure the similarity. The results of noise removal are not accurate. There are also some methods [32, 33, 34] that use contourlet Domain rather than in pixel domain. But most algorithms are only for certain noise, impulse noise or Gaussian noise. For the BILF, the weights can use both the spatial similarity and the pixel similarity. In this paper, a new method is proposed. We take the advantages of NLM and BILF, and add a weight value that describes the property of the interested area. The proposed filter can preserve the fine details and edges more effectively. And we also give more experimental result in different noise. The proposed method can remove impulse noise and Gaussian noise effectively.

The rest of this paper is structured as follows. In Section 2, we briefly review the related research work. In Section 3 we describe the methodology of improving the NLM in details. In Sections 4, we present the experiments and results. Finally, we conclude the paper in Section 5.

2. Related work

2.1 The NLM

The NLM method was proposed by Buades et al. [13]. Under the Gaussian noise assumption, the weights are calculated, which are used to measure the similarity between a central region patch and neighboring patches in a searching window. A color RGB image f is commonly represented as an array of $H \times W \times 3$, where every pixel is a three-component vector of integer values in the interval of $[0, 255]$ (that is $k = 3$, representing three channels).

$$g_k(x, y) = \frac{\sum_{u,v \in N} f_k(x+u, y+v)w(u, v)}{\sum_{u,v \in N} w(u, v)} \quad (1)$$

$$w(u, v) = \exp\left(-\frac{\sum_{p \in P} \|f_k(x+p, y+p) - f_k(x_0+p, y_0+p)\|_2^2}{h^2}\right) \quad (2)$$

The NLM method is represented as Equations (1) and (2). N is the searching window. P is the patch window. h is the parameter to control the degree of smoothness. g_k is the filtering result.

$w(u, v)$ is the weight that uses pixel information to measure the similarity between a central region patch and its neighboring patches (Equation (2)). $\|\bullet\|_2$ is Euclidean distance. (x_0, y_0) is the position of central pixel, (x, y) is the position of neighboring pixel in the searching window. Each pixel is filtered by Equation (1).

Fig.1 shows different filter results. Fig.1 (a) is the original image from Matlab. Fig.1 (b) is polluted with Gaussian noise with mean 0 and variance 0.01. Fig.1(c)-(f) are filter results with different searching window. Although increasing the searching size N can marginally enhance the denoising performance, it also incurs unwanted computational costs, and blocking artifact is increasing. The selection of the searching size N can be empirical, depending on specific applications. Fig.2 (a) shows the computational time. The computational time increases drastically while increasing the searching window size.

Fig.1 the performance of with different searching window: (a) the “onion” original image (b) the “onion” image with Gaussian noise (c) the filter result with a 5×5 searching window (d) the filter result with a 7×7 searching window (e) the filter result with a 9×9 searching window (f) the filter result with a 11×11 searching window

window (f) the filter result with a 11×11 searching window

Fig.2 the performance of the filtering result: (a) the computational time with “onion” image. (b) the filtering performance with different h

h is the parameter to control the degree of smoothness, and several parameters of the NLM filter can be adjusted to achieve the best deblocking effects. We use the NLM filter with different parameter value of h at 5, 10, 15, 20, 30. Fig.2 (b) shows the filtering performance with different h. The original image is corrupted with mixture noise that combines 3% impulse noise and Gaussian noise of variance 0.01. It is shown that the peak signal-to-noise ratio (PSNR) is lower, and blocking artifacts cannot be efficiently suppressed when $h=5$. The detailed information would be largely lost if it is deblocked by a smoothing filter with $h>30$. Even if a moderate h is adopted, for example $h=15$, deblocking still cannot bring acceptable results on the whole image. The NLM cannot remain at high effectiveness in removing Gaussian noises as shown in the experiment results. While the NLM fails to remove the common mixed noise, therefore, the denoising performance of the NLM still needs to be improved.

2.2 The BILF

The original function of the BILF is to preserve edges while smoothing out images. It is a non-linear filter that has been improved from Gaussian filter. The denoising image is also computed as a weighted average of each pixel's neighborhood [35].

$$g_k(x_0, y_0) = \frac{1}{\sum_{(x,y) \in \Omega(x_0, y_0)} w(x, y, x_0, y_0)} \sum_{(x,y) \in \Omega(x_0, y_0)} w(x, y, x_0, y_0) f_k(x, y) \quad (3)$$

$$\Omega(x_0, y_0) = \left\{ (x, y) \mid |x - x_0| \leq w_0 \text{ and } |y - y_0| \leq w_0 \right\} \quad (4)$$

$$w(x, y, x_0, y_0) = \exp\left(-\frac{\|f_k(x, y) - f_k(x_0, y_0)\|_2^2}{2h_1^2}\right) \exp\left(-\frac{(x - x_0)^2 + (y - y_0)^2}{2h_2^2}\right) \quad (5)$$

$g_k(x_0, y_0)$ is the filtering result (Equation (3)) which filters images through the combination of spatial and range Gaussian kernels (Equation (5)). w_0 (Equation (4)) is the distance between central pixel and neighboring pixel. $f_k(x_0, y_0)$ is the central pixel, and $f_k(x, y)$ is a neighboring pixel. $w(x, y, x_0, y_0)$, defined in Equation (5) is the weight value. $w(x, y, x_0, y_0)$ is combined the weight based on the similarity between pixel (x, y) and pixel

(x_0, y_0) with the weight based on Euclidean distance between those two pixels. Thus, the

BILF has two free parameters, h_1 and h_2 . These parameters make it possible to control the influence of the geometric distance and similarity properties of the neighbors, respectively. Fig.3 shows the influence of the geometric distance and similarity properties of the neighbors with 'onion' and 'hestain' image. The original image is influenced with mixture noise that combines 3% impulse noise and Gaussian noise of variance 0.01.

Fig.3 the filtering performance with different parameters: (a) the performance with various h_1
(b) the performance with h_2

The size of the filter window is 5×5 . In Fig.3 (a), $h_2 = 10$, then set h_1 to 1, 5, 10, 15, 20. In Fig.3 (b), $h_1 = 10$, then set h_2 to 1, 5, 10, 15, 20. From Fig.3, we can see that the h_2 value in the bilateral filter is relatively insensitive to the noise variance compared to the h_1 value. In our experiments, the values of h_1 and h_2 are empirically chosen. We should choose

the parameter settings that can achieve the best noise reduction results.

Blurring can be difficult to overcome with a BILF. Pixel values on an image are combined with the geometric space information which causes a significant smoothness across boundaries. It is vital to apply more enhanced techniques to deal with blurring.

3 The proposed method

For the NLM, the weights are calculated which only use pixel information to measure the similarity between a central region patch and its neighboring patches. For the BILF, the weights use the spatial similarity and the pixel similarity. In this paper, the proposed method is to combine the advantages of the NLM and the BILF with added texture information as weights.

Let S represent the mean squared deviation (MSD) in patch window (Equation (6)). Each window has an “S”. The MSD can differentiate the smooth area and edge of image. In smooth area, the MSD is nearly 0. For edge or spot, the MSD is large. So, it can reflect the patch texture information. g is the average in a patch window. p is the number of pixels in the patch window. $w_1(x, y, x_0, y_0)$ is the weight value that measures the similarity of the MSD (Equation (7)). $w_2(x, y, x_0, y_0)$ is the weight value that measures the similarity of spatially close to the current pixel (Equation (8)).

$$S = \frac{1}{\sqrt{3}p} \sum_{p=0}^{P-1} \|f_k(x, y) - g_k\|_2 f_k(x, y) \in PatchWindow \quad (6)$$

$$w_1(x, y, x_0, y_0) = \exp\left(-\frac{(S_{x,y} - S_{x_0,y_0})^2}{h_1}\right) \quad (7)$$

$$w_2(x, y, x_0, y_0) = \exp\left(-\frac{(x - x_0)^2 + (y - y_0)^2}{h_2}\right) \quad (8)$$

$$w(x, y, x_0, y_0) = \exp\left(-\frac{\sum_{p \in P} \|f_k(x+p, y+p) - f_k(x_0+p, y_0+p)\|_2^2}{h}\right) w_1(x, y, x_0, y_0) w_2(x, y, x_0, y_0) \quad (9)$$

We set $h_1 = 100, h_2 = 50, h_3 = 60$. A new weight is computed by Equation (9). The proposed improved non-local means (INLM) algorithm is described as follows.

Input: The noisy image $f_k(x, y)$, with size of $H \times W \times 3$

1: Initialize (searching window) $N = 5 \times 5$, (patch window) $P = 3 \times 3$, $h_1 = 100$,

$h_2 = 50, h_3 = 60$.

2: Use Equation (6) to compute the MSD of each patch window.

3: for $x=1$ to H ; $y=1$ to W

4: for Searching window $n=1$ to N

5: for PatchWindow $p=1$ to P

6: Use Equation (2) to compute $w(u, v)$.

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7:     end for
8: end for

9:     Compute  $w_1(x, y, x_0, y_0)$ ,  $w_2(x, y, x_0, y_0)$ 

10:    Use Equation (9) to compute  $w$ .
11:    Use Equation (1) to get the filtering value of position  $(x, y)$ .
12: end for

```

Output: The restored image $g_k(x, y)$

4 Experiments and results

An extensive set of experiments have been conducted in this research. The experiments aim at evaluating and analyzing the behavior of the proposed image filtering technique in comparing with other techniques. Most of the filtering images in other works are gray images, however our method mainly focuses on color images. We use some similar images as in [14,16], for example the “onion” image. Other images all come from the same public datasets in Matlab, including “hestain” image with 303×227 , “gantrycrane” image with 400×264 , “onion” image with 198×135 and “football” image with 320×256 . Fig.4 shows the original images.

We assess the performances of the algorithm with several popularly used test images using Matlab 7.0. The execution time (in seconds) running on a desktop PC with 2.50GHz CPU and 4.0GB RAM is measured.

A quantitative comparison was performed between the performances of the proposed denoising algorithm and other existing methods. Peak Signal-to-Noise Ratio (PSNR), normalized mean square error (NMSE), mean squared error (MSE) and structural similarity (SSIM) [11] are adopted to evaluate the performance of different denoising methods. MSE and NMSE are represented in pixels, and PSNR is represented in decibels (dB). SSIM a method for measuring the similarity between two images. These criteria are defined as follows (Equations (10) (11) (12) (13)).

$$PSNR = 10 \lg \frac{3 \times 255^2}{\frac{1}{HW} \sum_{x=1}^H \sum_{y=1}^W [g_k(x, y) - o_k(x, y)]^2} \quad (10)$$

$$NMSE = \frac{\sum_{x=1}^H \sum_{y=1}^W \|g_k(x, y) - o_k(x, y)\|_2^2}{\sum_{x=1}^H \sum_{y=1}^W \|o_k(x, y)\|_2^2} \quad (11)$$

$$MSE = \frac{1}{3HW} \sum_{x=1}^H \sum_{y=1}^W \|g_k(x, y) - o_k(x, y)\|_2^2 \quad (12)$$

$$SSIM(g, o) = \frac{(2\mu_g \mu_o + c_1) (2\sigma_{go} + c_2)}{(\mu_g^2 + \mu_o^2 + c_1) (\sigma_g^2 + \sigma_o^2 + c_2)} \quad (13)$$

(x, y) characterizes the sample position, $o_k(x, y)$ is the original, desired image and

$g_k(x, y)$ represents the output of the filter image, where μ_g and μ_o are the average of g and

o, respectively. σ_g^2 and σ_o^2 are the variance of g and o, respectively. σ_{go} is the covariance of g and o. $c_1 = (k_1 L)^2$, $c_2 = (k_2 L)^2$. L is the dynamic range of the pixel-values, $k_1 = 0.01$ and $k_2 = 0.03$ by default. To evaluate the performances of noise suppression and edge preservation, the proposed algorithm is compared with the NLM, BILF, a modified switching median filter (MSMF) by Wang et al. [4], FDNLM [20] and GNLMKIM [19]. All the images can be tested in the same way for Gaussian noise and mixture noise. Due to the limitation of the article length, we only present some of the testing results.

4.1 Gaussian noise

In this experiment, the color images are corrupted with Gaussian noise with different standard deviations.

(a)

(b)

(c)

(d)

Fig.4 The original images: (a) “hestain” (b) “gantrycrane” (c) “onion” (d) “football”

Fig.5 shows the filtering outputs from “hestain” image. We add Gaussian noise with a mean of 0 and variance of 0.02 to the original image. In the NLM, with an increasing searching window size, the blurring appears more severe. The computational time is also increasing. The size of the searching window is set to 7×7 , and the size of the patch window is 3×3 . In the BILF, the filtering window is 3×3 . For the INLM, the size of the searching window is 5×5 and the size of the patch window is 3×3 . In the MSMF, the filtering window is 3×3 . The MSMF can remove the impulse noise effectively, but it produces bad results with Gaussian noise.

The comparison results of the performances are shown in Tables 1-3. The MSMF has a

lower PSNR and a higher NMSE and MSE. It is demonstrated that the MSMF is excellent for removing the impulse noise, but is not so capable to remove Gaussian noise. The NLM and FDNLM has a longer computational time for “hestain” image. The INLM has a better performance, and its computational time is acceptable.

Fig.6 shows the filtering outputs for the “gantrycrane” image. We add Gaussian noise of mean 0 and variance of 0.03 to the original image. Fig.7 shows the filtering results in PSNR (dB) with the filters applied to the images.

Fig.5 Performance evaluation: (a) the “hestain” image with Gaussian noise (b) the NLM output (c) the BILF output (d) the MSMF output (e) the FDNLM output (f) the output from the proposed algorithm

Fig.6 Performance evaluation: (a) the “gantrycrane” image with Gaussian noise (b) the NLM output (c) the BILF output (d) the MSMF output (e) the FDNLM output (f) the output from the proposed algorithm

Fig.7 Filtering results in PSNR (dB) from the different filters applied to the images: (a) PSNR for the “hestain” image (b) PSNR for the “gantrycrane” image

4.2 Mixture noise

As the impact caused by Gaussian noise and impulse noise on images is different, little research has been reported on removing the mixture of both types of noise. In this paper, the proposed method combines the advantages of the NLM and the BILF, and exhibits good performances in removing the complicated mixtures. The comparison results of the performances are shown in Tables 4-6.

Fig. 8-9 and Fig. 11 show the filtering outputs from different filters for the different images. We added the mixture noise, combining with 3% impulse noise and Gaussian noise of mean 0 and variance 0.01, to original images. Fig.10 shows the filtering results in PSNR (dB) from the filters applied to the images.

Fig.8 Performance evaluation: (a) the “onion” image with mixture noise (b) the NLM output (c) the BILF output (d) the MSMF output (e) the FDNLM output (f) the output from the proposed algorithm

Fig.11 Performance evaluation: (a) the “football” image with mixture noise (b) the NLM output (c) the BILF output (d) the MSMF output (e) the FDNLM output (f) the output from the proposed algorithm

4.3 Discussion

The experimental results from Fig.7 and Fig.10 can be summarized. The NLM filter is better for dealing with Gaussian noise. When the level of Gaussian noise increases, the NLM performs better than the BILF. From Fig.7 and Fig.10, the density level of Gaussian noise increases from 0.01 to 0.03, and the NLM results a higher PSNR than that of the BILF. The experiments show that the MSMF cannot remove Gaussian noise effectively, however, the PSNR from the MSMF filter is 41.8259dB when 3% of impulse noise is added to the original image. For FDNLM, the filter works better for lower Gaussian noise. From Fig. 2, one can see that a bigger searching window contains more pixels and has higher statistical reliability but increases the computation time. In case of NLM, a big searching window would blur the images more. In this paper, the size of the searching window is chosen empirically.

Tables 1-3 are the performance comparisons for the “hestain”, “gantrycrane” and “onion” images with added Gaussian noise. From Table 1, we can see that our method has better performance when the variance of Gaussian noise is 0.01, 0.02 and 0.05. When the variance of Gaussian noise is 0.03, our method has a similar performance as GNLMKIM. In computer time, except for BILF, our method is faster than others. Tables 2-3 have the same conclusions. Tables 4-6 are the performance comparisons for the “onion”, “hestain” and “football” images with added mixture noise. From Table 4, we can see that our method has the best performance. The computer time is also acceptable. From Table 5, our method has better performance when the density of noise is low. When the density of noise is high, our method has a similar performance as GNLMKIM. From Tables 1-6, one can see that the computational time is longer for the FDNLM and NLM. The size of the searching window is 7×7 . The NLM needs to compute the similarities between a central region patch and its neighboring patches in a search window and thus consumes more time. In the proposed method INLM, the size of the searching window is set to 5×5 to reduce the computational time, but it is still the best with the highest PSNR and SSIM, lowest MSE and NMSE. For removing the mixture noise, the performance of INLM is almost as good as FDNLM, but the computation time is significantly less. For example, in Table 4 the computational time of INLM is 1-2 seconds whereas FDNLM is 10-11 seconds; in Table 5 the computational time of INLM is 3-4 seconds whereas FDNLM is 26-29 seconds. In these cases, the real-time performance of the proposed method is significantly better.

Table 1 Performance comparison for the “hestain” image with added Gaussian noise

Noise Algorithms	Gaussian noise of mean 0 and variance 0.01					Gaussian noise of mean 0 and variance 0.02				
	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	26.4173	0.0036	148.3717	0.6699	4.772590	25.2676	0.0058	193.3411	0.6690	5.023923
BILF	27.3346	0.0044	120.1204	0.6100	1.622203	25.7838	0.0051	171.6705	0.5611	1.684648
MSMF[4]	23.4167	0.0134	296.0820	0.5736	3.307964	21.6688	0.0132	442.7938	0.4815	3.466207
FDNLM[20]	27.1223	0.0050	138.7452	0.7104	27.74955	25.9487	0.0048	161.2211	0.6695	27.8416
GNLM KIM[19]	26.3920	0.0044	149.4430	0.6774	21.17379	25.9500	0.0049	165.2258	0.6759	21.19342
INLM	27.5517	0.0028	114.2647	0.7705	3.039173	26.2277	0.0046	154.9926	0.7204	3.482848
Noise Algorithms	Gaussian noise of mean 0 and variance 0.03					Gaussian noise of mean 0 and variance 0.05				
	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	24.4336	0.0070	234.2737	0.5273	5.063107	23.0335	0.0096	323.3958	0.5849	5.031775
BILF	24.6571	0.0066	222.5202	0.6089	1.701433	22.9716	0.0098	328.0370	0.4856	1.761296
MSMF[4]	20.4470	0.0174	586.6493	0.4225	3.587132	18.7509	0.0258	866.9503	0.3451	3.724869
FDNLM[20]	24.6820	0.0066	221.2491	0.6325	26.98131	23.4907	0.0087	291.0758	0.6243	27.16453
GNLMKIM[19]	25.2857	0.0057	192.5369	0.6751	21.68529	23.6346	0.0084	281.5897	0.6732	21.09615

INLM	25.1892	0.0059	196.8633	0.6870	3.511491	23.7128	0.0082	276.5681	0.6621	3.494458
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Table 2 Performance comparison for “gantrycrane” with added Gaussian noise

Noise Algorithms	Gaussian noise of mean 0 and variance 0.01					Gaussian noise of mean 0 and variance 0.02				
	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	22.773 2	0.0232	343.3695	0.5370	7.957388	22.6303	0.0239	354.8549	0.6811	7.902535
BILF	23.070 9	0.0216	320.0208	0.7098	2.721877	22.5319	0.0245	362.9832	0.4775	2.681040
MSMF[4]	22.224 6	0.0263	389.5989	0.4008	5.534327	20.4515	0.0395	586.0496	0.3210	5.494203
FDNLM[20]	23.235 1	0.0200	290.6636	0.7167	41.66524	22.8056	0.0215	340.2046	0.6942	41.78999
GNLMKIM[19]	22.990 3	0.0220	326.6233	0.7083	37.05799	22.7258	0.0234	347.1334	0.6935	34.51526
INLM	23.727 5	0.0186	275.6294	0.7486	5.160320	22.8462	0.0228	337.6415	0.7055	5.574742
Noise Algorithms	Gaussian noise of mean 0 and variance 0.03					Gaussian noise of mean 0 and variance 0.05				
	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	22.182 4	0.0265	393.4069	0.6174	7.886772	21.3588	0.0321	475.5556	0.5381	7.957532
BILF	22.122 8	0.0269	398.8403	0.5860	2.669104	20.9397	0.0353	523.7317	0.3475	2.695254
MSMF[4]	19.332 9	0.0511	758.2119	0.2771	5.737081	17.7217	0.0741	1.098e+003	0.2148	5.998339
FDNLM[20]	21.477 8	0.0312	462.6971	0.4181	42.32771	20.6845	0.0375	555.4303	0.4894	41.60379
GNLMKIM[19]	22.349 3	0.0255	378.5744	0.7016	34.46457	21.3110	0.0324	480.8218	0.6910	33.95962
INLM	22.196 1	0.0265	392.1644	0.7074	5.473537	21.5148	0.0309	458.7793	0.6982	5.515224

Table 3 Performance comparison for the “onion” image with added Gaussian noise

Noise Algorithms	Gaussian noise of mean 0 and variance 0.01					Gaussian noise of mean 0 and variance 0.02				
	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	28.2983	0.0074	96.2175	0.7940	9.054051	27.5160	0.0088	115.2087	0.7946	9.140724
BILF	26.3733	0.0115	149.8818	0.6715	7.021690	25.4059	0.0144	187.2800	0.6239	7.083796
FDNLM[20]	28.4857	0.0071	92.1532	0.8058	10.26517	27.2751	0.0093	121.7770	0.7659	10.186742

GNLMKIM[19]	28.3725	0.0073	94.5871	0.7930	7.741945	27.5422	0.0088	114.5151	0.7936	8.212901
INLM	28.4602	0.0071	92.6955	0.7948	9.186389	27.6890	0.0085	110.7083	0.7951	9.161111
Noise	Gaussian noise of mean 0 and variance 0.03					Gaussian noise of mean 0 and variance 0.05				
Algorithms	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	26.5427	0.0111	144.1487	0.7952	9.21583	24.2627	0.0187	243.6732	0.7842	9.121792
BILF	24.3940	0.0181	236.4169	0.5779	7.221277	23.0197	0.0249	324.4218	0.5115	7.143101
FDNLM[20]	26.1106	0.0122	159.2293	0.7156	10.17484	24.5156	0.0176	229.8919	0.6398	10.448825
GNLMKIM[19]	26.5991	0.0109	142.2871	0.7913	7.755470	24.2700	0.0186	243.2626	0.7906	7.798624
INLM	26.6541	0.0108	140.4966	0.7970	9.131547	24.3855	0.0182	236.8788	0.7928	9.167428

Table 4 Performance comparison for “onion” image with added mixture noise

Noise	3% impulsive noise plus Gaussian noise of mean 0 and variance 0.01					3% impulsive noise plus Gaussian noise of mean 0 and variance 0.02				
Algorithms	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	27.5767	0.0087	113.6094	0.7394	1.817586	26.0671	0.0123	160.8327	0.7463	1.792076
BILF	28.1025	0.0077	100.6532	0.6512	0.629034	26.1226	0.0122	158.7879	0.6002	0.614919
MSMF[4]	23.3636	0.0230	300.0121	0.4489	1.270196	21.5076	0.0352	459.5377	0.3733	1.298394
FDNLM[20]	28.3366	0.0073	95.3713	0.8054	10.23720	27.0634	0.0098	127.8613	0.7541	10.25267
GNLMKIM[19]	27.2660	0.0092	120.5987	0.7414	7.860038	26.5397	0.0111	144.2467	0.7516	8.092862
INLM	28.4632	0.0071	92.6313	0.8071	1.246791	26.8081	0.0104	135.6030	0.7491	1.230364
Noise	3% impulsive noise plus Gaussian noise of mean 0 and variance 0.03					3% impulsive noise plus Gaussian noise of mean 0 and variance 0.05				
Algorithms	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	25.0052	0.0157	205.3803	0.6941	1.772425	23.3445	0.0231	301.0475	0.6070	1.793721
BILF	24.8193	0.0164	214.3643	0.5472	0.602130	22.8719	0.0257	335.6536	0.4917	0.602628
MSMF[4]	20.2975	0.0466	607.1945	0.3169	1.317996	18.5359	0.0698	910.9470	0.2581	1.362528
FDNLM[20]	25.7784	0.0132	171.8861	0.6987	10.29378	23.9750	0.0200	260.3652	0.6288	10.30350
GNLMKIM[19]	25.7804	0.0132	171.8083	0.7027	7.900953	23.6462	0.0215	280.8426	0.7320	7.892369
INLM	25.8593	0.0129	168.7146	0.7475	1.226907	24.2557	0.0187	244.0673	0.7421	1.216469

Table 5 Performance comparison for “hestain” image with added mixture noise

Noise	3% impulsive noise plus Gaussian noise of mean 0 and variance 0.01					3% impulsive noise plus Gaussian noise of mean 0 and variance 0.02				
Algorithms	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)

NLM	25.7019	0.0052	174.9409	0.6451	4.879495	24.6812	0.0066	221.2906	0.6435	4.875592
BILF	26.6713	0.0042	139.9427	0.7131	1.666603	25.2382	0.0058	194.6517	0.5526	1.634524
MSMF[4]	23.1546	0.0094	314.4999	0.5594	3.160416	21.3313	0.0142	478.5715	0.4678	3.414356
FDNLM[20]	26.5767	0.0043	143.0243	0.7071	26.89121	25.5378	0.0054	181.6759	0.6718	26.930342
GNLMKIM[19]	25.7610	0.0051	172.5760	0.6495	22.18726	25.4542	0.0055	185.2101	0.6445	22.03886
INLM	26.8047	0.0040	135.7089	0.7369	3.396940	25.5564	0.0054	180.9011	0.6932	3.378729
Noise	3% impulsive noise plus Gaussian noise of mean 0 and variance 0.03					3% impulsive noise plus Gaussian noise of mean 0 and variance 0.05				
Algorithms	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	23.7601	0.0081	273.5718	0.6397	4.808518	22.3767	0.0112	376.1927	0.5725	4.799906
BILF	24.1028	0.0075	252.8125	0.5184	1.625290	22.4397	0.0110	370.7732	0.4708	1.617609
MSMF[4]	20.1664	0.0186	625.8034	0.4093	3.579840	18.4472	0.0277	929.7420	0.3297	3.702528
FDNLM[20]	24.6582	0.0066	222.4624	0.6339	28.03796	23.1979	0.0093	311.3789	0.5974	27.05902
GNLMKIM[19]	24.9390	0.0062	208.5357	0.6468	22.29054	23.5406	0.0086	287.7534	0.6415	22.02678
INLM	24.6662	0.0066	222.0538	0.6577	3.343473	23.2033	0.0092	310.9955	0.6360	3.316730

Table 6 Performance comparison for “football” image with added mixture noise

Noise	3% impulse noise plus Gaussian noise of mean 0 and variance 0.01		3% impulse noise plus Gaussian noise of mean 0 and variance 0.02		3% impulse noise plus Gaussian noise of mean 0 and variance 0.03		3% impulse noise plus Gaussian noise of mean 0 and variance 0.05	
Algorithms	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
NLM	26.4734	146.4660	25.3254	190.7840	24.3672	237.8836	22.9200	331.9568
BILF	26.9868	130.1354	25.5218	182.3482	24.3758	237.2636	22.7149	348.0113
MSMF[4]	25.4324	186.1385	24.5474	228.2109	23.7263	275.7078	22.5543	361.1204
FDNLM[20]	27.2612	122.1685	26.3707	149.9732	25.4284	186.3119	24.0130	258.0945
GNLMKIM[19]	27.1474	125.4113	26.3815	149.5983	25.4989	183.3113	23.4054	296.8518
INLM	28.0196	102.5925	27.3508	119.6748	26.7043	138.8826	25.4886	183.7496

4.4 Other works

We also test other recent methods to compare with the proposed method, for example [14,19,37]. The GNLMKIM proposed by Sun et al. [19] utilizes a two-step alternation to get filtering result and has three exponential kernel parameters. In our test, h_1 is set to 10, h_2 is set to 15, and P_i is set to 100. For example, in Table 1 the performance of the proposed method is compared with GNLMKIM as well as other methods using the “hestain” image. With lower

Gaussian noise, the performance of GNLMKLM is not very good. When the Gaussian noise increases, GNLMKLM performs slightly better but still not as good as the proposed method, and the computation time is much longer than the proposed method. Fig.12 shows the filtering outputs for the “hestian” image with Gaussian noise. The filtering output of GNLMKLM looks similar as the proposed but by evaluating PNSR, NMSE, MSE and SSIM the proposed is still better in overall. In Table 4, the performance is compared using the “onion” image with mixture noise, and the performance of the GNLMKIM is worse than the proposed. Fig.13 shows the filtering outputs for the “onion” image. Fig.13 (b), (e) is the output of GNLMKLM. Fig.13 (c), (f) is the output of the proposed method. Although Fig.13(c), (f) seem to have more noise, the proposed method can better preserve fine details. To show its performance, Fig.14 shows the zoom-in of image in Fig.13. We can see that GNLMKIM removes some edges and fine details, and makes the image blurred. The proposed method can preserve more details. In addition, the “lion” image that comes from Google “things” dataset [36] is also tested and the performance is compared in Table 7. Fig.15 shows the filtering outputs for the “lion” image. For the “onion” and “lion” images with Gaussian noise, even though the proposed method is slightly slower than GNLMKIM, all the other performances PNSR, NMSE, MSE and SSIM are better.

According to another method by Li and Suen [14], it applies grey relation to non-local means and make the solution simpler and faster. However, in our experiments the patch of image need to be reshaped as the sequence, and then compute the min and max to obtain the grey relation. We found that although the method provides good results in practice, it also increases the computation time significantly in processing certain images. For example, for the “gantrycrane” image with added Gaussian noise of mean 0 and variance 0.01 using Gaussian kernel, the computation time of [14] is 113.052712s whereas the proposed method is just 5.160320s. Due to its poor computation time, no further performance test is done.

Fig.12 Performance evaluation: (a) the “hestian” image with Gaussian noise of mean 0 and variance of 0.03 (b) the GNLMKIM output (c) the proposed output (d) the “hestian” image with Gaussian noise of mean 0 and variance of 0.05 (e) the GNLMKIM output (f) the proposed output

Fig.13 Performance evaluation: (a) the “onion” image with 3% impulse noise and Gaussian noise of mean 0 and variance of 0.01 (b) the GNLMKIM output (c) the proposed output (d) the “onion” image with 3% impulse noise and Gaussian noise of mean 0 and variance of 0.02 (e) the GNLMKIM output (f) the proposed output

Fig.14 zoom-in of images in the Fig.13. : (a) zoom-in of the original “onion”(b) zoom-in of the GNLMKIM (c) zoom-in of the proposed

Table 7 Performance comparison for the “lion” image with added Gaussian noise

Noise Algorithms	Gaussian noise of mean 0 and variance 0.01					Gaussian noise of mean 0 and variance 0.02				
	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	25.4301	0.0066	186.2408	0.7379	11.45593	25.0926	0.0072	201.2910	0.7368	13.521567
BILF	22.0681	0.0144	403.8954	0.5841	9.093267	21.4976	0.0164	460.5993	0.5475	11.189882
FDNLM[19]	24.3697	0.0085	237.7469	0.7228	12.86418	23.6930	0.0099	277.8306	0.6853	12.655751
GNLMKIM[18]	25.4248	0.0066	186.4654	0.7437	9.956551	25.0819	0.0072	201.7876	0.7425	10.474830
INLM	25.45381	0.0066	185.2258	0.7483	11.73104	25.2499	0.0069	194.1291	0.7502	12.494737
Noise	Gaussian noise of mean 0 and variance 0.03					Gaussian noise of mean 0 and variance 0.05				

Algorithms	PSNR	NMSE	MSE	SSIM	Time(s)	PSNR	NMSE	MSE	SSIM	Time(s)
NLM	24.4861	0.0082	231.4592	0.7351	11.27403	23.1770	0.0111	312.8854	0.7306	11.523196
BILF	21.0864	0.0180	506.3385	0.5135	7.035900	20.5120	0.0206	577.9309	0.4710	8.9323334
FDNLM[19]	23.1144	0.0113	317.4252	0.6595	12.79744	22.0551	0.0144	404.1034	0.6019	13.178568
GNLMKIM[18]	24.5859	0.0080	226.1989	0.7353	9.709179	23.1710	0.0111	313.3157	0.7341	10.110937
INLM	24.6705	0.0079	221.8353	0.7427	11.45487	23.3078	0.0108	303.5957	0.7414	11.873625

(a)

(b)

(c)

(d)

(e)

(f)

Fig.15 Performance evaluation: (a) the “lion” image with Gaussian noise of mean 0 and

variance of 0.05 (b) the NLM output (c) the BILF output (d) the FDNLM output (e) the GNLMKIM output (f) the output from the proposed algorithm

In addition, we also explain the proposed method and the reference paper [37]. The reference paper [37] is a graph-based filter for Gaussian noise. And it computes the Fourier-based dictionaries for each single patch which increase the complexity with the size of dictionary. Dictionary learning has been widely used in restoring Gaussian noise. In our method, it can not only apply Gaussian noise, but also impulse noise or mixture noise. In addition, in our method, we can see that the computer time is faster.

5 Conclusions

In this paper, we propose an improved non-local means (INLM) filter for color image denoising. The algorithm combines the advantage of the NLM and the BILF. It calculates a new weight by measuring the spatial similarity, the pixel similarity and the mean of differences. The proposed filter can remove Gaussian noise, impulse noise and the mixture of Gaussian and impulse noise that are added to the original images while preserve the image details very well at different noise ratios. From experimental results, the proposed method has a better denoising performance compared to the several other filters, such as the NLM, the BILF, the MSMF, the FDNLM and the GNLMKIM. In the future work, firstly, we plan to add texture feature to measure similarity of patches. Secondly, we will set up a fast optimization method to solve the model. All attempts can improve the proposed method aiming to remove mixture noise more effectively.

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