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image enhancement,
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NON-LOCAL MEAN-SHIFT FILTER FOR THE REDUCTION OF MULTIPLICATIVE NOISE IN DIGITAL IMAGES

In this paper a new method for the reduction of multiplicative noise in digital images is described. The proposed algorithm is a modification of the Mean-Shift (MS) filter which is based on the concept of the Non-Local Means (NLM) denoising. The proposed algorithm does not focus on single pixels only, as in the case of the mean-shift technique, but also on their neighborhoods. The performance of the novel approach is experimentally verified and the obtained results prove that the new design is superior both to the MS and NLM techniques.

1. Introduction

Noise suppression in digital images is one of the most important preprocessing steps. In this paper we address the problem of reduction of multiplicative noise, also known as speckle noise. This kind of noise strongly decreases the quality of synthetic aperture (SAR), microscope and medical ultrasonic images.

We propose a combination of the mean-shift (MS) and non-local means (NLM) filtering methods tailored for the suppression of the multiplicative noise. The new approach is able to suppress the impulses introduced by the noise process, which removal is not possible using the MS and NLM methods. Furthermore our approach offers better edge enhancement combined with the ability to preserve image details.

In Sections 2 and 3 we describe the non-local means and mean-shift methods and in Section 4 the novel algorithm is proposed. Then the comparison with other filters is provided and in the final Section the conclusions are presented.

2. Non-local means filtering

The main idea of the non-local means denoising algorithm is to estimate a new value of a pixel, taking into account similar pixels in a so called search window. The similarity of pixels in the search window is calculated not only using the difference of their intensity, but also considering their neighborhoods. The original NLM algorithm was described in [1], [3] and [2], but many modifications were also proposed [8], [9].

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In this method, to denoise an image u, we have to compute for each pixel p

$$\hat{u}(p) = \frac{\sum_{q \in B(p,r_a)} w(p,q) \cdot u(q)}{\sum_{q \in B(p,r_a)} w(p,q)}, \tag{1}$$

where $B(p, r_a)$ indicates a neighborhood centered at p of size $(2r_a+1) \times (2r_a+1)$. Because of the increasing computational complexity, the size of the search window is limited. It depends on the noise intensity, and generally larger windows are capable to suppress intensive noise.

In the original version of the algorithm, the weight $w(p, q)$ depends on the squared Euclidean distance $d^2 = d^2(B(p, r_f),\ B(q, r_f))$ of the $(2r_f + 1) \times (2r_f + 1)$ pixel patches centered respectively at p and q, where r_f is the size parameter of the search window

$$d^2(B(p,r_f), B(q,r_f)) = \frac{1}{(2r_f+1)^2} \sum_{j \in B(0,r_f)} (u(p+j) - u(q+j))^2. \tag{2}$$

The weight $w(p, q)$ is computed using an exponential kernel:

$$w(p,q) = \exp\left(-\frac{\max(d^2 - 2\sigma^2, 0)}{h^2}\right), \tag{3}$$

where σ is the standard deviation of the noise and h is a filtering parameter depending on σ [3]. As can be observed, the weights for patches with squared distances smaller than σ^2 are set to 1. For larger distances the weight decreases exponentially.

3. Mean-shift filtering

The mean-shift technique was introduced in 1975 by Fukunaga and Hostetler [7] and later by Cheng [4]. The method was used for image preprocessing by Comaniciu in the seminal papers [5], [6]. Mean-shift is an iterative method which is seeking for local modes of a probability density function and is widely used for image denoising and segmentation.

In this paper we focus on the mean-shift filter, working in space-range domains. The algorithm is as follows [11]:

1) define the feature vector $\boldsymbol{p} = [\boldsymbol{p}^d,\ \mathrm{f(p)}]^T$, where $\boldsymbol{p}^d$ denotes the spatial coordinates of image pixels and $f(p)$ - intensity values of the original image pixels,
2) for each pixel in image:
   a) set the initial location $\boldsymbol{q}_j = \boldsymbol{p}$, $j = 1$,
   b) $j \leftarrow j + 1$, K_s - spatial kernel, K_r - range kernel, σ_s, σ_r - spatial and intensity bandwidth, compute:

$$\boldsymbol{q}_{j+1} = \frac{\sum_{i=1}^{n} \boldsymbol{p}_i \cdot K_s\left(\left|\left|\frac{\boldsymbol{q}_j^d - \boldsymbol{p}_i^d}{\sigma_s}\right|\right|^2\right) K_r\left(\left|\left|\frac{f(q_j)-f(p_i)}{\sigma_r}\right|\right|^2\right)}{\sum_{i=1}^{n} K_s\left(\left|\left|\frac{\boldsymbol{q}_j^d - \boldsymbol{p}_i^d}{\sigma_s}\right|\right|^2\right) K_r\left(\left|\left|\frac{f(q_j)-f(p_i)}{\sigma_r}\right|\right|^2\right)},$$

   c) compute the mean-shift:

$$m(\boldsymbol{q}_j) = \boldsymbol{q}_{j+1} - \boldsymbol{q}_j$$

   d) repeat two above steps until the mean-shift converges, $m(\boldsymbol{q}_j) = 0$,
   e) set the computed pixel as the final result.

Choosing the proper kernel is important, however two kernels - the Epanechnikov and the Gaussian - are commonly used [11]. Because of the computational complexity, the iterative process is usually terminated when the $m(\boldsymbol{q}_j)$ is lower than a given value, or a predefined number of iteration has been reached.

4. Proposed non-local mean-shift filter

The proposed denoising method is based on the concept of the mean-shift filter [11]. The new approach differs in the definition of the weights used in finding the local maxima. We do not focus on single pixels only, but consider also their neighborhoods. The computation of the weights is similar to the approach followed in the non-local means denoising algorithm [1].

First, we declare a search window $B(p, r_a)$ centered at p_0 (marked red in Fig. 1) of size $(2r_a + 1) \times (2r_a + 1)$. Then for each pixel in $B(p, r_a)$, we declare a neighborhood N_q centered at q_0 with the size of $(2r_f + 1) \times (2r_f + 1)$ and we compare it together with the neighborhood of the central pixel N_p calculating the weights:

$$w(N_p, N_q) = \frac{1}{(2r_f + 1)^2} \exp\left(-\frac{||\boldsymbol{p}_0 - \boldsymbol{q}_0||^2}{2\sigma_d^2}\right) \cdot \sum_{p \in N_p, q \in N_q, i \in B(0, r_f)} \exp\left(-\frac{(f(p_i) - f(q_i))^2}{2\sigma_r^2}\right) \quad (4)$$

We use a Gaussian kernel, where σ_d and σ_r are domain and range bandwidths, respectively. We treat each pixel as a vector containing spatial information $\boldsymbol{p}_i$ and intensity $f(p)$. The weights are calculated for each N_q in the search window.

In Fig. 1, we present the arrangement of pixels contained in the local neighborhood window.

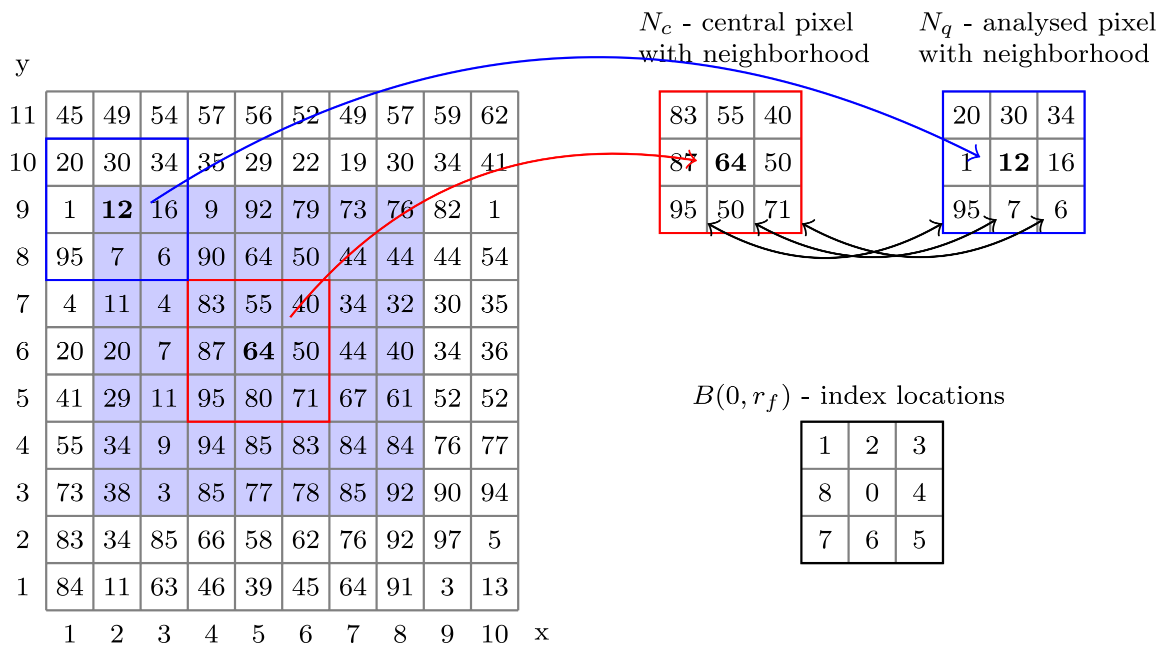


Fig. 1: Computation of weights for the central pixel with its neighborhood.

The second step is to calculate the new value of the central pixel considering its neighborhood, denoted as N_c:

$$\forall_{\boldsymbol{c} \in N_c, i \in B(0, r_f)} \ \boldsymbol{c}_i = \frac{\sum_{\boldsymbol{q} \in B(p, r_a)} w(N_p, N_q) \cdot \boldsymbol{q}_i}{\sum_{\boldsymbol{q} \in B(p, r_a)} w(N_p, N_q)}, \quad f(c_i) = \frac{\sum_{\boldsymbol{q} \in B(p, r_a)} w(N_p, N_q) \cdot f(q_i)}{\sum_{\boldsymbol{q} \in B(p, r_a)} w(N_p, N_q)}. \quad (5)$$

Each pixel $\boldsymbol{q}_i$ and its gray level value $f(q_i)$ in N_q are multiplied by the weight computed in Eq. 4 to obtain its new value.

In the next step, we compare the new calculated N_c with the previous N_p. If they differ, we move our search window to the location computed in Eq. 5 and repeat our computations from the first step, assuming that N_p becomes N_c. We repeat the above algorithm until N_c and

N_p converge. Because of computation complexity, the iterative algorithm can be stopped when $||N_c - N_p||^2 < \varepsilon$, where ε is a fixed value or when it performs a certain number of iterations, e.g. 10.

5. EXPERIMENTS

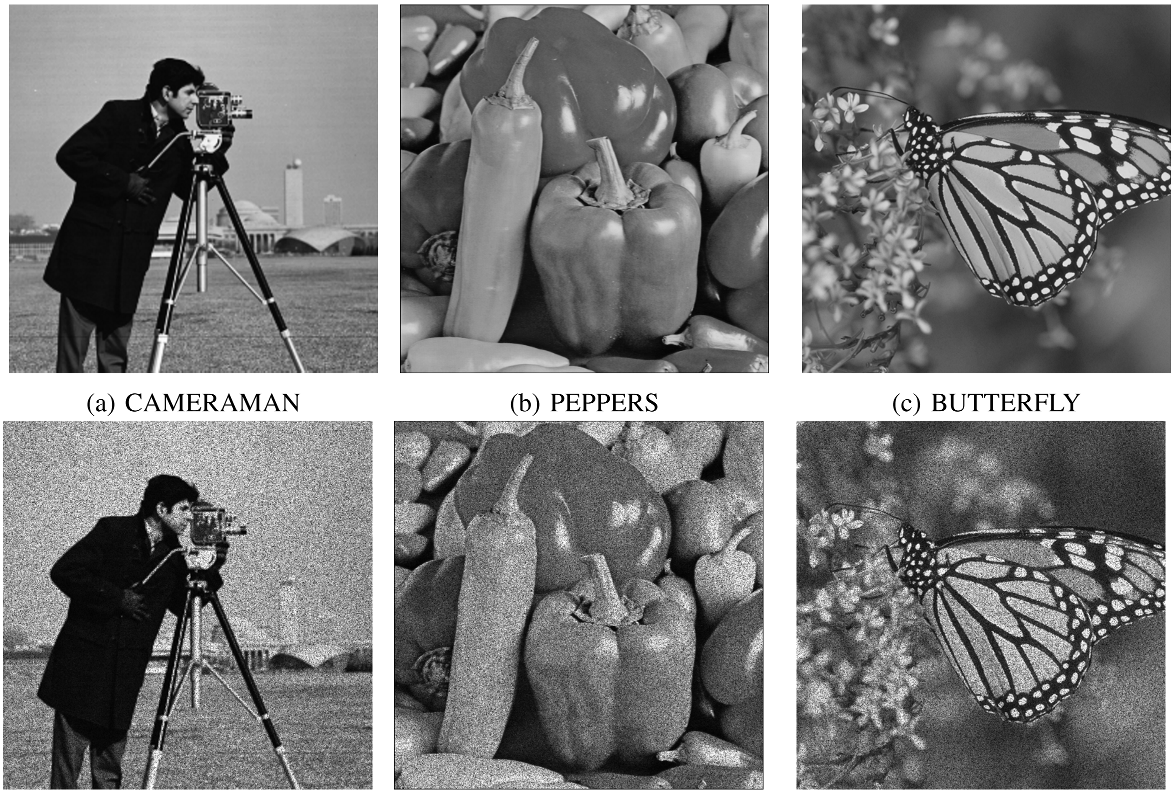
The proposed algorithm was compared with the standard mean-shift and the non-local means filter. For the objective evaluation of results we have used the Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR) and Mean Absolute Error (MAE) quality metrics. For test purposes three images were chosen, which are depicted in Fig. 4.

Two types of multiplicative noise denoted as G and U were modelled. In the first one we used a Gaussian distribution, (noise model G) and the noisy pixel can be defined as:

$$\hat{u}(p) = u(p) + u(p) \cdot \delta, \tag{6}$$

where δ is a random variable with Gaussian distribution.

The second type of multiplicative noise differs in the definition of δ, which is an uniformly distributed random variable, (noise model U). Images in Figs. 2a to 2c were contaminated with noise modelled by Eq. 6 with intensity controlled by δ with standard deviation 0.1 - 0.3 and denoted respectively as $G_{0.1}$ - $G_{0.3}$ for noise model G and as $U_{0.1}$ - $U_{0.3}$ for model U.



(a) CAMERAMAN (b) PEPPERS (c) BUTTERFLY

(d) CAMERAMAN $G_{0.3}$ (e) PEPPERS $G_{0.3}$ (f) BUTTERFLY $G_{0.3}$

Fig. 2: Test images used in the experiments.

In Tab. 1 the comparison of the proposed filter with the standard mean-shift and non-local means filter in terms of PSNR is provided. We performed the experiments on three test images, choosing the radiuses of search windows r_a ($2 \leq r_a \leq 5$) and the σ values ($1 \leq \sigma \leq 150$)

to obtain best possible results. As can be observed, the proposed algorithm yields significantly better PSNR values than the standard NLM and MS, especially for images contaminated with strong multiplicative noise.

Table 1. : Filter efficiency in terms of PSNR.

		Noisy	MS	NLM	NLMS
CAMERAMAN	$G_{0.3}$	16.46	27.07	27.25	**27.64**
	$G_{0.2}$	19.72	29.15	29.23	**29.69**
	$G_{0.1}$	25.67	32.93	33.24	**33.38**
	$U_{0.3}$	16.25	26.87	27.01	**27.50**
	$U_{0.2}$	19.69	28.89	29.19	**29.65**
	$U_{0.1}$	25.68	32.76	33.29	**33.40**
PEPPERS	$G_{0.3}$	17.52	29.12	27.63	**29.58**
	$G_{0.2}$	20.90	30.96	29.87	**31.36**
	$G_{0.1}$	26.84	34.14	33.31	**34.34**
	$U_{0.3}$	17.41	28.88	27.42	**29.47**
	$U_{0.2}$	20.85	30.63	29.72	**31.28**
	$U_{0.1}$	26.86	33.97	33.32	**34.31**
BUTTERFLY	$G_{0.3}$	18.15	26.12	25.74	**26.53**
	$G_{0.2}$	21.47	28.24	27.84	**27.55**
	$G_{0.1}$	27.38	31.55	32.06	**32.13**
	$U_{0.3}$	18.04	25.74	25.23	**26.43**
	$U_{0.2}$	21.43	28.00	27.74	**28.46**
	$U_{0.1}$	27.32	31.38	31.96	**32.07**

Table 2 presents the dependence of PSNR on radius r_a and σ values. As can be seen, for greater search window radiuses, better results are obtained. However, the bigger the radius the more computations has to be performed. The increase in computational load is disproportionate to gained PSNR values. This effect can be observed in Fig. 3. For r_a bigger than 5, the increase of PSNR is less than 0.01.

Using neighborhood radius r_f larger than 1 results in much longer computations and gives lower PSNR gains. For $r_f = 1$, the neighborhood is of size 3×3 and the new algorithm is about 5 times slower than the mean-shift filter.

Table 2. : Filtering efficiency in terms of PSNR for the CAMERAMAN test image contaminated with noise $G_{0.3}$ for different search window radius r_a.

NLMS				MS			
σ_r	σ_d	r_a	PSNR	σ_r	σ_d	r_a	PSNR
39	1.75	2	27.33	127.5	1.55	2	26.98
37	1.55	3	27.60	113	1.45	3	27.06
37.5	1.55	4	27.63	111.5	1.4	4	27.07
37.5	1.55	5	27.64	111.5	1.4	5	27.07

In Fig. 4 the filtering results obtained using the test images distorted by the multiplicative noise $G_{0.3}$ are presented. As can be seen, the new algorithm offers sharper, better preserved edges than the non-local means technique and smoother texture regions than the mean-shift. This effect is especially visible in Fig. 4d. Furthermore the NLMS algorithm eliminates single impulses which are preserved when using the MS technique, (Fig. 4h). The images are also visually more pleasing than the results obtained using the two other techniques, on which NLMS is based upon.

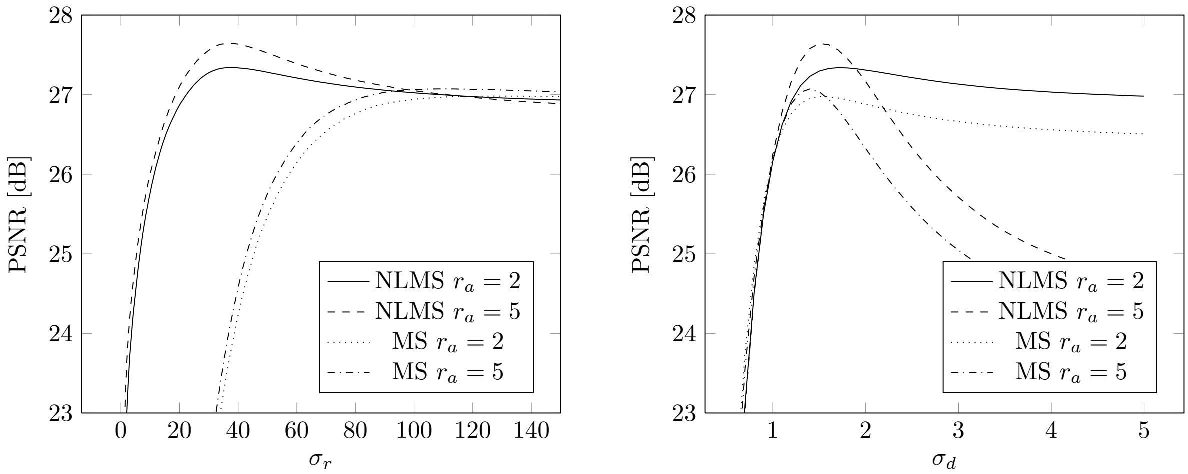


Fig. 3: Dependence of PSNR values obtained using NLMS and MS on range (left) and domain (right) bandwidth using CAMERAMAN test image distorted by noise $G_{0.3}$.

6. Conclusions

The proposed algorithm is an improved version of the mean-shift filter. The new technique utilizes the concept of non-local means which significantly ameliorates its denoising properties. The performed experiments revealed, that the novel filtering scheme has the ability to suppress even strong multiplicative noise while retaining image edges and tiny details.

The performed experiments show that the new techniques yields much better results than the standard mean-shift algorithm. The beneficial feature of the proposed algorithm is its ability to suppress the impulsive noise, which cannot be removed by the standard mean-shift technique.

The novel technique of multiplicative noise suppression can be applied for the enhancement of ultrasound images which are very often distorted by multiplicative noise.

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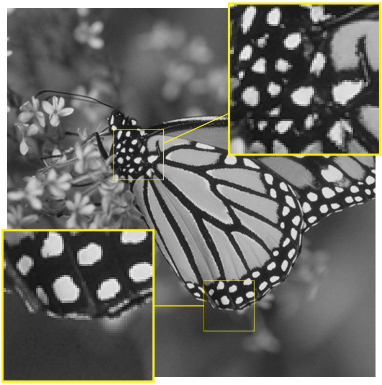
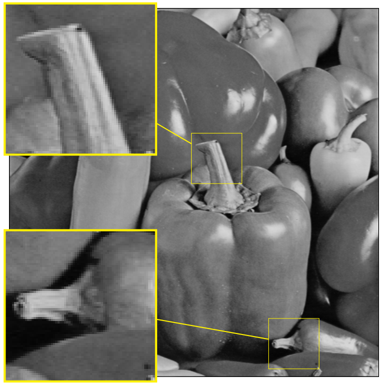
(a) CAMERAMAN

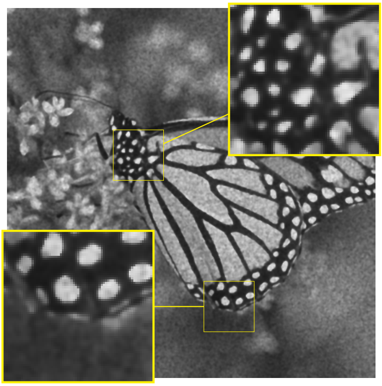


(b) BUTTERFLY

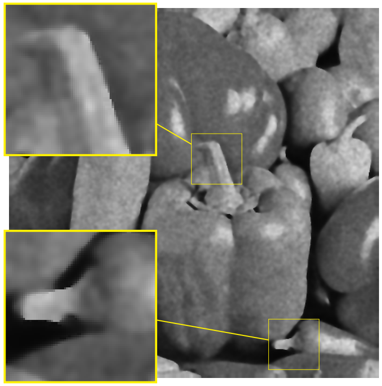


(c) PEPPERS

(d) CAMERAMAN: NLMS

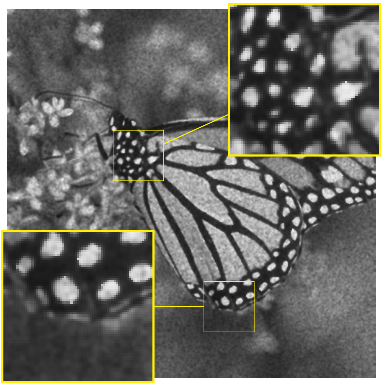


(e) BUTTERFLY: NLMS

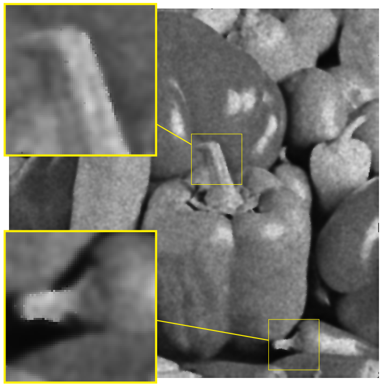


(f) PEPPERS: NLMS

(g) CAMERAMAN: MS

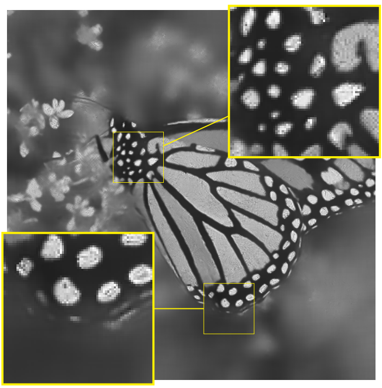


(h) BUTTERFLY: MS

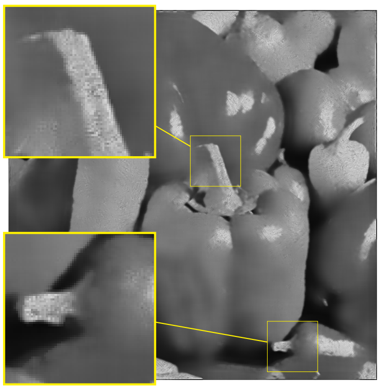


(i) PEPPERS: MS

(j) CAMERAMAN: NLM



(k) BUTTERFLY: NLM



(l) PEPPERS: NLM

Fig. 4: Comparison of the efficiency of the proposed NLMS filter with the NLM and MS techniques using test images contaminated with multiplicative noise $G_{0.3}$.