비지역적 평균 필터 기반의 개선된 커널 함수를 이용한 가우시안 잡음 제거 기법

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Gaussian Noise Reduction Technique using Improved Kernel Function based on Non-Local Means Filter

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Abstract

A Gaussian noise is caused by surrounding environment or channel interference when transmitting image. The noise reduces not only image quality degradation but also high-level image processing performance. The Non-Local Means (NLM) filter finds similarity in the neighboring sets of pixels to remove noise and assigns weights according to similarity. The weighted average is calculated based on the weight. The NLM filter method shows low noise cancellation performance and high complexity in the process of finding the similarity using weight allocation and neighbor set. In order to solve these problems, we propose an algorithm that shows an excellent noise reduction performance by using Summed Square Image (SSI) to reduce the complexity and applying the weighting function based on a cosine Gaussian kernel function. Experimental results demonstrate the effectiveness of the proposed algorithm.

1. Introduction

Digital devices generate noise due to characteristics of sensors and storage media in the process of acquisition or storage of images. The noise is caused by surrounding environment or channel interference when transmitting image. The noise represents in the form of Gaussian noise in the acquired image [1]. The Gaussian noise not only degrades image quality but also reduces image processing performance at high level. Therefore, the image processing technique that removes the Gaussian noise included in the image is one of the most basic preprocessing processes.

Conventional filtering methods to reduce the image include Mean filter, Median filter, Gaussian filter, and Bilateral filter (BF) etc. The Mean filter removes Gaussian noise by smoothing the average pixel values in the mask. The filtering method exhibits an excellent noise removal performance in low frequency regions where the brightness variation of the image is small, however, the image information is not preserved in the high frequency region which changes greatly at the gray level. To overcome this problem, a nonlinear filtering technique such as the Median filter developed. In the Median filter, a pixel value in a mask is sorted from a pixel value having a small size, and then a middle pixel value in the mask is selected. Although the filtering technique shows an excellent noise reduction performance in impulse noise and is not suitable for Gaussian noise [2]; The Gaussian filter determines the mask value using the Gaussian coefficient value. When it applies a Gaussian filter in the image for removing the noise, an information loss such as edge and texture of image occurs [3]. The Gaussian filter has a disadvantage that a deterioration occurs in the edge region. Since the BF represents a different value from the surrounding pixel values in the edge region and can detect the edge region [4]. Conventional filtering techniques (Median filter, Gaussian filter) show the loss of the edge region because image information is removed together with the noise without considering the edge region in the image. Since the BF takes pixel values as well as pixel distances into consideration, it exhibits a better edge preservation performance than conventional filtering methods (Median filter, Gaussian filter); however, the BF shows gradient reversal artifacts due to a low preservation performance around the edge region [5]. Although the conventional filtering methods showed an excellent noise reduction performance, it exhibited a low the texture details and edge preservation performance. Therefore, Buades *et al.* [6] proposed a Non-Local Means (NLM) filter which is a spatial domain filter; The NLM filter refers to the pixel values of the entire image without referring to only the surrounding pixel values in order to recover the pixel values of the noise-free. However, the weighted kernel function in NLM filter adopted an exponential weighted kernel function which represents an over-smoothness in the edge region and shows a blurring phenomenon. The kernel function of exponential or cosine type cannot also adapt to a change of noise. To overcome this problem, Lu *et al.* [7] proposed a SSIM-based NLM filter. In [7], the exponential weighted kernel function was replaced by a cosine coefficient weighted Gaussian kernel function. And they incorporate the structural similarity into the NLM filter. The problem with the algorithm is that it does not exhibit a blurring phenomenon in the edge region, but shows a low noise removal performance.

In this paper, we propose an algorithm applying SSI algorithm and the cosine Gaussian kernel function to NLM filter to improve Gaussian noise removal performance and complexity.

The composition of the paper is as follows. Section 2 describes the existing algorithm. Section 3 explains the proposed algorithm. In Section 4, we evaluate the proposed algorithm and present experimental results. Finally, we draw the conclusions in Section 5.

2. Conventional algorithm

2.1 Non-Local Means Filter

The original image is distorted by signal-independent additive noise. In the two-dimensional coordinate system, the noise model of the (i,j)th pixel is expressed as equation (1) [8].

$$V(i,j) = U(i,j) + N(i,j) \tag{1}$$

where $V(i,j)$ is the observed image, $U(i,j)$ is the original image, and $N(i,j)$ is the noise component. (i,j) is the position of the pixel. To recover $U(i,j)$ with noise-free image in the noise image $V(i,j)$, the NLM filter refers to the pixel values of the entire image. Equation (2) represents the NLM filter.

$$NL[V](p) = \frac{1}{C(p)}\sum_{q\in I} w(p,q)v(q) \tag{2}$$

where $C(p) = \sum_{q\in I} w(p,q)$ is the normalized parameter. $w(p,q)$ represents a weight according to the degree similar to the pixel value at (i,j). The range of $w(p,q)$ is $0 \le w(p,q) \le 1$, and the total sum is $\sum_{q\in I} w(p,q) = 1$. The similarity between $v(N_p)$ and $v(N_q)$ uses Euclidean distance as follows.

$$\left\| v(N_p) - v(N_q) \right\|_{2,\beta}^2 \tag{3}$$

The weight $w(p,q)$ of equation (2) is calculated as follows:

$$w(p,q) = \frac{1}{Z(p)} e^{\frac{\left\| v(N_p) - v(N_q) \right\|_{2,\beta}^2}{h^2}} \tag{4}$$

where $Z(p)$ is the normalized operator. h is the filter parameter which controls the decay rate of the exponential function.

2.2 Weighted Kernel Function

The weights of the NLM filter give a large weight to neighboring pixels that exhibits a high similarity, and allocates a low weight to pixels that shows a low similarity. When the similarity between neighboring pixels is low, the weight affects the efficiency of the algorithm and the quality of the final result image [8]. Therefore, in order to achieve an excellent noise reduction performance, they chose a weighted kernel function. The various models about weighted kernel functions are analyzed, including cosine model and Gaussian model etc [9]. When the noise variance is low, the original NLM filtering method with the two models of kernel functions become better than the original method; however, the noise reduction performance of cosine model and Gaussian model decline when the signal strength increases. The cosine model exists the problem of an excessive weighting while the Gaussian model has an excessive weighting problem. Based on these studies, a novel kind of cosine Gaussian kernel function is inferred. The definition is inferred. The definition is expressed as Equation (5).

$$f(p,q) = \begin{cases} f(p,q) = \exp\left(\frac{d^2(p,q)}{{h_1}^2}\right)\cos\left(\frac{\pi d(p,q)}{2h_2}\right) & d(p,q) \le h_2 \\ 0 & d(p,q) \le h_2 \end{cases} \tag{5}$$

where h_1 and h_2 represent filter parameters.

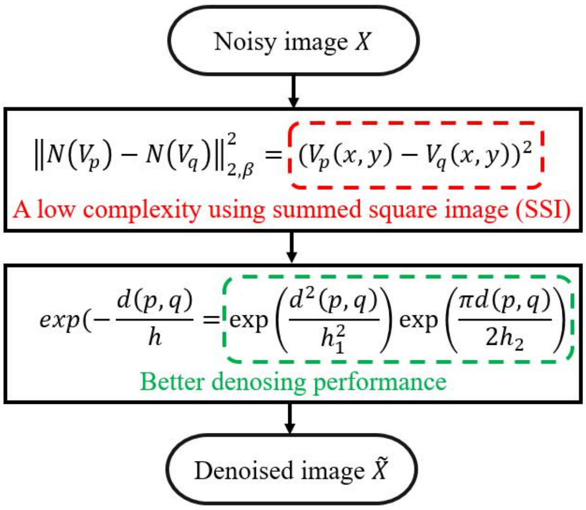


Fig. 1. Flow chart of Proposed scheme

2.3 Summed Square Image (SSI)

If the coordinate value of the input image is (i,j), the integral image contains the sum of all the pixels of the upper left part of the (i,j), coordinate. Equation (6) represents the integral image.

$$SSI(x_0, y_0) = \sum_{x\le x_0,\ y\le y_0} I^2(x,y) \tag{6}$$

where $SSI(x_0, y_0)$ is the integral image and $I^2(x,y)$ is the original image. The advantage of the SSI algorithm is that linear time can be obtained in proportion to the image size. The SSI algorithm takes the following algorithm to calculate it efficiently:

$$\begin{aligned} &\text{for } x_0 > 0, y_0 > 0 \\ &SSI(x_0, y_0) = S_{A\cup B\cup C\cup D} + S_A - S_{A\cup C} - S_{A\cup B} \\ &\quad = SSI(x_1,y_1) + SSI(x_0,y_0) - SSI(x_0,y_1) - SSI(x_1,y_0) \end{aligned} \tag{7}$$

Using the SSI algorithm, each pixel in the original image is computed only once, so the computational complexity for calculating SSI algorithm is $O(n^2)$. n^2 is the size of the image.

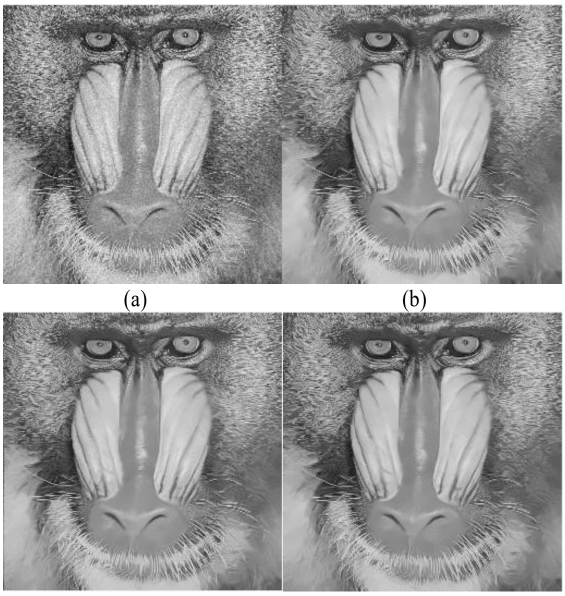
3. Proposed Algorithm

The NLM filtering method shows a high computational complexity. A fast non-local means (FNLM) [10] is proposed to reduce the complexity, but shows a low noise reduction performance. Conventional filtering techniques [7, 9] show a low noise removal performance and a high computational complexity. In order to overcome the above problem, we propose an algorithm to reduce the computational complexity and remove the Gaussian noise by applying the SSI algorithm [7] and the cosine Gaussian kernel function [8]. The process of the proposed algorithm is shown in Figure 1.

First, we will explain the SSI algorithm that reduces the computational complexity. Conventional NLM filter compares pixel values of mask using Euclidean distance and is a filter that finds the most similar blocks in the entire image. Therefore, it exhibits a high computational complexity (Equation (8)).

$$s_t(x) = \left\| v(p) - v(p+t) \right\|^2 \tag{8}$$

where t is a translation vector. x represents the similarity of pixel value between p and q. q is p plus t. The proposed algorithm r educes



(a) (b)

(c) (d)

Fig. 2. Simulation result of *Baboon* image: (a) Noisy image, (b) NLM filter, (c) Lu algorithm, (d) Proposed algorithm

the computational complexity by using the SSI algorithm. The prop osed algorithm reduces the computational complexity by replacing t he Euclidean distance used for finding similar blocks in the NLM filter with the SSI algorithm. A method of reducing the computatio nal complexity using the SSI algorithm is as follows (Equation (9)).

$$SSI(x) = \sum_{1\leq x_1, 1\leq x_2} s_t(x)^2, \ x = (x_1, x_2) \in \Omega \tag{9}$$

where Ω represents an image size.

As mentioned above, the existing models (cosine model, Gaus sian model) is affected by the Gaussian noise removal performance by the variance of the noise and the intensity of the signal. To b etter provide visual quality, the existing weight $w(p, q)$ of NLM fi ltering method would be replaced the weighting function based the cosine Gaussian

(a) (b)

(c) (d)

Fig. 3. Simulation result of *Peppers* image: (a) Noisy image, (b) NLM filte r, (c) Lu algorithm, (d) Proposed algorithm

Table 1. PSNR (in dB) values of various noise suppression methods.

Test imag e	Noise s td.	NLM	Lu *et al.*	PROPOSE D
Baboon (256x256)	5	25.74	**25.87**	25.84
	10	25.45	**25.61**	**25.61**
	15	24.64	24.83	**24.85**
	20	23.44	23.66	**23.67**
	25	21.93	22.14	**22.15**
Peppers (256x256)	5	34.04	**34.13**	34.11
	10	33.03	**33.18**	**33.18**
	15	30.84	30.99	**31.01**
	20	27.57	27.76	**27.78**
	25	24.48	24.69	**24.70**

kernel function [7]. The definition is as follows:

$$w(f(p,q)) = \frac{1}{Z(p)} e^{\left(\frac{d^2(p,q)}{h_1{}^2}\right) \cos\left(\frac{\pi d(p,q)}{2h_2}\right)} \tag{10}$$

The cosine Gaussian kernel function can preserve better noise redu ction performance in different noise variances. Therefore, the propo sed algorithm shows Gaussian noise reduction performance with dif ferent variance values in the image and low computational complex ity.

4. Experimental Results

In order to test the performance of the proposed algorithm, w e used experiments on two images: *Baboon* (256x256) and *Peppers* (256x256). During the process of experiments, we added Gaussian noise with mean value 0 and variance 5-25 to the images. We us ed Peak Signal to Noise Ratio (PSNR) [7], Structural Similarity (S SIM) [7], and execution time to compare performance the proposed algorithm with the existing filtering techniques (NLM [6], Lu *et a l.* [7]). For the experiments, a computer with Intel Core i5-3470 3.20GHz CPU and a 4GB of RAM memory has been used. The operating system is Windows 10 64-bit version. All image processing was implemented using MATLAB 2018a.

Figures 2 and 3 show the results of conventional filtering t echniques and the proposed algorithm when the Gaussian noise of $\sigma =$ 10 is added to *Baboon* image and *Peppers* image. In Figs. 2 and 3, (a) is a noise image and (b) to (d) are simulation results of the NLM filter [6], Lu *et al.* [7], and the proposed algorithm, respect ively. It is confirmed that the existing filtering techniques and the i mages applied by the proposed algorithm show excellent noise redu ction and edge preservation performance.

Tables 1 and 2 show the performance of the proposed algorit hm and the existing filtering techniques according to the change of Gaussian noise variance in the *Baboon* and *Peppers* images, respe ctively. The existing filtering techniques exhibited an excellent nois e reduction performance in the images including a low variance of noise (Table 1). On the other hand, the proposed algorithm showed better noise reduction and feature

Table 2. SSIM values of various noise suppression methods.

Test image	Noise std.	NLM	Lu *et al.*	PROPOSED
Baboon (256x256)	5	0.7951	0.7962	**0.8057**
	10	0.7889	0.7982	**0.8044**
	15	0.7737	0.7876	**0.7993**
	20	0.7156	0.7280	**0.7342**
	25	0.6317	0.6432	**0.6527**
Peppers (256x256)	5	0.9192	0.9195	**0.9292**
	10	0.9116	0.9225	**0.9257**
	15	0.8498	0.8519	**0.8638**
	20	0.6925	0.7060	**0.7104**
	25	0.5302	0.5440	**0.5587**

Table 3. Execution Time of various noise suppression methods.

Test image	Noise std.	NLM	Lu *et al.*	PROPOSED
Baboon (256x256)	5	18.47	19.08	**0.99**
	10	18.68	19.56	**0.92**
	15	18.54	22.32	**0.95**
	20	19.29	19.24	**1.03**
	25	17.73	19.62	**0.93**
Peppers (256x256)	5	17.42	19.84	**0.97**
	10	17.77	19.11	**0.96**
	15	18.25	18.99	**0.96**
	20	17.78	19.17	**0.93**
	25	17.75	19.60	**0.94**

preservation performance than the existing techniques (Tables 1 and 2).

To improve the noise removal performance, the algorithms [3, 6] based on NLM filter increases the computational complexity because of the iteration operations. Therefore, the execution time of the existing filtering techniques represented 17 times to 19 times that of the proposed algorithm (Table (3)).

5. Conclusions

In this paper, we propose an algorithm using the SSI algorithm and the cosine coefficient weighted Gaussian kernel function to the NLM filter. The proposed algorithm improves the weight and the computational complexity of existing kernel functions. The computation of the proposed algorithm based on the SSI algorithm is up to 19 times faster than the NLM and Lu' algorithm. Also, it shows an excellent noise removal performance in the images including the Gaussian noise at high variance. The proposed algorithm shows an effective noise reduction and a low complexity compared with the existing filtering techniques.

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