Color Image Denosing by NL-means Filtering with a constraint among color components

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Abstract: As for color image denoising, independent filtering to each RGB component dose not generally give a high quality image due to *undesirable color effects*. To overcome this problem, color image denosing by non-local (NL) -means filtering with a constraint among color components (color-constrained NL-means filtering), in which same weights are used to all color components, is proposed in this paper. The denoising performance is assessed from three points of view: PSNR, CIEDE2000, and processing time. As a result, it is shown that the proposed filtering decreases both undesirable color effects and processing time, compared to conventional methods.

Key–Words: Adaptive grouping, block matching, image denoising, Non-local means, CIEDE2000,

1 Introduction

In recent years, image denoisng and restoring have developed exponentially by several powerful methods for adaptive processing of multidimensional data. Examples include moving least square [1], the bilateral filter [2, 3], anisotropic diffusion [4], kernel [5], non-local (NL) -means and its variants [6], and Bregman iterations [7]. Especially, the NL-means filtering has been widely used as a typical nonlinear filtering for denoising of images, because of its superior performance and its more natural physical appearance than local prior, e.g., total variation [8], [9]. However, it requires large computational cost instead of its high availability in denoising. In addition, studies on NL-means filtering have mainly focused on gray scale image denoising [10–12].

As for color image denoising, *inter-channel correlation* among color components which natural images have [13] needs to be taken care to avoid undesirable color effects, as shown in Figure 1. To overcome such a situation, numerous denoising schemes such as regularization and vector-valued signals for color image have been studied [9], [13], [14], but it is unfit to apply their schemes to NL-means filtering. Therefore in generally, color image denoising with NL-means is proceeded by filtering to only intensity component, or by filtering to each RGB component independently, although they result in the degradation of the image quality. In addition, the computational complexity for color image denoising increases three times as many as that of gray scale, when the filtering to RGB components is used.

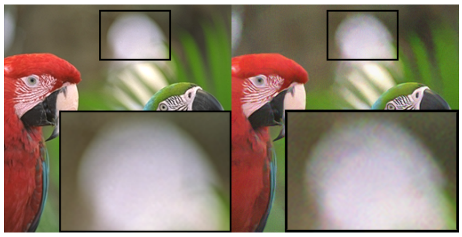

Figure 1: An undesirable color effects in color image denoising: On the left is a original *Parrots* image, and on the right is the NL-means filtering estimate which is proceeded by filtering to each RGB component independently.

Recently, to improve the denoising performance, *block-matching and 3-D filtering* (BM3D) [15], [16], has been considered for color image denoising. In the filtering, weights are calculated by using the luminance component, and then the weights are used for the luminance component and the chroma ones. In [16], it is shown that BM3D is effective for color image denoisng under the PSNR metrics and computational cost. However, undesirable color effects are not assessed yet, because only PSNR was used to evaluate the denoising performance. In addition the evaluation is limited to in BM3D.

Therefore, in this paper, NL-means filtering with a constraint among color components (color-constrained NL-means filtering) is used for color im-

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age denoising, and evaluated by not only PSNR but also CIEDE2000 [17], which is a color difference formula based on CIEDE1976 [18]. In addition, the results are compared with some other denoising methods, e.g., Vectorial Total Variation (VTV) [19].

In view of the above, the following conclusions are shown through the computer simulations: the color-constrained NL-means filtering decreases undesirable color effects and processing time.

2 Preliminaries

A noise model is described, and some conventional denosing methods are shown.

2.1 Noise model

Let us consider a simple Gaussian denoising problem. A noise model which is assumed in this paper is provided as follows. The pixel value of i-th pixel is expressed by x_i, and its observed luminance is modeled as $y_i = x_i + e_i$ where e_i is nosie with zero-mean and wtih the standard deviation σ. As for color images, e_i is added in each color channel independently.

2.2 NL-means algorithm for image denoising

In general, the target of denoising is given as the weighted least squares problem [2], [20], i.e.,

$$x_{i,o} = \arg\min_{x_i} \sum_{j=1}^{n} [y_j - x_i]^2 \, W(l_i, l_j, y_i, y_j) \tag{1}$$

where l_i and l_j are the locations of pixel values y_i and y_j respectively. $W(\cdot)$ is a symmetric weight (or kernel) function, and $x_{i,o}$ shows the optimum value. As described in [2], there are many algorithms for estimating $\bar{x}_i$ using (1) with a specific weight function $W(\cdot)$. In this paper, NL-means filtering is employed and its weights w_{ij} are calculated as below. The estimated pixel intensity $\bar{x}_i$ is obtained by the equation

$$\bar{x}_i = \frac{1}{z_i} \sum_{j \in R_i} w_{ij} y_i \tag{2}$$

where R_i shows the set of blocks in the search region. The weights w_{ij} and the normalization z_i are calculated by

$$w_{ij} = \exp\left(-\frac{\|\mathbf{y}_{Ni} - \mathbf{y}_{Nj}\|^2}{h^2} \right) \tag{3}$$

$$z_i = \sum_j \exp\left(-\frac{\|\mathbf{y}_{Ni} - \mathbf{y}_{Nj}\|^2}{h^2} \right) \tag{4}$$

where h is a bandwidth parameter and selected as the standard deviation σ of the noise signal which was assumed to be known a priori. N_k denotes a square neighborhood region centered at pixel x_k, and $\mathbf{y}_{Ni}$ shows the vector whose components are the values of pixels in N_k. Most cost in NL-means filtering is in the computation of this w_{ij}.

This computation is performed in one component for gray scale image denoisng. On the other hand, for typical color images denoising, it is performed in three components independently (hereinafter referred to as ”independent filtering”). In the independent filtering, x_i and w_{ij} are computed in each color component, by applying the same algorithm as for gray scale images (2)-(4). However the resulting images include undesirable color effects as shown in Figure 1, and the computational cost for color image denoising rises three times as many as that of gray scale one. There is also an approach of filtering to only the luminance component for color images denoising. This approach decreases both undesirable color effects and processing time, whereas it results in quality deterioration of images. The aim of this paper is to decrease both undesirable color effects and processing time.

3 Proposed filtering

NL-means Filtering with a constraint among color components is proposed as follows.

3.1 Color-constrained NL-means filtering

As for a color image, the estimated image is obtained by the equation (5), with consideration for multiple color components,

$$\begin{aligned} \bar{x}_{ci} =& \frac{1}{z_{ci}} \sum_{j \in R_{ci}} w_{pij} y_{ci}, \\ & c \in \{R, G, B, Y, Cb, Cr\} \end{aligned} \tag{5}$$

where subscript c and p are one of components. Y is the luminance component of a color image, and Cb and Cr are the chroma components respectively [21]. y_{ci} is observed pixel value in a component c.

In the constrained filtering, w_{pij} calculated from a component p are used for all color components. The process diagram of the constrained filtering is shown in Figure 2.

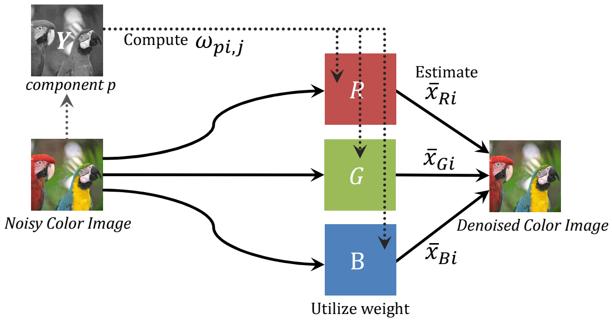

Figure 2: Flowchart of color-constrained NL-means filtering.

3.1.1 Calculation of weights w_{pij}

First, by using a component p, weights w_{pij} are calculated according to (6) and (7) as below.

$$w_{pij} = \exp\left(-\frac{\|\mathbf{y}_{Npi} - \mathbf{y}_{Npj}\|^2}{h^2}\right) \tag{6}$$

$$z_{pi} = \sum_{pj} \exp\left(-\frac{\|\mathbf{y}_{Npi} - \mathbf{y}_{Npj}\|^2}{h^2}\right) \tag{7}$$

Arbitrary component may be selected as p. For example, if component Y is selected, w_{pij}, $p \in \{Y\}$ will be expressed as w_{Yij}.

3.1.2 Utilizing of weights w_{pij}

In the independent filtering, $\bar{x}_{ci}$, $c \in \{R, G, B\}$ is calculated by each correspondent weight w_{pij}, $p \in \{R, G, B\}$. On the other hand, in color-constrained NL-means filtering, when $p = Y$ or $p = G$, $\bar{x}_{ci}$ is computed as

$$\bar{x}_{ci} = \frac{1}{z_{ci}} \sum_{j \in R_{ci}} w_{Yij} y_{ci},\ c \in \{R, G, B\} \tag{8}$$

$$\bar{x}_{ci} = \frac{1}{z_{ci}} \sum_{j \in R_{ci}} w_{Gij} y_{ci},\ c \in \{R, G, B\} \tag{9}$$

where each $\bar{x}_{ci}$, $c \in \{R, G, B\}$ is calculated by utilizing the same weights w_{Yij} or w_{Gij}. Therefore, the weights are computed in only one component, and the correlation among RGB channels is expected to be kept. As a result, the color-constrained filtering enables to reduce not only the computational cost but also the undesirable color effects.

4 Simulation

In this section, the effectiveness of the color-constrained filtering is examined by comparing with other approaches.

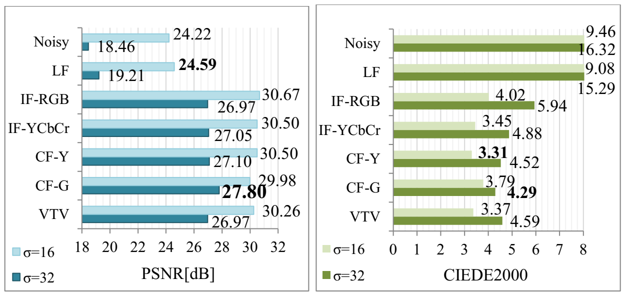

Figure 4: PSNR and CIEDE2000 comparison for the donoising of the *Parrots* color image with $\sigma = 16,\ 32$.

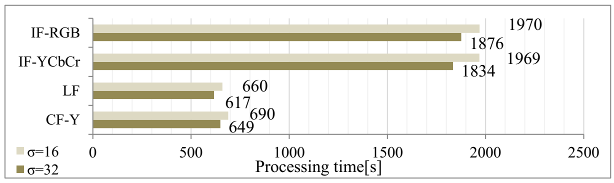

Figure 5: Processing time comparison for the donoising of the *Parrots* color image with $\sigma = 16,\ 32$.

4.1 Datasets and comparisons

12 natural color images with 256×256 pixels are used from SIDBA (Standard Image Data-BAse) datasets. We consider noisy images with zero-mean Gaussian noise of standard deviation σ (16 or 32). NL-means filtering is used as one of the nonlocal prior, and additionally, VTV [19] as one of the local prior is used for comparison. As far the NL-means filtering, five frameworks are compared with each other: 1) the color-constrained filtering using Y component, w_{Yij} (CF-Y), 2) the color-constrained filtering using G component, w_{Gij} (CF-G), 3) independent filtering to RGB components (IF-RGB), 4) independent filtering to YCbCr components (IF-YCbCr), and 5) filtering to only luminance component (LF).

4.2 Parameter Selection

The search region for NL-means filtering, R_i was the square of size 13×13, the size of square neighborhood region, N_k was 7×7, and the bandwidth parameter h was σ as well as in [6]. In VTV, the number of iteration was 200, and the regularization parameters λ were $12/256$, ($\sigma = 16$) and $24/256$, ($\sigma = 32$) as well as in [19].

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Noisy	LF	IF-RGB	IF-YCbCr	CF-Y	CF-G	VTV
22.42 dB, 9.46	24.59 dB, 9.08	**30.67** dB, 4.02	30.5 dB, 3.45	30.50 dB, **3.31**	29.98 dB, **3.79**	30.26 dB, 3.37

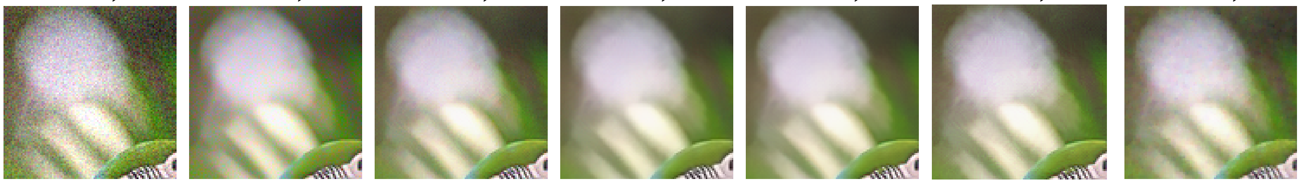

Figure 3: Some fragments of denoised color *Parrots* images ($\sigma = 16$) , with their PSNR values and CIEDE2000 ones.

4.3 Simulation results

The fragments of resulting images are shown with their PSNR values and CIDEDE2000 ones in Figure 3. It is confirmed from this Figure that the images filtered by CF-Y, CF-G or by IF-YCbCr contain much less undesirable color effects than those by IF-RGB or by VTV. Figure 4 provides the output PSNR results and CIEDE2000 ones. Each value in Figure 4 is based on the average value over 12 images. CIEDE2000, where a smaller value of CIEDE2000 shows a higher quality image, is known as a better color quality assessment than PSNR.

In Figure 4, it is shown from CIEDE2000 values that the CF-G and the CF-G outperform other methods, and the CF-G keep almost the same PSNR performances as that of IF-RGB. The filtering by LF results an insufficient denoisng performance. Both the PSNR values and the CIEDE2000 ones in the IF-YCbCr filtering are nearly same as those in the IF-RGB filtering. The filtering by CF-G also results image quality in terms of PSNR and CIEDE2000. The denoisng performance of the VTV is few inferior to that of the CF-Y. The results of processing time for NL-frameworks are shown in Figure 5. Each value in Figure 5 is based on the average value over 12 images. Figure 5 indicates that the computational cost for CF-Y is approximately one third as low as that of IF-RGB and that of IF-YCbCr, because most computational complexity is subjected to block matching [22, 23].

5 Conclusion

In this paper, we verified color-constrained NL-means filtering and assessed it with PSNR, CIEDE2000, and processing time. As a result, it was confirmed that the proposed filtering is effective for suppressing the undesirable color effects, and enables to reduce the computational complexity approximately one third as compared to those of independent filtering frameworks. Furthermore this scheme improves denoising performance more by considering an appropriate component instead of using the component Y where the weights are calculated.

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