COLLABORATIVE NOISE REDUCTION USING COLOR-LINE MODEL

Wei-Chih Tu, Chia-Liang Tsai, and Shao-Yi Chien

Media IC and System Lab
Graduate Institute of Electronics Engineering and Department of Electrical Engineering
National Taiwan University
BL-421, No. 1, Sec. 4, Roosevelt Rd., Taipei 10617, Taiwan

ABSTRACT

Recently, more and more natural image statistics are found useful for image restoration problems. In this paper, we propose a noise reduction technique by use of color-line assumption for natural color images. Based on the color-line model, we propose an algorithm to analyse local color statistics and recover the original image by promoting color linearity of a local patch. Moreover, the proposed method is employed on superpixels to alleviate the boundary effect of the denoising operation. The experimental results show that the proposed method can collaborate with existing noise reduction methods to successfully further boost the quality in both perceptual and objective evaluations.

***Index Terms*—** Noise reduction, natural image processing, color-line model

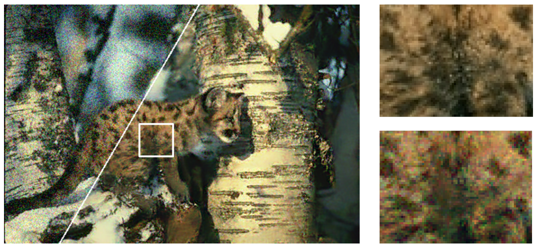


Fig. 1. Noisy image with $\sigma^2 = 35$ and denoised result by NLM. Right column shows the highlighted patch of the original image (upper) and the denoised image generated by NLM (lower).

1. INTRODUCTION

Image noise reduction is an essential procedure in image processing applications. The goal of image noise reduction is to restore the clean image from a noisy measurement. The noisy image can be modeled as

$$y_i = x_i + n_i, \tag{1}$$

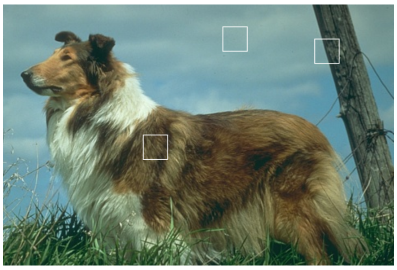
where y_i is the observed value, x_i is the original value, and n_i models the presence of noise at a pixel i. Noises are usually considered as additive i.i.d. Gaussian values with zero mean and variance σ^2.

Many denoising algorithms have been proposed to recover the clear image. Among these algorithms, the assumptions for noise model and the real image may be different, but many of them share the same smoothing procedure, such as edge-preserve filtering and denoising by use of patch-based structure similarity, just to name a few. One example of edge-preserve filter is bilateral filter [1]. This type of filters smooth images with content-adaptive weighting, with which noisy signals are filtered out while strong structures like edges can be preserved. The other type of denoising algorithms utilize the patch-based structure similarity. The non-local means filter (NLM) [2] evolves the bilateral filter by extending pixel similarity to patch similarity and smooths pixels with ones that have similar structures. The BM3D algorithm [3] and its variant [4] further expand the effectiveness of structural similarities by aggregating similar patches and filtering them collaboratively in transformed domain or in locally-learned dictionaries. That is, they recover the original contents from noisy signals by enhancing repeating structures and eliminating non-repeating noise.

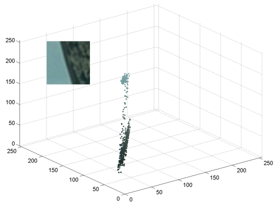
Although smoothing-based algorithms achieve state-of-the-art quality in image denoising, they still cannot generate satisfactory results when noise level is high, especially for highly textured regions where the smooth assumption does not hold well. An example of image denoised by NLM is shown in Fig. 1, where the highlighted patch still contains noisy pixels in the textured region which are difficult to be eliminated simply by smoothing.

This paper introduces a new technique to improve natural image denoising for previous works with the following contributions. First, we exploit the recent research in natural color image statistics [5], which claims that colors of a local region typically forms a line in color space. Based on the color-line model, the effects of noise is analysed. Second, a noise reduction method is proposed based on local color analysis in a superpixel. The proposed method is simple and easy to collaborate with previous smoothing-based algorithms to further boost the image quality.

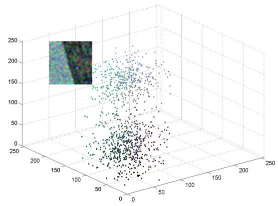
978-1-4799-2893-4/14/$31.00 ©2014 IEEE



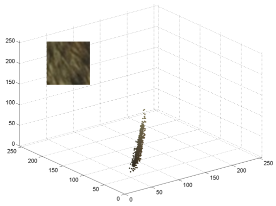
(a) An example of natural color image.



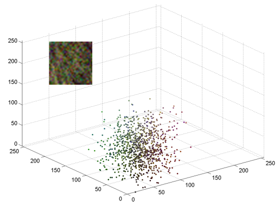
(b)



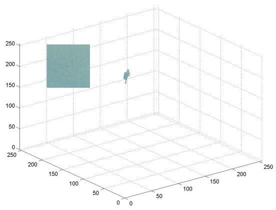
(c)



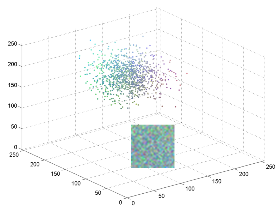
(d)



(e)



(f)



(g)

Fig. 2. Natural color patches form strong linearity in RGB color space in (b) strong edge region, (d) smooth region, and (f) flat region. (c)(e)(g) the corresponding patches degraded by Gaussian noise and their color distributions.

This paper is organized as follows. Section 2 introduces the color-line model for natural images and analyses the effects of noise. Based on the analysis, a denoising algorithm is proposed in Section 3 by recovering the color line in each superpixel. Next, the experimental results are shown in Section 4, where both subjective and objective results are demonstrated. Finally, the conclusion of this paper is given in Section 5.

2. COLOR-LINE MODEL

Recently, more and more properties for natural images are discovered for better conditioning natural image restoration problems. The color-line model [5] shows that local color statistics of natural images usually forms a line in RGB color space, as shown in Fig. 2. An edge region forms a sparse line, as shown in Fig. 2(b); a smooth region forms a shorter but denser color-line, as shown in Fig. 2(d); a flat region like blue sky or white walls in natural scenes forms a dense cluster in color space, as shown in Fig. 2(f). The rise of color-line model benefits many ill-posed problems, such as matting [6], depth estimation [7] and deblurring [8].

For image denoising, most literatures assume additive Gaussian noise, as described in (1). In the view of color-line model, extra noise expands the color distribution in all three dimensions of the color-line. As shown in Figs. 2(c)(e) and (g), color distributions become swollen compared to the original ones, while the main orientations are still preserved. According to the color-line assumption, image denoising can be regarded as to recover the color line by shrinking the expanded color distribution.

The smoothing-based methods do not explicitly encourage this natural image property. They aggregate patches with similar structures and smooth them in different manners. The smoothing operation is equivalent to averaging color distributions of several similar patches. It would enhance the original signal and dilute the effect of noise. If the stack of similar patches is good enough, the smoothing result can be expected to form a line. However, if a patch lacks of similar correspondence, it is prone to derive bad averaging result because the noise signal cannot be reduced successfully, as shown in Fig. 1.

3. PROPOSED ALGORITHM

Based on the color-line model, a noise reduction technique is proposed in this paper. By promoting the linearity of local color statistics, we can reduce noise in natural color images. The linearity is recovered by suppressing non-principal components of a local patch, which is described in the next subsection. The selection of local patch is also discussed to reduce artifacts.

3.1. Suppression of Non-Principal Components

principal component analysis (PCA) is employed to analyse the local color statistics of a local patch, and major orientation of the color line is extracted. After extracting the principal component, we suppress the other two dimensions to reduce noise.

Let P denote a color patch to be denoised and M_P is the vectorized form of P. Here, M_P is a N-by-3 matrix, where

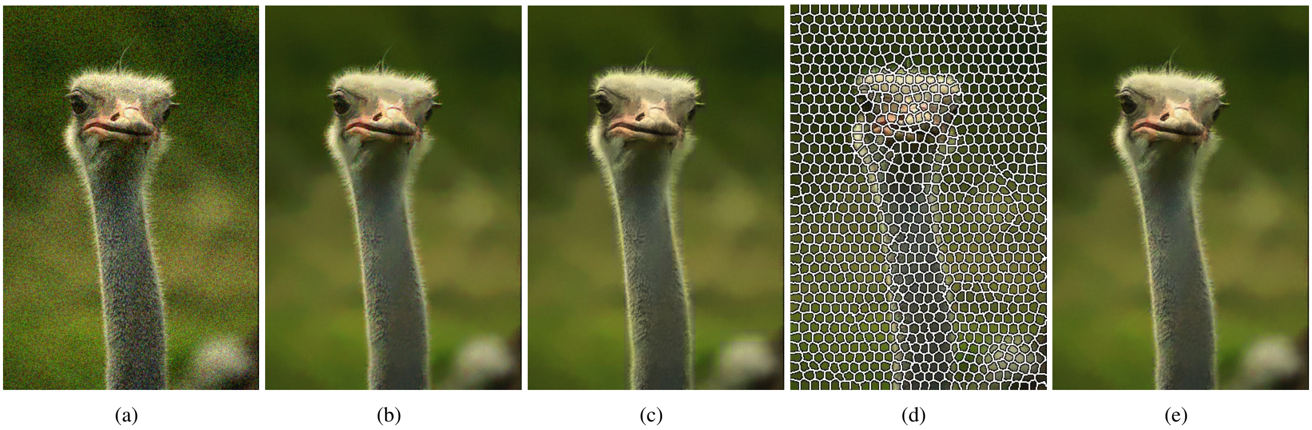


Fig. 3. (a) Noisy image($\sigma^2 = 25$). (b) NLM result (PSNR = 29.73 dB). (c) NLM + non-overlapped block grouping (PSNR = 30.36 dB). (d) Superpixels segmented from (b) using [9]. (e) NLM + superpixel-based grouping (PSNR = 30.93 dB). We encourage readers to compare above images on the paper in electronic version.

N is the number of pixels in P. We then factorize M_P by singular value decoposition (SVD), and the principal component is given by

$$M_P = U_P \Lambda_P V_P^T \tag{2}$$

where the singular values of Λ_P, say λ_1, λ_2 and λ_3, reveal the distribution of a local color cluster. If the color cluster is linearly distributed, λ_1 will be large and the others should be relatively small. On the other hand, to promote linearity in a local color cluster, all we need to do is to keep its principal component and suppress the other two minor components. Non-principal components suppression is achieved by decreasing the two minor eigenvalues of Λ_P in (2). In this paper, we directly set λ'_2 and λ'_3 to be 0 by assuming perfect color-line distribution of restored images.

Nevertheless, for the case of high noise level, directly applying PCA to local color clusters leads to inaccurate results since the principal component is also affected by the noise signal, a prefiltering to mitigate the noise level beforehand is thus required. In this paper, we incorporate the analysis and noise reduction technique with bilateral filter[1] and non-local means[2]. It is easy to extend our technique to other denoising schemes or natural image applications. That is, the proposed method can further boost the image quality of existing denoising algorithms by taking color-line model into consideration.

Fig. 3 shows an example of applying our technique to the result of NLM. It shows that more than 1dB gain in PSNR can be achieved with the proposed method.

3.2. Pixel Grouping

Pixel grouping, or the forming of local patches, plays an important role in the proposed algorithm. There are many ways to group pixels for local color statistical analysis. Naïve non-overlapped block grouping causes unsatisfactory blocking artifacts around object boundaries as shown in Fig. 3(c) and its zoom-in Fig. 4(b). In order to mitigate the blocking artifacts, the block size should be small enough, while the blocking natural may still degrade the perceptual quality of tiny structures or complicated textures.

Fig. 4. Zoomed in region of Figs. 3(b)(c) and (e). (a) Noise is still heavy around object boundaries after NLM denoising. (b) Non-overlapped block grouping results in blocking artifacts. (c) Superpixel-based grouping produces satisfactory results.

A better pixel grouping strategy is to take the image contents into account. The grouping size and shape should be adjusted adaptively. A superpixel segmentation technique, SLIC [9], is employed to generate local patches. Superpixels segmented by SLIC are nearly uniform sized, and their shapes are well aligned to the image contents as shown in Fig. 3(d). The adaptation preserves the image structures and results in better perceptual quality, as demonstrated in Fig. 3(e) and Fig. 4(c).

4. EVALUATION

We evaluate the proposed technique collaborating with [1] and [2]. Our test images are listed in Fig. 5. Noise levels are simulated as $\sigma^2 = 25$ and $\sigma^2 = 35$. The noisy image is denoised by [1] or [2] first, and then the image is segmented to

Table 1. Evaluation for $\sigma^2 = 25$. For each test image, the first row shows PSNR(dB) and the second row is for SSIM.

Test Image	BF	BF + Proposed	NLM	NLM + Proposed
Castle	25.5541	26.0695	27.0527	29.4254
	0.6719	0.7729	0.8109	0.8508
Ocelot	25.1817	25.6024	25.1833	27.2062
	0.7484	0.7864	0.7394	0.8321
Fireman	24.5257	24.7001	25.9577	28.0371
	0.6776	0.7365	0.774	0.8192
Ostrich	27.8918	28.8435	29.7337	30.9319
	0.6201	0.7342	0.8156	0.8394

Table 2. Evaluation for $\sigma^2 = 35$.

Test Image	BF	BF + Proposed	NLM	NLM + Proposed
Castle	23.9123	24.5440	26.0348	27.5598
	0.5911	0.7134	0.7872	0.8120
Ocelot	23.7333	24.2815	24.0253	25.7267
	0.6875	0.7408	0.7022	0.7641
Fireman	22.8794	23.1642	24.5440	25.8979
	0.5928	0.6661	0.7173	0.7491
Ostrich	25.6532	25.6128	29.0024	29.3396
	0.5322	0.6605	0.7911	0.7986

(a) Castle (b) Ocelot (c) Fireman (d) Ostrich

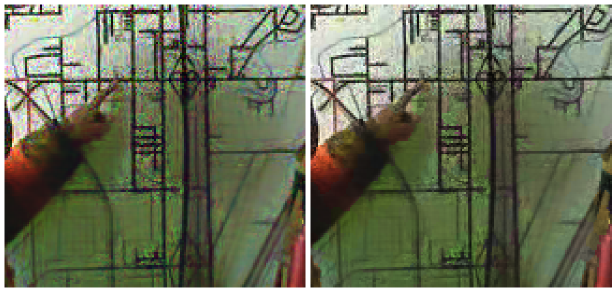
Fig. 5. Test images are from BSDS300 dataset [10].

small clusters by superpixel segmentation. Local color analysis is applied to every cluster. Next, the principal component of each color cluster is preserved and non-principal components are suppressed to reduce noise. All results are evaluated by use of both PSNR and SSIM.

Tables 1 and 2 show the evaluation results, where for each image, the first row shows the PSNR value and the second row shows SSIM value. It shows that the proposed technique can successfully further boost the image quality by collaborating other smoothing-based denosing methods. Figs. 3, 4, and 6 also show the output images of the proposed method for subjective evaluation. It demonstrates that our methods can significantly further reduce the noise after NLM is applied.

5. CONCLUSION

In this paper, we first analyse the effects of noise in color-line model, and then propose a technique for noise reduction by promoting linearity of local color statistics. For local pixel grouping, we employ superpixel-based segmentation to achieve better quality both in objective evaluation and perception. The evaluation demonstrates that the proposed method is useful for natural image noise reduction. The proposed technique is simple and effective. It is expected that the proposed technique can also be extended to other natural image processing applications.



(a) NLM (b) NLM + Proposed

Fig. 6. Highlight region of *fireman*. Original noise level is $\sigma^2 = 35$.

6. ACKNOWLEDGMENT

This work was supported by Himax Technologies, Inc.

7. REFERENCES

[1] Carlo Tomasi and Roberto Manduchi, "Bilateral filtering for gray and color images," in *Computer Vision, 1998. Sixth International Conference on*. IEEE, 1998, pp. 839–846.

[2] Antoni Buades, Bartomeu Coll, and J-M Morel, "A non-local algorithm for image denoising," in *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*. IEEE, 2005, vol. 2, pp. 60–65.

[3] Kostadin Dabov, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian, "Image denoising by sparse 3-d transform-domain collaborative filtering," *Image Processing, IEEE Transactions on*, vol. 16, no. 8, pp. 2080–2095, 2007.

[4] Priyam Chatterjee and Peyman Milanfar, "Clustering-based denoising with locally learned dictionaries," *Image Processing, IEEE Transactions on*, vol. 18, no. 7, pp. 1438–1451, 2009.

[5] Ido Omer and Michael Werman, "Color lines: Image specific color representation," in *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*. IEEE, 2004, vol. 2, pp. II–946.

[6] Anat Levin, Dani Lischinski, and Yair Weiss, "A closed-form solution to natural image matting," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 30, no. 2, pp. 228–242, 2008.

[7] Yosuke Bando, Bing-Yu Chen, and Tomoyuki Nishita, "Extracting depth and matte using a color-filtered aperture," in *ACM Transactions on Graphics (TOG)*. ACM, 2008, vol. 27, p. 134.

[8] Neel Joshi, C Lawrence Zitnick, Richard Szeliski, and David J Kriegman, "Image deblurring and denoising using color priors," in *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*. IEEE, 2009, pp. 1550–1557.

[9] Radhakrishna Achanta, Appu Shaji, Kevin Smith, Aurelien Lucchi, Pascal Fua, and Sabine Susstrunk, "Slic superpixels compared to state-of-the-art superpixel methods," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 34, no. 11, pp. 2274–2282, 2012.

[10] D. Martin, C. Fowlkes, D. Tal, and J. Malik, "A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics," in *Proc. 8th Int'l Conf. Computer Vision*, July 2001, vol. 2, pp. 416–423.