COLLABORATIVE NOISE REDUCTION USING COLOR-LINE MODEL

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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

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

\[ y_i = x_i + n_i, \]

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 \( \sigma^2 \).

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.

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).
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.
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 decomposition (SVD), and the principal component is given by

$$M_P = U_P \Lambda_P V_P^T$$

where the singular values of $\Lambda_P$, say $\lambda_1$, $\lambda_2$, and $\lambda_3$, reveal the distribution of a local color cluster. If the color cluster is linearly distributed, $\lambda_1$ 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 $\Lambda_P$ in (2). In this paper, we directly set $\lambda'_2$ and $\lambda'_3$ 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. Naive 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.

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
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 denoising 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.

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7. REFERENCES


