Adaptive Non-Local Means Filtering of Images corrupted by Colored Noise

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Abstract— **Recently, the NLMeans Filter has been proposed by Buades et al. for the suppression of white Gaussian noise. This filter exploits the repetitive character of structures in an image, unlike conventional denoising algorithms, which typically operate in a local neighborhood. In this paper, we present an extension of this technique to the noise reduction of colored (correlated) noise, which is applicable in more realistic scenarios. Visual and PSNR results show a significant improvement in denoising performance compared to recent wavelet-based techniques.**

I. Introduction

Digital imaging devices inevitably produce noise, originating from the analog circuitry in these devices. Noise reduction by means of digital post-processing is often desirable, but also very challenging. In this paper, we focus on the design of a noise reduction method for stationary Gaussian noise, that preserves image details and that has a high visual quality.

In the last decades, numerous and diverse denoising methods have been proposed, e.g. [1–6]. These methods only exploit the spatial redundancy in a local neighborhood and are therefore referred to as *local* methods.

More recently, a number of *non-local* methods have been developed. In contrast to local techniques these methods rely on the presence of similar patterns and features in the image. This relatively new class of denoising methods originates from the Non-Local Means (NLMeans) filter, introduced by Buades et al. [7] and is designed for *white* noise. Unfortunately, in practice the image noise is mostly *colored* and the NLMeans filter yields poor results in this case. For this reason, we extend this filter to deal with colored noise.

The remainder of this paper is as follows: in Section II we briefly present the NLMeans filter. In Section III we describe how the NLMeans filter is adapted to colored noise. Visual results are given in Section IV. Finally, Section V concludes this paper.

II. Non-local means filtering

We assume that the image is corrupted by zero-mean *white* stationary Gaussian noise. The denoised value of the local neighborhood at position i in the image is robustly estimated as the weighted average of all neighborhoods in the image[1], which can be seen as a linear spatially adaptive filter:

$$\hat{\mathbf{x}}_i = \arg\min_{\mathbf{x}} \sum_{j=1}^{N} \rho(\mathbf{x} - \mathbf{y}_j) \tag{1}$$

$$= \frac{\sum_{j=1}^{N} w(i,j)\mathbf{y}_j}{\sum_{j=1}^{N} w(i,j)} \tag{2}$$

where $\mathbf{y}_j$ denotes a local neighborhood vector at position j in the observed noisy image and N is the number of pixels in the image. The weights $w(i,j)$ depend on the similarity between the neighborhoods. For the Leclerc robust function $\rho(\mathbf{r})$ (see [8]) the weights are:

$$w(i,j) = \exp\left(-\frac{||\mathbf{y}_i - \mathbf{y}_j||^2}{2h^2}\right) \tag{3}$$

where h is a constant, proportional to the noise standard deviation σ_n. The weights decay at an

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[1] A one dimensional index is used here, such as in raster scanning

exponential rate, which results in large weights for similar neighborhoods and small weights for non-similar neighborhoods.

III. Proposed extension to colored noise

In this Section, we assume that the image noise is *colored*. Applying the NLMeans filter without modifications to images corrupted by correlated noise yields poor denoising performance, because of the model mismatch. Fortunately, a robust estimator for correlated noise can be obtained by replacing the Euclidean distance $||\mathbf{y}_i - \mathbf{y}_j||$ by the Mahalanobis distance $\sqrt{(\mathbf{y}_i - \mathbf{y}_j)^T \mathbf{C}_n^{-1} (\mathbf{y}_i - \mathbf{y}_j)}$, where $\mathbf{C}_n$ is the noise covariance matrix. This gives the following estimator:

$$\hat{\mathbf{x}}_i = \arg\min_{\mathbf{x}} \sum_{j=1}^{N} \rho \left(\mathbf{C}_n^{-1/2} (\mathbf{x} - \mathbf{y}_j) \right) \quad (4)$$

where $(\cdot)^{1/2}$ is the square root of a positive definite matrix. The weights now become:

$$w(i,j) = \exp\left(- \frac{||\mathbf{C}_n^{-1/2} (\mathbf{y}_i - \mathbf{y}_j)||^2}{2h^2} \right) \quad (5)$$

The correlatedness of the noise only affects the weights $w(i,j)$ and not the averaging. Hence, Eq. 2 can be used to estimate the noise-free image, but with weights defined in Eq. 5.

IV. Results

In Figure 1, the visual performance of the proposed method is compared to the wavelet-based state-of-the-art (local) method for colored noise from [4]. To be able to compute the objective quality in terms of PSNR, artificial noise is generated and added to a noise-free image. The proposed technique brings an improvement both visually as in PSNR: there are almost no ringing artifacts and reconstructed edges are much sharper.

V. Conclusion

By exploiting the self-similarity of images, a significant gain in denoising performance is obtained compared to purely local filtering methods. In this work, we have presented an extension of the NLMeans filter that offers a superior visual and objective quality compared to state-of-the-art local methods for the restoration of images corrupted by colored noise.

(PSNR=16.1 dB) (PSNR=24.8 dB) (PSNR=25.4 dB)

(PSNR=18.6 dB) (PSNR=29.3 dB) (PSNR=30.7 dB)

Figure 1. Denoising results for two images. From left to right: the noisy image, the restored image using [4], the restored image using the proposed method.

References

[1] L. Rudin and S. Osher, "Total variation based image restoration with free local constraints," in *Proc. of IEEE International Conference on Image Processing (ICIP)*, Nov. 1994, vol. 1, pp. 31–35.

[2] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *Proceedings International conference on computer vision*, 1998, pp. 839–846.

[3] D. L. Donoho, "De-Noising by Soft-Thresholding," *IEEE Trans. Inform. Theory*, vol. 41, pp. 613–627, May 1995.

[4] J. Portilla, V. Strela, M. Wainwright, and E.P. Simoncelli, "Image denoising using scale mixtures of gaussians in the wavelet domain," *IEEE Transactions on image processing*, vol. 12, no. 11, pp. 1338–1351, 2003.

[5] A. Pižurica and W. Philips, "Estimating the probability of the presence of a signal of interest in multiresolution single- and multiband image denoising," *IEEE Transactions on image processing*, vol. 15, no. 3, pp. 654–665, 2006.

[6] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3d transform-domain collaborative filtering," *IEEE Transactions on image processing*, vol. 16, no. 8, pp. 2080–2095, 2007.

[7] A. Buades, B. Coll., and J.M Morel, "A non local algorithm for image denoising," in *Proc. Int. Conf. Computer Vision and Pattern Recognition (CVPR)*, 2005, vol. 2, pp. 60–65.

[8] M. Elad, "On the Origin of the Bilateral Filter and Ways to Improve it," *IEEE Transactions on Image Processing*, vol. 11, no. 10, pp. 1141–1151, 2002.