Data-adaptive Color Image Denoising and Enhancement Using Graph-based Filtering

H. Sadreazami, *Member, IEEE,* A. Asif, *Senior Member, IEEE,* and A. Mohammadi, *Member, IEEE*

***Abstract*—Image denoising methods have been rapidly advanced in past few years. Image denoising is a challenging process of suppressing unwanted noise components from an image while retaining image details as mush as possible. Motivated by the recent advances in graph signal processing, in this paper, we address image denoising and enhancement problems from a new graph-based viewpoint. In particular, non-local similar patches of each color channel are grouped into a block for which a graph-based framework is proposed to construct a novel dictionary. The proposed graph-based sparse coding results in removing unwanted high frequency noise from the image. In addition and to further improve the contrast level of the image, a novel enhancement method is proposed based on iterative graph filtering. Simulations are conducted to evaluate the performance of the proposed color image denoising and enhancement method and to compare it with that of the other existing methods. The proposed method is shown to provide significantly improved visual quality for denoised images as well as higher peak signal-to-noise-ratio values as compared to other existing methods.**

***Index Terms*—Graph signal processing, graph filtering, sparse coding, dictionary learning, enhancement, denoising.**

I. Introduction

The notion of Internet of Things (IoT) requires an unprecedented level of connectivity and accordingly a huge amount of raw data. In IoT and big data problems, collected data are often nonlinear and have complex structures. To analyze such data using signal processing algorithms, one needs to generalize traditional signal processing solutions and extend their applicability to emerging problems with large data sets. In other words, rendering typical signal processing solutions may no longer be capable of properly handling big-data problems. Recently, graph signal processing [1]-[3] has provided a new framework for representing model relations among data samples for signals with irregular and regular structures. For data-oriented applications [3], a weighted graph can be identified to capture the similarities between data samples. For instance, an image may be represented by associating image pixels with graph nodes and corresponding graph can be analyzed using newly-defined graph-based signal processing techniques [1].

The focus of this paper is on devising innovative graph-based solutions in the context of color image denoising. Color image denoising has received considerable attention in the image processing and computer graphics communities due to an increasing demand for high quality images. Denoising is an indispensable task to restore the image features from the corrupted low quality images and improve the perceptual quality of images [4]. Image denoising has been extensively studied in past few years and variety of methods have been proposed such as Bayesian and statistical modeling approaches [5], [6], bilateral [7], non-local means (NLM) [8], dictionary learning [9], BM3D [10] and their variants. Among them, the NLM-based methods have achieved superior performance as compared to the other regularization approaches which only consider the local correlation of the image pixels [10]-[12]. There has been a recent surge of interest in denoising using sparse representations. In sparse representation of images, many approaches consider the fact that most image signals can be sparsely represented using decorrelation transforms, i.e., non-adaptive dictionaries, such as wavelet or contourlet transforms [13]-[17], so that the signal can be well separated from the noise. Beside these transforms, some other methods have employed adaptive bases that can be adaptively learned from the image content such as K-SVD [9] and its variants. Recently, the graph signal processing framework provides a tool for effectively handling the inverse problems like denoising by taking advantage of the underlying structure of the signal [2]. So far, only few attempts have been made to address the image denoising problem using the graph signal processing framework. In [18], a multiscale image decomposition approach has been proposed to enhance images in the graph spectral domain. In [19], a bilateral filter for image denoising has been proposed in the graph spectral domain. A joint denoising and contrast enhancement method has been proposed in [20] using the graph Laplacian operator. An optimal graph Laplacian regularization has been proposed in [21] for denoising natural images.

Leveraging the new framework of graph signal processing, in this paper, we address the problems of color image denoising and enhancement from a new point of view. To this end, we propose a new color image denoising by using sparse coding and graph-based dictionary learning as well as a new enhancement method by using a graph-based sharpening filter. The proposed graph-based dictionary learning is realized by eigendecomposing the graph Laplacian matrix for a group of similar patches of each color channel, i.e., structural clustering. The proposed dictionary-based sparse image representation is followed by performing sparse coding to remove noise components from the image and enhancing the contrast of the denoised image through sharpening. Experiments are conducted to evaluate the effectiveness of the proposed graph-based methods for denoising and enhancement of color images and to compare them with that of the existing works.

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II. Graph Construction

Graph signal processing is an emerging field that offers a framework for applying classical signal processing mechanisms to large data sets by defining signals on graphs [2]. To exploit the repetitive patterns in images, let an image Y be decomposed into n overlapping patches $\{x_i\}_{i=1}^{n}$ of size $l \times l$. The patches are treated as the vertices V of a weighted graph $G = (V, E, K)$ consisting of a finite set V of vertices (patches) and a finite set E of edges with the corresponding weights $k_{pq} \in K$, denoting similarity between vertex (patch) p and q. A patch x_q is considered to be similar to patch x_p, if it is within the first κ closest patches to x_p, i.e., κ-nearest neighbors set of patches $q \in \kappa$. The similarity weights are represented as $K = [k_{pq}]$, where k_{pq} is defined by the standard Gaussian kernel as

$$k_{pq} = \exp\left(-\left[\frac{d_{pq}^2}{2\sigma_{pq}^2}\right]\right), \tag{1}$$

where $d_{pq}^2 = (x_p - x_q)^2$ and $\sigma_{pq} = \frac{1}{\kappa}\sum_p \sum_q \|x_p - x_q\|_2^2$ controls the level of similarity achieved by (1), x_p and x_q denote the pixel vectors of patches p and q, respectively. If $\|x_p - x_q\|_2^2 << \sigma_{pq}$, the weight k_{pq} will be approximately 1. In contrast, if $\|x_p - x_q\|_2^2 > \sigma_{pq}$, i.e., $q \notin \kappa$, the weight is 0. Suppose for each patch x, we can find a group of κ similar patches to it. By grouping all the similar patches, an average patch is computed and denoted by $\overline{\boldsymbol{x}}$. The pixels of the average patch are regarded as vertices of a new graph for which the similarity matrix $\overline{K}$ is constructed using 8-connected graph with the kernel same as that in (1). Having the average graph similarity matrix $\overline{K}$, the corresponding graph Laplacian matrix is defined as $\overline{L} = D - \overline{K}$ [1], where

$$D = \text{diag}\left\{\sum_q \overline{k}(1, q), ..., \sum_q \overline{k}(n, q)\right\}. \tag{2}$$

The graph Laplacian matrix plays an important role in describing the underlying structure of the graph signal. More specifically, spectral graph theory studies the graph properties in terms of eigenvalues and eigenvectors associated with the graph Laplacian matrix [1].

III. Proposed Color Image Denoising and Enhancement Methods

Without loss of generality, we assume that the original color image X is corrupted by a zero-mean independent and identically distributed (i.i.d.) Gaussian noise η with standard deviation σ_η. The image is corrupted by the Gaussian noise, resulting in the corresponding noisy image $Y = X + \eta$. Dictionary learning has been widely used in restoration and compression problems [22]. An optimal dictionary leads to the sparsest representation of the recovered image patches. A dictionary Δ can be learned from the observation Y and further used to sparsely represent the data X using only a few atoms, i.e., $X = \Delta\theta$.

In this work, since the noise is Gaussian, the sparse coding model is formulated as $\underbrace{\min}_{\Delta,\theta} \|Y - \Delta\theta\|_2^2$, s.t. $\|\theta\|_0 \leq \chi$, where Δ is the dictionary to be learned, θ is the coefficients, χ is a parameter to make a trade-off between fidelity and sparsity terms and $\|.\|_0$ denotes the l_0 pseudo norm counting χ nonzero elements.

A. Single-dictionary driven

In this work, to avoid the expensive procedure of dictionary updating, we take advantage of the Fourier-based dictionaries build upon the eigenvectors of the graph Laplacian matrix. To this end, one way is to obtain the dictionary $\Delta_{\acute{k}}$ for each single patch from its Laplacian matrix $L_{\acute{k}}$ as

$$\underbrace{\min}_{\theta} \left\|y_{\acute{k}} - \Delta_{\acute{k}}\theta_{\acute{k}}\right\|_2^2 + \zeta\left\|\theta\right\|_0. \tag{3}$$

In order to compute θ for each patch, (3) can be solved by employing the Augmented Lagrangian Methods [23]. The matrix $L_{\acute{k}}$ is a real symmetric matrix, thus diagonalizable to its eigenbases as

$$L_{\acute{k}} = \sum_i \lambda_i \delta_i \delta_i^T, \tag{4}$$

where $\boldsymbol{\lambda} = \{\lambda_i\}_{i=1,\dots,n}$ is the set of eigenvalues and $\boldsymbol{\Delta} = \{\delta_i\}_{i=1,\dots,n}$ the set of orthogonal eigenvectors. The set $\boldsymbol{\Delta}_{\acute{k}}$ constitutes the basis function for the underlying signal defined on graph, and $\boldsymbol{\lambda}$ is known as the corresponding graph frequencies [1]. A more computationally efficient dictionary can be driven when the common information of the similar patches are taken into account, as will be discussed next.

B. Group-dictionary driven

A common assumption on image patches is that they are similar and when representing these patches, it is natural to expect that their corresponding atoms on the same dictionary should also be similar [10]. More specifically, the patch x_p and its κ-nearest neighbors should share the same dictionary atoms, that is, they should be coded by the same atoms but with different coefficients. In view of this and to take into account the common information shared by the similar patches, we extend the sparse coding problem from sub-dictionaries to a group-dictionary and jointly code a group of patches. The dictionary $\overline{\Delta}$ is defined once for the average patch using the eigenvectors of its Laplacian matrix $\overline{L}$, and used to sparsify a set of similar patches together as

$$\underbrace{\min}_{\theta} \sum_{\acute{k}=1}^{N} \left\|y_{\acute{k}} - \overline{\Delta}\theta_{\acute{k}}\right\|_2^2 + \zeta\left\|\Theta\right\|_{row,0}, \tag{5}$$

where ζ is pre-determined to make a balance between the two terms. The coefficient matrix and $\|.\|_{row,0}$ counts the number of nonzero rows of a matrix, indicating that the coefficient matrix Θ should be row sparse. To solve (5), the simultaneous orthogonal matching pursuit algorithm is applied [24], as its computational complexity is linear with the size of dictionary. After all the patches are estimated, the denoised image is reconstructed by averaging over all the overlapping patches.

Fig. 1. Kodak test images.

C. Enhancement

The resulting denoised image needs to be further processed to increase the contrast level without any artifacts along edges and enhance the visual quality of the image. To this end, we propose a new data-adaptive sharpening filter based on the underlying graph structure of the image. It is known that the graph Laplacian matrix can be regarded as a data-adaptive highpass operator [25]. In view of this, we propose an iterative sharpening filter as

$$X_{\text{sh}} = h_{\text{sh}}(L)X = (I + \gamma L^m)X = (I + \gamma(D - K)^m)X, \quad (6)$$

where X_{sh} is the sharpened version of X, m is the iteration index and the sharpening parameter γ is a contrast enhancement controlling factor. The more the value of γ is, the more the detail enhancement level of the filter increases. Note that, (6) aims at highlighting high frequency details by adding a weighted highpass-filtered version of the denoised image to itself. Correspondingly, the spectral response of the proposed iterative sharpening filter $h_{\text{sh}}(\lambda)$ obtained using the graph normalized Laplacian matrix is given by

$$h_{\text{sh}}(\lambda) = (I + \gamma\lambda^m). \quad (7)$$

It should be noted that the enhancement procedure needs to be performed after denoising otherwise the sharpening filter may amplify the high frequency noise components in the image.

IV. Simulation Results

Experiments are performed on Kodak color test images, shown in Fig. 1, each resized to 256×256 pixels, to evaluate the performance of the proposed denoising method and to compare the results with that provided by the other existing methods. The synthetically-noisy images are obtained by adding the zero-mean i.i.d. Gaussian noise with various standard deviations to each color channel. Parameters ζ and γ are set to 0.005 and 0.9, respectively. Each noisy channel is decomposed into n overlapping patches of size 9×9. A group of similar patches is identified when each patch is connected to its κ-nearest neighbor patches and an average patch is obtained by averaging over the similar patches. The average patch pixel values are then regarded as vertices of a graph and a sparse weighted similarity graph matrix $\overline{K}$ is constructed according to the 8-connected graph. Accordingly, the dictionary $\overline{\Delta}$ is learned from the eigenvectors of the graph Laplacian matrix of the average patch. The denoised images are then further enhanced by adding a highpass filtered version of the image to itself using the proposed sharpening filter in (6). Table I gives the objective performance comparison results, i.e., the peak signal-to-noise-ratio (PSNR) values, obtained using various denoising methods for Kodak image dataset. It is seen from this table that the performance of the proposed color image denoising and enhancement methods due to the use of graph-based dictionary learning and sharpening is superior to that of the other existing methods, as indicated by the higher PSNR values.

TABLE I
PSNR VALUES (IN *dB*) OBTAINED USING VARIOUS DENOISING METHODS FOR KODAK TEST IMAGES. (BEST RESULTS ARE SHOWN IN BOLD)

σ_η	10	20	30	40
	Red riding hood			
Surelet [5]	34.84	31.72	29.74	28.61
ProbShrinkMB [6]	35.11	32.01	30.32	28.04
NLMC [8]	35.33	31.82	29.92	27.37
CBM3D [10]	35.24	32.03	30.32	28.16
MNLF [11]	36.11	32.49	30.66	28.31
WNNM [12]	35.80	32.22	30.60	28.34
KQSVD [26]	34.91	31.80	29.99	28.72
TriSF-JBF [27]	35.91	32.17	30.44	28.21
Proposed	**36.20**	**32.53**	**30.89**	**28.52**
	Beach bums			
Surelet [5]	35.55	32.19	30.02	28.89
ProbShrinkMB[6]	35.74	32.25	30.12	29.05
NLMC [8]	35.16	32.43	30.76	29.77
CBM3D [10]	35.85	32.85	31.07	30.32
MNLF [11]	36.90	33.55	31.90	30.78
WNNM [12]	36.00	33.02	31.40	30.40
KQSVD [26]	35.69	32.50	30.75	29.98
TriSF-JBF [27]	36.49	33.28	31.84	30.67
Proposed	**36.98**	**33.64**	**31.93**	**30.88**
	Average			
Surelet [5]	34.75	31.09	28.89	27.85
ProbShrinkMB[6]	34.94	31.25	29.12	28.05
NLMC [8]	34.76	31.19	29.06	27.97
CBM3D [10]	35.02	31.39	29.25	28.10
MNLF [11]	35.45	31.79	29.72	28.54
WNNM [12]	35.37	31.69	29.49	28.21
KQSVD [26]	34.94	31.13	28.91	27.85
TriSF-JBF [27]	35.31	31.62	29.47	28.15
Proposed	**35.53**	**31.94**	**29.90**	**28.73**

Fig. 2 shows the noisy *Girl* image as well as its denoised and enhanced versions using the proposed graph-based method. The corresponding structural similarity (SSIM) index value is also obtained for each image. It can be seen from this figure that the proposed method provides denoised images with high quality and is capable of preserving more details. It is also seen from this figure that the proposed sharpening filter enhances the contrast level of the denoised image. This point is reinforced by the given SSIM values. It should be noted that by increasing the iteration index m in (6), the contrast level of the image increases.

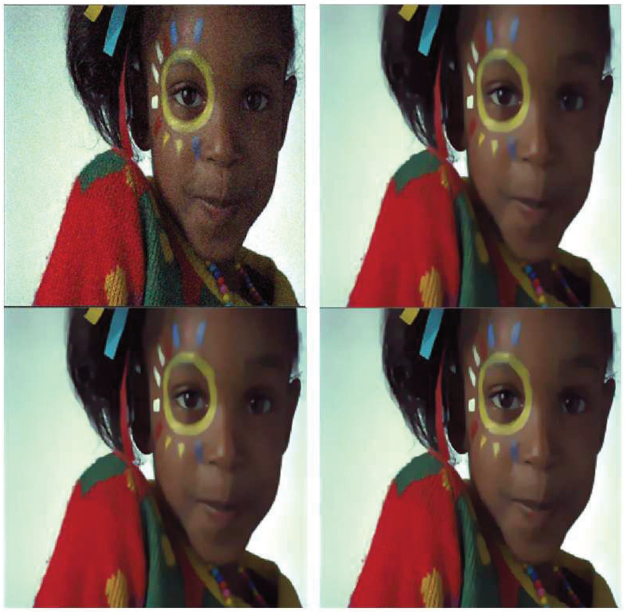

Fig. 2. Top-left: noisy *Girl* image with $\sigma_\eta = 10$, SSIM = 0.431, Top-right: Denoised image using the proposed graph-based method, SSIM = 0.924, Bottom-Left: Enhanced image using the proposed method with $m = 1$, SSIM = 0.946, Bottom-right: Enhanced image using the proposed method with $m = 3$, SSIM = 0.972.

V. Conclusion

In this paper, we have proposed novel methods for color image denoising and enhancement. The proposed denoising method has been established by exploiting the non-local similarities in images through constructing a graph-based dictionary learning framework obtained from non-local similar patches in each color channel. The adaptive learned dictionary has been followed by the iterative sparse coding for denoising purposes. A sharpening filter has also been proposed to enhance the contrast level of the denoised image. Experiments have been conducted using a set of color images. The proposed method has been shown to perform better than the current filtering operations due to its inherent nature in exploiting the signal structure by the use of the graph-based dictionary learning and sparse coding for restoration along with graph-based sharpening filter for enhancement, by providing higher values of peak signal-to-noise-ratio. It has also been shown that the proposed enhancement method is capable of iteratively enhance the visual quality of the denoised image.

References

[1] D. I. Shuman, S. K. Narang, P. Frossard, A. Ortega and P. Vandergheynst, "The emerging field of signal processing on graphs: Extending high-dimensional data analysis to networks and other irregular domains," *IEEE Signal Processing Magazine,* vol. 30, no. 3, pp. 83-98, 2013.

[2] A. Sandryhaila and J. M. F. Moura, "Big data processing with signal processing on graphs," *IEEE Signal Processing Magazine,* vol. 31, no. 5, pp. 80-90, 2014.

[3] J. Ma and J. M. F. Moura, "Signal processing on graphs: performance of graph structure estimation," in *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),* pp. 6165-6169, 2016.

[4] P. Milanfar, "A tour of modern image filtering," *IEEE Signal Processing Magazine,* vol. 30, no. 1, pp. 106-128, 2013.

[5] F. Luisier and T. Blu, "SURE-LET multichannel image denoising: Interscale orthonormal wavelet thresholding," *IEEE Transactions on Image Processing,* vol. 17, no. 4, pp. 482-492, 2008.

[6] A. Pizurica and W. Philips, "Estimating the probability of the presence of a signal of interest in multiresolution single and multiband image denosing," *IEEE Transactions on Image Processing,* vol. 15, no. 3, pp. 645-665, 2006.

[7] S. Paris, P. Kornprobst, J. Tumblin and F. Durand, "Bilateral filtering: theory and applications," *Fundamental and Trends in Computer Graphics and Vision,* vol. 4, no. 1, 1-73, 2008.

[8] A. Buades, B. Coll and J-M. Morel, "A non-local algorithm for image denoising," in *Proc. IEEE International Conference on Computer Vision and Pattern Recognition (CVPR),* pp. 60-65, 2006.

[9] M. Elad and M. Aharon, "Image denoising via sparse and redundant representation over learned dictionaries," *IEEE Transactions on Image Processing,* vol. 15, no. 12, pp. 3736-3745, 2006.

[10] K. Dabov, A. Foi, V. Katkovnik and K. Egiazarian, "Color image denoising via sparse $3D$ collaborative filtering with grouping constraint in luminance-chrominance space," in *Proc. IEEE Int. Conf. on Image Processing (ICIP),* pp. I-313I-316, 2007.

[11] J. Dai, O. Au, L. Fang, C. Pang, F. Zou and J. Li, "Multichannel nonlocal means fusion for color image denoising," *IEEE Transactions on Circuits and Systems for Video Technology,* vol. 23, no. 11, pp. 13151329, 2013.

[12] S. Gu, L. Zhang, W. Zuo, and X. Feng "Weighted nuclear norm minimization with application to image denoising," in *Proc. IEEE Conf. on Computer Vision and Pattern Recognition,* pp. 28622869, 2014.

[13] H. Sadreazami, M. O. Ahmad and M. N. S. Swamy, "Image denoising utilizing the scale-dependency in the contourlet domain," in *Proc. IEEE Inter. Symp. on Circuits and Systems (ISCAS),* pp. 2149-2152, 2015.

[14] H. Sadreazami, M. O. Ahmad and M. N. S. Swamy, "Ultrasound image despeckling in the contourlet domain using the Cauchy prior," in *Proc. IEEE Inter. Symp. on Circuits and Systems (ISCAS),* pp. 33-36, 2016.

[15] H. Sadreazami, M. O. Ahmad and M. N. S. Swamy, "A study on image denoising in contourlet domain using the alpha-stable family of distributions," *Signal Processing,* vol. 128, pp. 459-473, 2016.

[16] H. Sadreazami, M. O. Ahmad and M. N. S. Swamy, "Contourlet domain image denoising using the alpha-stable distribution," in *Proc. IEEE International Midwest Symposium on Circuits and Systems (MWSCAS),* pp. 141-144, 2014.

[17] H. Sadreazami, M. O. Ahmad and M. N. S. Swamy, "Despeckling of synthetic aperture radar images in the contourlet domain using the alpha-stable distribution," in *Proc. IEEE International Symposium on Circuits and Systems (ISCAS),* pp. 121-124, 2015.

[18] S. Yagyu, A. Sakiyama and Y. Tanaka, "Pyramidal image representation with deformation: reformulation of domain transform and filter designs," in *Proc. IEEE Int. Conf. on Image Processing (ICIP),* pp. 1222-1226, 2016.

[19] A. Gadde, S. K. Narang and A. Ortega, "Bilateral filter graph spectral interpretation and extensions," in *Proc. IEEE Int. Conf. on Image Processing (ICIP),* pp. 1222-1226, 2013.

[20] X. Liu, G. Cheung and X. Wu, "Joint denoising and contrast enhancement of images using graph Laplacian operator," in *Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Process. (ICASSP),* pp. 2274-2278, 2015.

[21] J. Pang, G. Cheung, A. Ortega and O. Au, "Optimal graph Laplacian regularization for natural image denoising," in *Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP),* pp. 2294-2298, 2015.

[22] J. Mairal, M. Elad and G. Sapiro, "Sparse representation for color image restoration," *IEEE Transactions on Image Processing,* vol. 17, no. 1, pp. 53-69, 2008.

[23] A. Yang, Z. Zhou, A. Balasubramanian, S. Sastry and y. Ma, "Fast l_1-minimization algorithms for robust face recognition," *IEEE Transactions on Image Processing,* vol. 22, no. 8, pp. 3234-3246, 2013.

[24] J. A. Tropp, A. C. Gilbert and M. J. Strauss, "Algorithms for simultaneous sparse approximation. Part I: Greedy pursuit," *Signal Processing,* vol. 86, no. 3, pp. 572-588, 2006.

[25] H. Sadreazami, A. Asif and A. Mohammadi, "Iterative graph-based filtering for image abstraction and stylization," *IEEE Transactions on Circuits and Systems II: Express Briefs,* 2017.

[26] Y. Xu, L. Yu, H. Xu, H. Zhang and T. Nguyen, "Vector sparse representation of color image using quaternion matrix analysis," *IEEE Transactions on Image Processing,* vol. 24, no. 4, pp. 13151329, 2015.

[27] H. Yu, L. Zhao and H. Wang, "Image denoising using trivariate shrinkage filter in the wavelet domain and joint bilateral filter in the spatial domain," *IEEE Transactions on Image Processing,* vol. 18, no. 10, pp. 2364-2349, 2009.