Texture Variation Adaptive Image Denoising With Nonlocal PCA

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***Abstract*— Image textures, as a kind of local variations, provide important information for the human visual system. Many image textures, especially the small-scale or stochastic textures, are rich in high-frequency variations, and are difficult to be preserved. Current state-of-the-art denoising algorithms typically adopt a nonlocal approach consisting of image patch grouping and group-wise denoising filtering. To achieve a better image denoising while preserving the variations in texture, we first adaptively group high correlated image patches with the same kinds of texture elements (texels) via an adaptive clustering method. This adaptive clustering method is applied in an over-clustering-and-iterative-merging approach, where its noise robustness is improved with a custom merging threshold relating to the noise level and cluster size. For texture-preserving denoising of each cluster, considering that the variations in texture are captured and wrapped in not only the between-dimension energy variations but also the within-dimension variations of PCA transform coefficients, we further propose a PCA-transform-domain variation adaptive filtering method to preserve the local variations in textures. Experiments on natural images show the superiority of the proposed transform-domain variation adaptive filtering to traditional PCA-based hard or soft threshold filtering. As a whole, the proposed denoising method achieves a favorable texture-preserving performance both quantitatively and visually, especially for irregular textures, which is further verified in camera raw image denoising.**

***Index Terms*— Texture-preserving denoising, adaptive clustering, principal component analysis transform, suboptimal Wiener filter, LPA-ICI.**

I. Introduction

TEXTURE, as a systematic local variation of image values, is an essential component of natural visual information reflecting the physical properties of the surrounding environment [1]. There are two basic types of texture pattern:

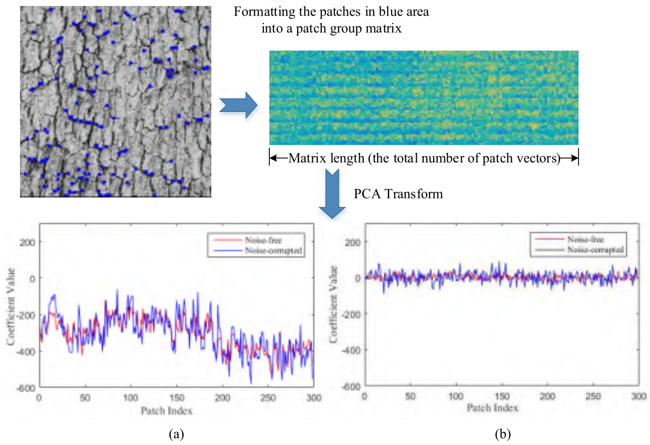

Fig. 1. The between- and within-dimension variations of PCA trans-

- Besides of additive Gaussian noise reduction, the proposed denoising method is applied to remove Poisson-Gaussian noise in the camera raw image.

The rest of the paper is organized as follows. In Section II we introduce the noise model. Section III, IV and V are about the details of the adaptive patch clustering, texture variation adaptive filtering for PCA coefficients and the sliding window and aggregation technique, respectively. Experimental results are displayed in Section VI. Finally, conclusion is given in Section VII.

II. Noise Model

The additive white Gaussian noise (AWGN) is written as:

$$y = x + n, \tag{1}$$

where x is noise-free data, y is noisy, and n follows the normal distribution with zero mean and variance σ^2. AWGN is signal-independent.

Being different from AWGN, the Poisson-Gaussian noise corrupting the camera raw images that are acquired from digital cameras is typically signal-dependent noise. Let x be a noise-free signal at the position c. The observed data with Poisson-Gaussian noise can be written as:

$$y(\mathbf{c}) = \rho/\alpha + b\upsilon, \tag{2}$$

where $\rho \sim P(\alpha(x(\mathbf{c}) - p))$ is a Poisson variable with the parameter $\alpha(x(\mathbf{c}) - p)$, υ follows the normal distribution $N(0, 1)$, and α, b, p are parameters of the Poisson-Gaussian noise.

After applying a variance stabilization transform for the signal-dependent Poisson-Gaussian noisy signal, we can remove the noise using the denoising methods for additive white Gaussian noise. One well-known variance stabilization transform is called generalized Anscome transform (GAT) [26], [27]. GAT can approximately transform Poisson-Gaussian noise into additive white Gaussian noise with unitary variance:

$$f(y) = \begin{cases} 2\sqrt{y' + \frac{3}{8} + \sigma'^2}, & y' > -\frac{3}{8} - \sigma'^2 \\ 0, & y' \leq -\frac{3}{8} - \sigma'^2 \end{cases} \tag{3}$$

where $y' = \alpha y$ and $\sigma' = \alpha b$.

Let x be the noise-free data, and the denoised data is treated as $E[f(y)|x]$. The exact unbiased inverse of the GAT is defined as:

$T^{($

clusters according to a custom threshold. To this end, there are two problems that need to be solved:

a) clustering a huge number of clusters requires a huge computational burden due to the high dimensionality of image patches;
b) finding a way to calculate a suitable merging threshold for merging similar clusters.

For the first problem, we adopt the divide and conquer technique [28], [29]. The divide and conquer technique is a two-stage clustering scheme, which accelerates the K-means clustering with improved performance: It first clusters a small number of clusters using K-means, and then within each cluster it performs the K-means clustering again to further increase the cluster number.

For the second problem, we derive the merging threshold on the distance of any two similar clusters according to the noise level and cluster size. Specifically, we consider one special case, where we have two similar clusters $\mathbf{A} \in \mathbb{R}^{M \times L_a}$ and $\mathbf{B} \in \mathbb{R}^{M \times L_b}$ with very different sizes $L_a \gg 1$ and $L_b = 1$. Supposing the noise variance in the center of the large cluster $\mathbf{A}$ is small enough to be ignored, we further denote by $\mathbf{y}_a = \mathbf{x}$ and $\mathbf{y}_b = \mathbf{x} + \mathbf{n}$ the centers of $\mathbf{A}$ and $\mathbf{B}$ respectively, where $\mathbf{x}$ is noise-free, and the entries n

RxR1a) 1Tf.915408670Tc(:)Tj/F11Tf.78290890Tc(A(1Tf7.5716TDTD(R)Tj/Fi1Tf.78290T468Tc(A(1Tf7.

Algorith[redacted]
Iterative [redacted]

Input: [redacted]

detection has been used in some image denoising algorithms such as SADCT [20] and BM3DSAPCA [8], to adaptively detect the spatial variations of image value and collect similar pixel samples. However, the proposed algorithm uses LPA-ICI for signal variation detection in the PCA transform-domain.

Standard linear LPA tries to fit the signal $y(n)$ locally with polynomial functions of order m. Here, since we only use it to detect variations and find neighborhood with high internal similarity, we simply apply the zero-order polynomial fitting ($m = 0$) to find a suitable window of size h (a window containing $N_h = 2h + 1$ data points) where all the similar signal in the window can be approximated by a constant amplitude signal $\hat{y}(n, h) = C$. The computation of $\hat{y}(n, h)$ in LPA is related to the following loss function:

$$\mathfrak{J}_h(n) = \frac{1}{N_h} \sum_{s=1}^{N_h} \rho_h(n_s - n)(y(n_s) - \hat{y}(n, h))^2 \qquad (10)$$

where $y(n_s)$, $1 \leq s \leq N_h$ is the signal at the point in a window of size h with n as its center, $\rho(\cdot)$ is a basic window function, and $\rho_h(\cdot) = \rho(\cdot/h)/h$. For simplicity, we use the square uniform window, where $\rho(\cdot) = 1$ in $[-1, 1]$, and $\rho(\cdot) = 0$, otherwise. So there is $\rho_h(\cdot) = 1/h$ in $[-h, h]$, and $\rho(\cdot) = 0$, otherwise.

For a certain window size h, by minimizing the loss function, we have the estimate of $y(n)$: $\hat{y}(n, h) = \frac{1}{N_h} \sum_{s=1}^{N_h} y(n_s)$ and its standard deviation $std(n, h) = \frac{\sigma}{\sqrt{N_h}}$. So the confidence interval of the estimate can be

$$\begin{aligned} D &= [L, U] \\ U &= \hat{y}(n, h) + \Gamma \cdot std(n, h) \\ L &= \hat{y}(n, h) - \Gamma \cdot std(n, h) \end{aligned} \qquad (11)$$

where Γ is a threshold parameter.

Given a finite set of window size $H = h_1 < h_2 < \cdots < h_J$ starting from the minimum window size h_1, for each window we can use the LPA to get a estimate $\hat{y}(n, h_i)$ and a corresponding standard deviation $std(n, h_i)$, thereby determining a sequence of the confidence intervals $D(i)$, $1 \leq i \leq J$ of the biased estimates:

$$\begin{aligned} D(i) &= [L_i, U_i] \\ U_i &= \hat{y}(n, h_i) + \Gamma \cdot std(n, h_i) \\ L_i &= \hat{y}(n, h_i) - \Gamma \cdot std(n, h_i) \end{aligned} \qquad (12)$$

The ICI technique considers the optimal h to be the maximum window length satisfying $\underline{L}_i < \overline{U}_i$ where

TABLE I

THE AVERAGE DENOISING PERFORMANCE OF ACVA USING ADAPTIVE CLUSTERING WITH DIFFERENT PARAMETERS ON TEST IMAGES FROM THE MCGILL DATASET

σ	Index	AC(0,0.7)	AC(0,1.0)	AC(100,0.7)	AC(200,0.9)	AC(200,0.7)	AC(200,0.5)	AC(200,0.3)	AC(400,0.7)
10	PSNR	32.50	32.50	32.50	32.50	32.50	32.50	32.50	32.50
	SSIM	0.9195	0.9196	0.9196	0.9196	0.9196	0.9196	0.9197	0.9196
	FSIM	0.9564	0.9568	0.9566	0.9567	0.9567	0.9566	0.9566	0.9566
20	PSNR	28.88	28.91	28.91	28.91	28.91	28.91	28.91	28.91
	SSIM	0.8383	0.8409	0.8409	0.8409	0.8409	0.8410	0.8410	0.8409
	FSIM	0.9141	0.9158	0.9152	0.9154	0.9153	0.9152	0.915	

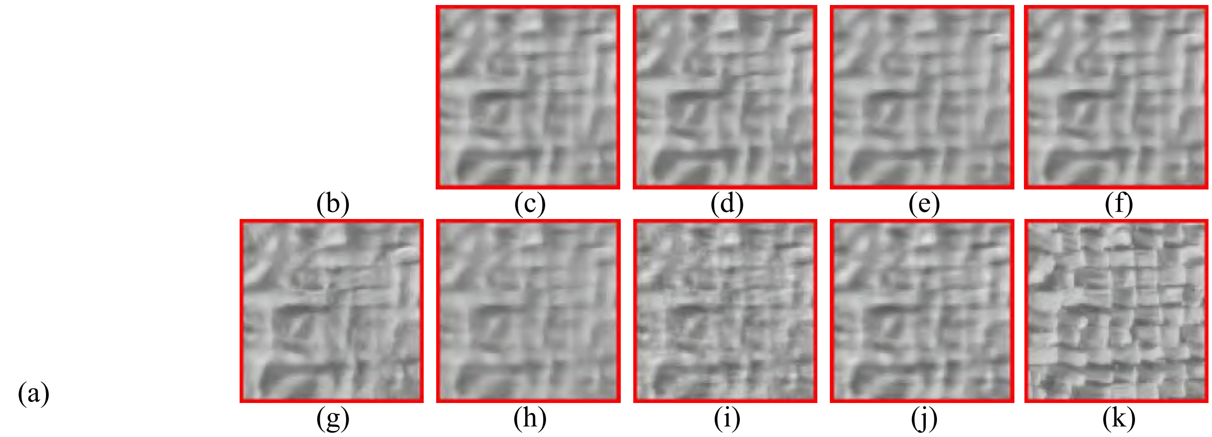

Fig. 9. Denoising the Grid image at $\sigma = 50$: (a) Grid image, (b) Noisy block, (c) BM3D, (d) BM3DSAPCA, (e) WNNM, (f) SLRD, (g) DnCNN-S, (h) SGHP, (i) AC-PT, (j) ACVA, (k) Noise-free block.

TABLE III

THE AVERAGE PSNR(dB), SSIM, FSIM RESULTS ON 16 IMAGES WITH IRREGULAR TEXTURES FROM THE USC-SIPI DATASET

Methods	σ	10	20	30	40	50

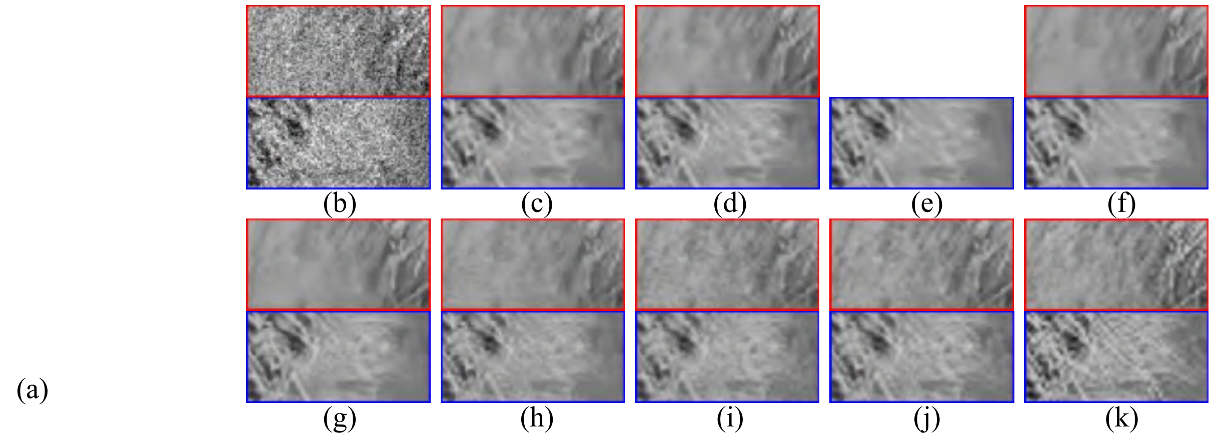

Fig. 10. Denoising the Mandrill image at $\sigma = 30$ with image details in the zoomed areas (red and blue boxes): (a) Mandrill image, (b) Noisy block, (c) BM3D, (d) BM3DSAPCA, (e) WNNM, (f) SLRD, (g) DnCNN-S, (h) SGHP, (i) AC-PT, (j) ACVA, (k) Noise-free block.

it can be observed that the proposed method outperforms other methods in restoring the textures of the fur (in Fig. 10) and water surface (in Fig. 11).

B. Camera RAW Image Denoising

1) Camera RAW Image Simulation: Four standard RGB test images, specifically, Peppers, Lena, Baboon, and House are selected for camera raw image denoising simulation. We adopt the simulation method used in [46]. To transform the RGB images into simulated raw images, we first scale the RGB images (within the bounds of [0, 1]) to the domain of raw images:

$$[r'_{i,j}, g'_{i,j}, b'_{i,j}]^T = R_{max} \times [r_{i,j}, g_{i,j}, b_{i,j}]^T \tag{19}$$

where r, g, and b denote the signal in red, green, and blue channels, respectively, i and j are the x-coordinate and y-coordinate of any image pixel, respectively.

Then the pixels are further arranged into four subimages, R, $G1$, $G2$, and B for simulation of the color filter array (CFA) [47].

$$\begin{aligned} R &= \{r''_{i,j} = r'_{2i-1,2j-1}\}, \\ G1 &= \{g''_{i,j} = g'_{2i-1,2j}\}, \\ G2 &= \{g''_{i,j} = g'_{2i,2j-1}\}, \\ B &= \{b''_{i,j} = b'_{2i,2j}\}. \end{aligned} \tag{20}$$

Finally, all the four subimages are arranged into a single image to simulate the RAW image.

To better simulate the noise in the real RAW image, we set the noise parameters $\alpha > 0$, $b = 0$, $p = 0$ as [46]. Based on Poisson-Gaussian noise reduction scheme described in Section II, we apply the proposed algorithm to denoise R, G1, G2, and B separately and then compute the average PSNR (SSIM and FSIM) results for evaluation.

Table V compares the quantitative performance of nine competing algorithms on simulated camera RAW images. We can see that the proposed algorithm is superior to all other algorithms in terms of SSIM and FSIM on average.

TABLE V

PSNR (dB), SSIM, FSIM RESULTS OF CAMERA RAW IMAGE SIMULATION ON THE RGB IMAGES SHOWN IN FIG. 7

	α	200			400			600			800			1000		
Method	Image	PSNR	SSIM	FSIM	PSNR	SSIM	FSIM	PSNR	SSIM	FSIM	PSNR	SSIM	FSIM	PSNR	SSIM	FSIM
	House	32.91	.8797	.9428	34.59	.9109	.9609	35.66	.9272	.9691	36.44	.9377	.9739	37.07	.9470	.9779
	Baboon	28.09	.8883	3												
BM3D																

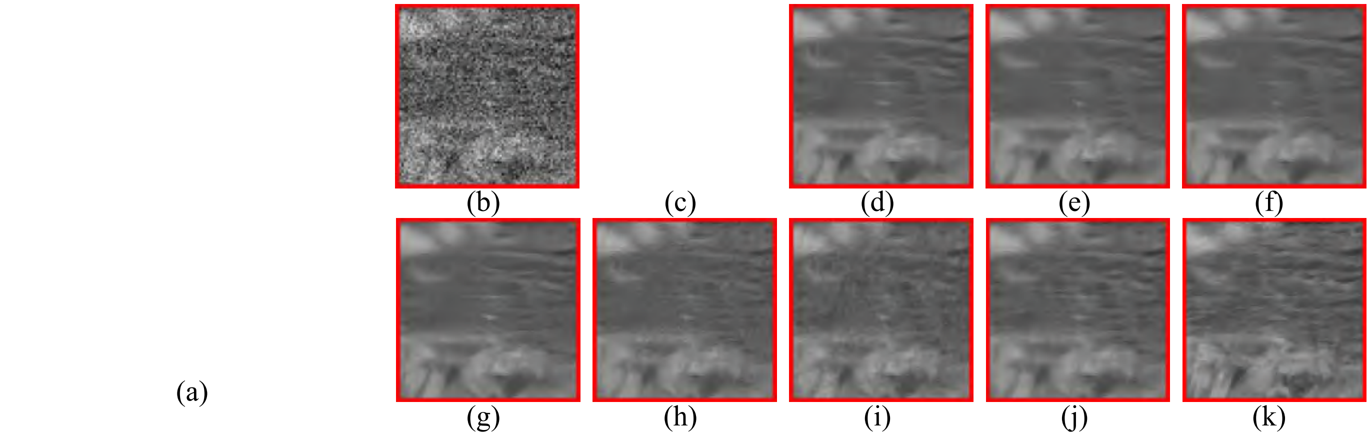

Fig. 11. Denoising the Stream image at $\sigma = 25$ with image details in the zoomed areas (red boxes): (a) Stream image, (b) Noisy block, (c) BM3D, (d) BM3DSAPCA, (e) WNNM, (f) SLRD, (g) DnCNN-S, (h) SGHP, (i) AC-PT, (j) ACVA, (k) Noise-free block.

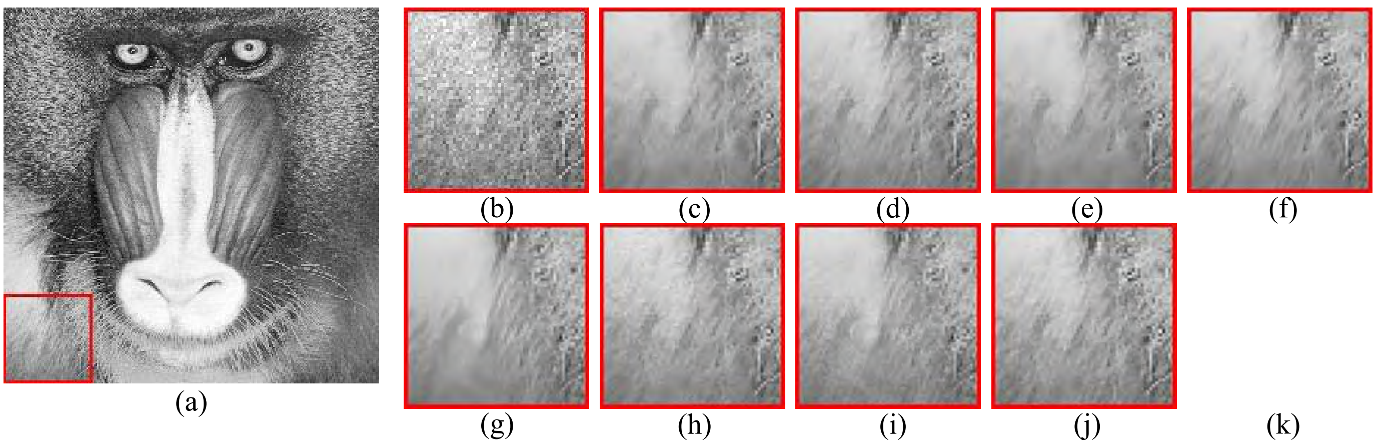

Fig. 12. Performance comparison on the red channel of Baboon image with image details in the zoomed areas (red boxes): (a) The red channel, (b) Noisy block ($\alpha = 200$), (c) BM3D, (d) BM3DSAPCA, (e) NCSR, (f) WNNM, (g) DnCNN-S, (h) SGHP, (i) AC-PT, (j) ACVA, (k) Noise-free block.

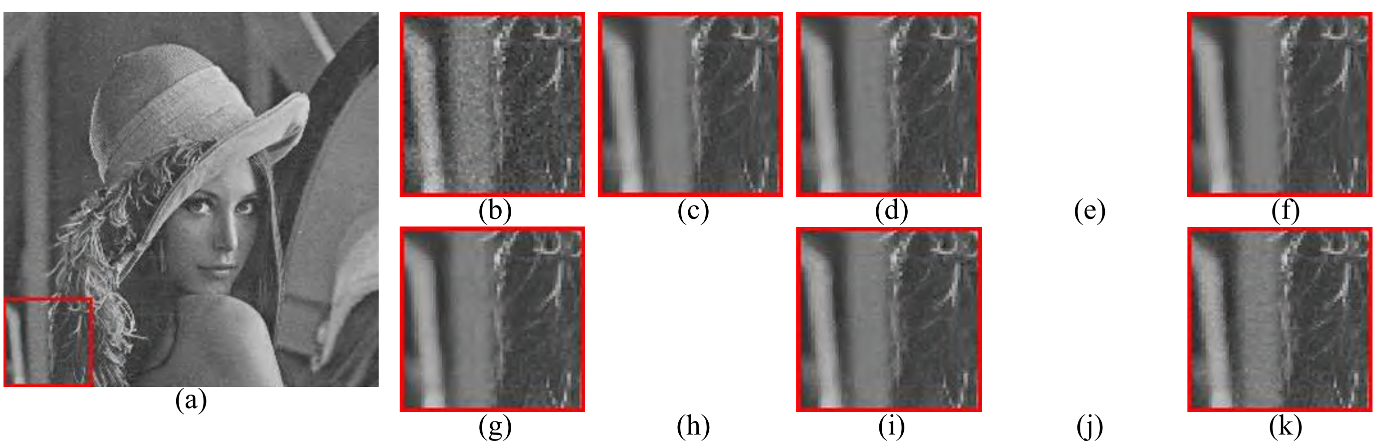

Fig. 13. Performance comparison on the blue channel of Lena image with image details in the zoomed areas (red boxes): (a) The blue channel, (b) Noisy block ($\alpha = 400$), (c) BM3D, (d) BM3DSAPCA, (e) NCSR, (f) WNNM, (g) DnCNN-S, (h) SGHP, (i) AC-PT, (j) ACVA, (k) Noise-free block.

As for the visual texture-preserving performance, ACVA also outperforms the state-of-the-art denoising algorithms. Figs. 12-13 compare the bottom-left corner of the denoising results of image Baboon and Lena. From the zoom-in area, the proposed method outperforms other methods in restoring the special textures of the fur (in Fig. 12) and doorframe (in Fig. 13). In addition, as shown in [46], EFBMD is also inferior to ACVA in preserving the fur texture at the bottom-left corner of image Baboon.

2) Denoising on Real RAW Images: The RAW image of size 3744×5616 is captured by a Canon EOS 5D Mark II. We cut down a 402×402 square from the raw image for denoising tests. The noise parameters (α and b) in Poisson-Gaussian noise model are estimated by the method in [26]. We assume

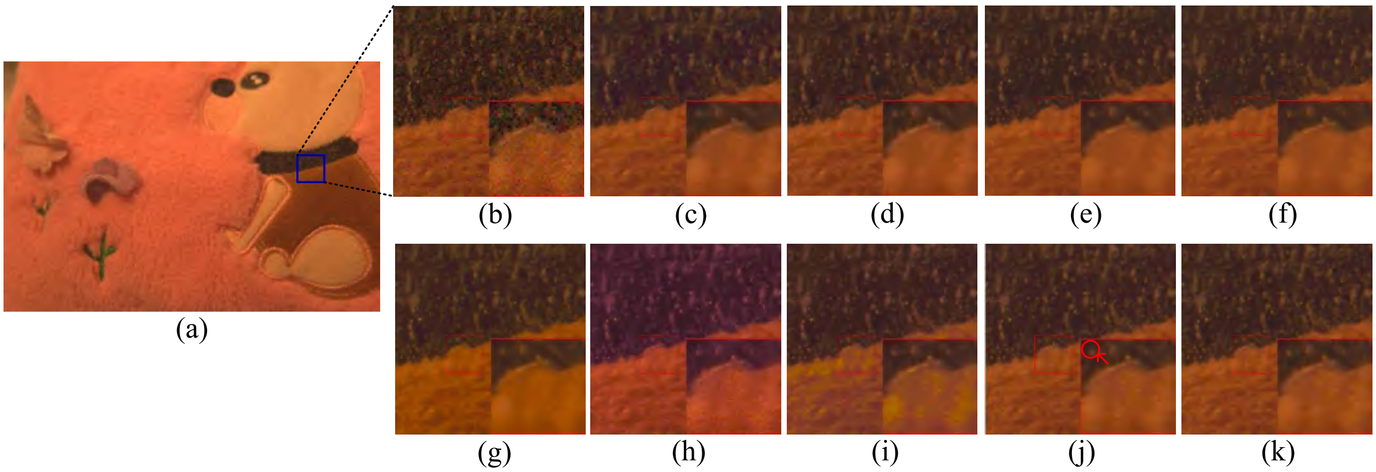

Fig. 14. Denoising the real camera raw image with image details in the zoomed areas (red boxes): (a) Noisy image, (b) Small sample cut down from the blue square, (c) BM3D, (d) BM3DSAPCA, (e) NCSR, (f) WNNM, (g) SLRD, (h) DnCNN-S, (i) SGHP, (j) AC-PT, (k) ACVA.

the noise level is invariant across the whole image. To avoid over-estimate of noise level, we select the top-left 200×200 flat area, estimate its R, G1, G2, B subimage separately, and adopt the minimum estimates of a and b, respectively. After applying the GAT on the RAW image based on the estimated parameters, we denoise the real camera raw image using the considered algorithms directly. To visualize the denoised image, we adopt the method in [47] to transform the results into RGB images.

Fig. 14 shows that ACVA protects zoom-in details (such as singular points and textures) best compared with other algorithms. Specifically, we can also find that there is a noisy black dot mistakenly preserved by AC-PT. And serious color distortion can be observed in the results by SGHP and DnCNN-S, while BM3D, BM3DSAPCA, NCSR, SLRD, and WNNM just blur the isolated white points and brown texture. The serious color distortion by DnCNN-S implies that this state-of-the-art deep learning based denoising algorithm distorts heavily the special textures resulted from the CFA, and how to control this kind of distortion remains an unsolved problem.

VII. Conclusions

In this paper, we have proposed a texture-preserving nonlocal denoising algorithm ACVA. In ACVA, an adaptive clustering method is designed to adaptively and robustly cluster similar patches. A state-of-the-art PCA-based denoising filter is proposed in a transform-domain texture variation adaptive filtering approach to perform a texture-preserving denoising of each cluster. The denoising performance of ACVA is further improved via a sliding window and aggregation approach. When compared with the existing PG techniques (especially the adaptive clustering method in AC-PT), the proposed adaptive clustering method achieves more robust performance at the high noise level. Meanwhile, the proposed DF shows superior denoising performance to other PCA (or SVD) based DFs.

ACVA achieves satisfactory texture-preserving Gaussian denoising performance both quantitatively and visually. Especially on images with irregular textures, ACVA can outperform all the other denoising algorithms tested here in terms of PSNR, SSIM and FSIM results. The noise removal results for camera raw images containing special textures of CFA further verify ACVA's excellent texture-preserving Poisson-Gaussian denoising performance for real application, while the deep learning based denoising algorithm DnCNN works [43] poorly on the real images with CFA patterns that have irregular or stochastic textures. The future work will explore potential benefits of ACVA for improving the overall performance in processing low SNR and low contrast images with irregular textures, such as OCT vessel images [23], low-dose X-ray vessel images [48]–[50] and fluorescence microscopy images [51], [52].

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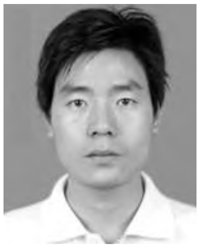

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