SINGLE-IMAGE DERAINING USING AN ADAPTIVE NONLOCAL MEANS FILTER

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ABSTRACT

An adaptive rain streak removal algorithm for a single image is proposed in this work. We observe that a typical rain streak has an elongated elliptical shape with a vertical orientation. Thus, we first detect rain streak regions by analyzing the rotation angle and the aspect ratio of the elliptical kernel at each pixel location. We then perform the nonlocal means filtering on the detected rain streak regions by selecting nonlocal neighbor pixels and their weights adaptively. Experimental results demonstrate that the proposed algorithm removes rain streaks more efficiently and provides higher restored image qualities than conventional algorithms.

Index Terms— Image enhancement, deraining, rain streak removal, nonlocal means filter, and kernel regression.

1. INTRODUCTION

Many image processing and computer vision algorithms, such as object detection, tracking, recognition, and surveillance, depend on the qualities of input images. However, an outdoor image on a rainy day generally suffers from quality degradation. More specifically, rain streaks refract and blend light rays, and they make observed scene colors brighter in the corresponding pixel locations in general. Therefore, attempts have been made to develop efficient *deraining* algorithms for removing rain streaks in images and restoring the original scenes.

Most deraining algorithms [1–5] have focused on the removal of rain streaks in video sequences, which are captured with static cameras. These algorithms detect and remove rain streaks by exploiting high temporal correlation between consecutive frames. They assume that rain streaks are shifted between consecutive frames and detect the rain streak regions by observing the temporal brightness change. Then, they restore rain-free pixels in each frame by taking the average pixel values of the previous frame and the following frame. Barnum *et al.* [6] proposed an alternative approach based on the frequency analysis of rain streaks. Assuming that rain streaks in an entire video sequence have similar shapes and orientations, they detected the rain streaks by selecting repeatedly occurring frequency components through the video sequence. All these algorithms [1–6] can remove rain streaks effectively, but they require the temporal information in video sequences. Therefore, they are not applicable to still images.

A single-image deraining scheme, which removes rain streaks using only a single input image, can be employed in a wider range of applications. However, it is challenging due to the lack of temporal information. Recently, Kang *et al.* [7] proposed a single-image rain streak removal algorithm based on the morphological component analysis. Their algorithm decomposes a rainy image into basis vectors based on the sparse representation. It then clusters the basis vectors into two kinds of components: geometrical components and rain streak components. Finally, it employs only the geometrical components to reconstruct a rain-free image. The performance of their algorithm depends on the clustering of basis vectors. When the clustering is not effective, their algorithm may erase textures, as well as rain streaks, and yield visual artifacts in a restored image.

In this work, we propose a simple but efficient single-image deraining algorithm using an adaptive nonlocal means filter. We first detect rain streak regions based on a kernel regression method. Specifically, we compute the covariance matrix of gradients within a local block centered at each pixel, extract the rotation angle and the aspect ratio of the rain kernel via the singular value decomposition (SVD), and then determine the locations of rainy pixels based on the assumption that rain streaks have elongated elliptical shapes. Next, we recover the rain streak regions using the nonlocal means filter, in which the weights for nonlocal neighbor pixels are adaptively determined to suppress the impacts of rainy pixels on the restoration. Experimental results demonstrate that the proposed algorithm removes rain streaks more effectively than the conventional denoising and deraining algorithms [7, 8], while preserving image textures more faithfully.

The rest of this paper is organized as follows. Section 2 briefly reviews the nonlocal means filtering. Section 3 describes the proposed single-image deraining algorithm. Section 4 presents experimental results. Finally, Section 5 concludes the paper.

2. NONLOCAL MEANS FILTER

The nonlocal means filter in [8] reduces pixel noise by replacing a noisy pixel with a weighted average of nonlocally neighboring pixels in an entire image. In other words, the color $I(\mathbf{p})$ of pixel $\mathbf{p}$ is processed into the filtered one $\hat{I}(\mathbf{p})$, which is the weighted average of the colors $I(\mathbf{q})$'s of nonlocal neighbors $\mathbf{q}$'s.

$$\hat{I}(\mathbf{p}) = \frac{\sum_{\mathbf{q}} \exp\left(-\frac{\|\mathbf{B_p}-\mathbf{B_q}\|^2}{\sigma^2}\right) I(\mathbf{q})}{\sum_{\mathbf{q}} \exp\left(-\frac{\|\mathbf{B_p}-\mathbf{B_q}\|^2}{\sigma^2}\right)}, \tag{1}$$

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where $\mathbf{B_p}$ and $\mathbf{B_q}$ are the column vectors, representing the pixel colors within blocks centered at $\mathbf{p}$ and $\mathbf{q}$, respectively, and σ is a Gaussian parameter. Notice that, when block $\mathbf{B_q}$ is more similar to block $\mathbf{B_p}$, $I(\mathbf{q})$ is assigned a larger weight in the weighted averaging. In this work, the color $I(\mathbf{q})$ of each pixel $\mathbf{q}$ is a three-dimensional vector in the RGB color space.

3. PROPOSED ALGORITHM

The proposed algorithm adopts the nonlocal means filter to remove rain streaks. However, the nonlocal means filter was developed to denoise an image, assuming that pixels were corrupted by zero mean white Gaussian noise. The characteristics of rainy images are considerably different from those of noisy images. Specifically, in contrast to independent noise components, a rain streak consists of connected pixels with an underlying structure. Also, unlike zero mean noise, the value of a rainy pixel is usually larger than that of a rain-free pixel. Therefore, if the nonlocal means filter is straightforwardly applied to deraining, it may cause blurring artifacts around rain streaks and make a restored image brighter than an input image. To overcome these drawbacks, we first detect rain streaks and then apply the nonlocal means filter adaptively to the rainy pixels only.

3.1. Detection of Rain Streaks

We detect rain streak regions using shape and orientation features. We assume that each rain streak has an elliptical shape as in [3], and extract elliptical components in an image by employing the kernel regression method in [9]. Let $W_\mathbf{p}$ denote a window centered at pixel $\mathbf{p}$. We analyze the structure of $W_\mathbf{p}$ using the covariance matrix $\mathbf{C_p}$, which is given by

$$\mathbf{C_p} = \frac{1}{|W_\mathbf{p}|} \sum_{\mathbf{q} \in W_\mathbf{p}} \begin{bmatrix} g_x^2(\mathbf{q}) & g_x(\mathbf{q})g_y(\mathbf{q}) \\ g_x(\mathbf{q})g_y(\mathbf{q}) & g_y^2(\mathbf{q}) \end{bmatrix}, \quad (2)$$

where $g_x(\mathbf{q})$ and $g_y(\mathbf{q})$ denote the gradient values at pixel $\mathbf{q}$ in the horizontal and the vertical directions, respectively, and $|W_\mathbf{p}|$ is the number of pixels in $W_\mathbf{p}$. We obtain the gradients using only the luminance values extracted from the RGB color vectors.

The shape and the orientation of an ellipse in $W_\mathbf{p}$ can be determined by applying the SVD to the covariance matrix $\mathbf{C_p}$, *i.e.*

$$\mathbf{C_p} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{V}^T, \quad (3)$$

$$\mathbf{U} = \begin{bmatrix} \cos\theta_\mathbf{p} & -\sin\theta_\mathbf{p} \\ \sin\theta_\mathbf{p} & \cos\theta_\mathbf{p} \end{bmatrix}, \quad (4)$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} \lambda_\mathbf{p} & 0 \\ 0 & \mu_\mathbf{p} \end{bmatrix}, \quad (5)$$

where $\mathbf{U}$ and $\boldsymbol{\Lambda}$ are the rotation matrix and the scaling matrix, respectively. Also, $\theta_\mathbf{p}$ is the rotation angle of the elliptical kernel, and two eigenvalues $\lambda_\mathbf{p}$ and $\mu_\mathbf{p}$ represent the kernel scales in the directions of the major and the minor axes. Fig. 1 illustrates three types of elliptical kernels found in the "Mountain" image: rain streak, horizontal edge, and textureless region.

The kernel regression method in (2)$\sim$(5), however, may be adversely affected by other image structures within the window, *e.g.* object edges. To alleviate the effects of these other structures and detect rain streaks more reliably, we modify the covariance matrix in (2) by weighting the gradient at each pixel adaptively. We exploit three properties of rain streaks: First, a rainy pixel tends to be brighter than a rain-free pixel. Second, a rain streak has a spatially compact shape. Third, pixels in a rain streak have similar colors.

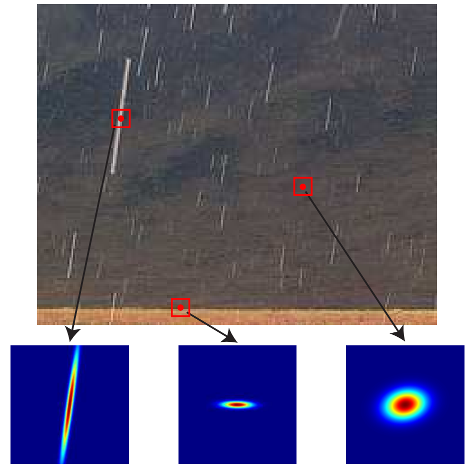


Fig. 1. Various structures of elliptical kernels: the rain streak (left) yields a highly elongated ellipse, the horizontal edge (middle) is associated with an ellipse with the horizontal major axis, and the textureless region (right) provides an ellipse of an almost circular shape.

The first property is related to the luminance levels of pixels. As described in [3], pixels in a rain streak region are brighter than those in a rain-free region in general. Hence, we design a weight $w_l(\mathbf{q})$ for pixel $\mathbf{q}$ using the difference between its luminance $Y(\mathbf{q})$ and the average luminance $\bar{Y}_\mathbf{p}$ in the window $W_\mathbf{p}$, given by

$$w_l(\mathbf{q}) = \frac{1}{1 + e^{-\kappa\left(Y(\mathbf{q}) - \bar{Y}_\mathbf{p}\right)}}, \quad (6)$$

where κ controls the sensitivity of the luminance weight function and is fixed to 0.1 in our experiments. Note that, as the luminance $Y(\mathbf{q})$ becomes brighter, $\mathbf{q}$ is more likely to be a rainy pixel and thus assigned a bigger weight $w_l(\mathbf{q})$.

The second is the distance weight $w_d(\mathbf{q})$, which is defined to be inversely proportional to the distance between $\mathbf{q}$ and the center pixel $\mathbf{p}$ within the window,

$$w_d(\mathbf{q}) = \exp\left(-\frac{\|\mathbf{p} - \mathbf{q}\|^2}{\sigma_d^2}\right) \quad (7)$$

where $\sigma_d = 3$ in this work. We assign a bigger weight to pixel $\mathbf{q}$, if it is spatially closer to the center pixel $\mathbf{p}$. This is because, if two pixels are far from each other, they are less likely to belong to the same rain streak.

The third is the color weight $w_c(\mathbf{q})$, which is defined as

$$w_c(\mathbf{q}) = \exp\left(-\frac{\|I(\mathbf{p}) - I(\mathbf{q})\|^2}{\sigma_c^2}\right) \quad (8)$$

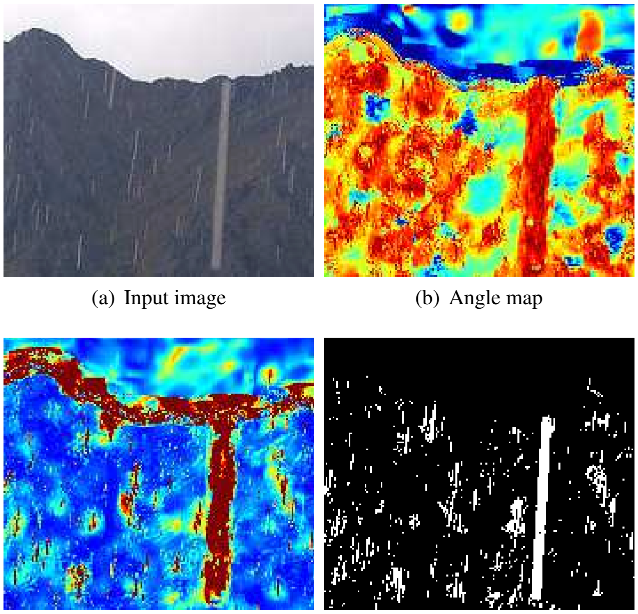
where σ_c is set to 9 in this work. This weight assumes that pixels in a rain streak have similar colors. Thus, $w_c(\mathbf{q})$ gets larger, as the color vector of $\mathbf{q}$ is more similar to that of the center pixel $\mathbf{p}$.

We determine the overall weight $w(\mathbf{q})$ by combining the three weights in (6), (7), and (8),

$$w(\mathbf{q}) = w_l(\mathbf{q})w_d(\mathbf{q})w_c(\mathbf{q}). \quad (9)$$

Then, instead of (2), we obtain the modified covariance matrix $\tilde{\mathbf{C}}_\mathbf{p}$ as

$$\tilde{\mathbf{C}}_\mathbf{p} = \frac{1}{Z_\mathbf{p}} \sum_{\mathbf{q} \in W_\mathbf{p}} w^2(\mathbf{q}) \begin{bmatrix} g_x^2(\mathbf{q}) & g_x(\mathbf{q})g_y(\mathbf{q}) \\ g_x(\mathbf{q})g_y(\mathbf{q}) & g_y^2(\mathbf{q}) \end{bmatrix}, \quad (10)$$



(a) Input image (b) Angle map

(c) Ratio map (d) Rain streak map

Fig. 2. Detection of rain streaks in the "Mountain" image in (a). In the angle map in (b), a red color depicts a vertical angle close to $\pi/2$, whereas a blue color depicts a horizontal angle. In the ratio map in (c), red and blue colors correspond to large and small ratios, respectively. In the rain streak map in (d), white and black pixels represent rainy and rain-free pixels, respectively.

where $Z_{\mathbf{p}} = \sum_{\mathbf{q} \in W_{\mathbf{p}}} w^2(\mathbf{q})$. Consequently, rainy pixels contribute more to the modified covariance matrix than rain-free pixels.

Next, we obtain the rotation angle $\theta_{\mathbf{p}}$ in (4) and the scaling parameters $\lambda_{\mathbf{p}}$ and $\mu_{\mathbf{p}}$ in (5) by applying the SVD to the modified covariance matrix $\tilde{\mathbf{C}}_{\mathbf{p}}$. Then, we detect rain streaks, assuming that the shape of a rain streak is a highly elongated ellipse with a vertical orientation. We define the binary rain streak map $\mathcal{M}$, which has value $\mathcal{M}(\mathbf{p}) = 1$ if $\mathbf{p}$ is a rainy pixel and $\mathcal{M}(\mathbf{p}) = 0$ otherwise. Pixel $\mathbf{p}$ is declared to be rainy, *i.e.* $\mathcal{M}(\mathbf{p}) = 1$, when the following three conditions are satisfied.

$$\begin{aligned} \left|\theta_{\mathbf{p}} - \frac{\pi}{2}\right| &< \alpha, && (11)\\ \frac{\lambda_{\mathbf{p}}}{\mu_{\mathbf{p}}} &> \beta, && (12)\\ \mu_{\mathbf{p}} &> \gamma. && (13) \end{aligned}$$

The thresholds are empirically set as $\alpha = \pi/6$, $\beta = 2$, and $\gamma = 10$. The first condition in (11) means that a rain streak should have a vertical orientation. The second and the third conditions in (12) and (13) indicate that a rain streak should have an elongated elliptical shape and it should be also prominent with large eigenvalues in the directions of both major and minor axes.

Fig. 2 shows an example of the rain streak map. Fig. 2(a) is an input image, and Figs. 2(b) and (c) illustrate the rotation angle $\theta_{\mathbf{p}}$ and the ratio $\lambda_{\mathbf{p}}/\mu_{\mathbf{p}}$ of eigenvalues, respectively. Fig. 2(d) is the extracted rain streak map. We see that the proposed algorithm detects the locations of rain streaks successfully.

3.2. Adaptive Removal of Rain Streaks

We remove the detected rain streaks by adopting the nonlocal means filter in (1). While the Buades *et al.*'s denoising algorithm [8] applies the nonlocal means filter to all pixels in an image, we filter only the rainy pixels $\mathbf{p}$'s with $\mathcal{M}(\mathbf{p}) = 1$ in the proposed algorithm.

Also, in (1), the weight for a nonlocal neighbor $\mathbf{q}$ is determined by the squared distance $\|\mathbf{B}_{\mathbf{p}} - \mathbf{B}_{\mathbf{q}}\|^2$ between $\mathbf{B}_{\mathbf{p}}$ and $\mathbf{B}_{\mathbf{q}}$. However, when either $\mathbf{B}_{\mathbf{p}}$ or $\mathbf{B}_{\mathbf{q}}$ contains rain streaks, the squared distance may not convey the similarity information between the two blocks faithfully. In other words, even when the two blocks are similar to each other, the squared distance can be large due to rain streaks. Therefore, we exclude rainy pixels in $\mathbf{B}_{\mathbf{p}}$ and $\mathbf{B}_{\mathbf{q}}$ from the weight computation. Let $\mathbf{R}_{\mathbf{p}}$ and $\mathbf{R}_{\mathbf{q}}$ represent the binary column vectors, which correspond to the blocks centered at $\mathbf{p}$ and $\mathbf{q}$ in the rain streak map, respectively. Then, instead of $\mathbf{B}_{\mathbf{p}}$ and $\mathbf{B}_{\mathbf{q}}$ in (1), we use the modified vectors

$$\begin{aligned} \tilde{\mathbf{B}}_{\mathbf{p}} &= \mathbf{B}_{\mathbf{p}} \otimes (\mathbf{1} - \mathbf{R}_{\mathbf{p}}) \otimes (\mathbf{1} - \mathbf{R}_{\mathbf{q}}), && (14)\\ \tilde{\mathbf{B}}_{\mathbf{q}} &= \mathbf{B}_{\mathbf{q}} \otimes (\mathbf{1} - \mathbf{R}_{\mathbf{p}}) \otimes (\mathbf{1} - \mathbf{R}_{\mathbf{q}}), && (15) \end{aligned}$$

where the operator $\otimes$ denotes the element-wise multiplication between two vectors, and $\mathbf{1}$ is the column vector whose all elements are 1. Then, we replace the rainy pixel $\mathbf{p}$ with $\hat{I}(\mathbf{p})$ using the adaptive nonlocal means filter, given by

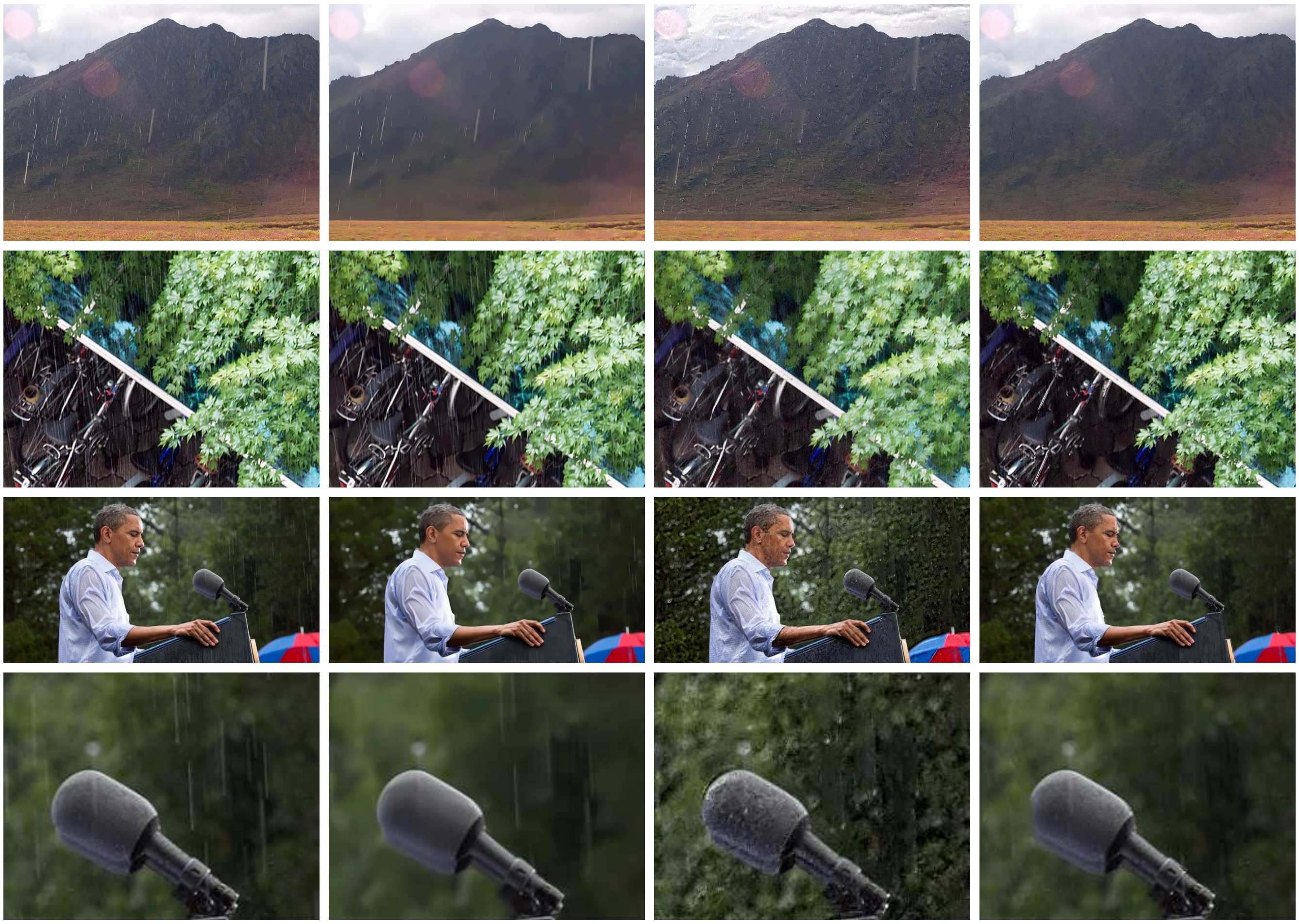
$$\hat{I}(\mathbf{p}) = \frac{\sum_{\mathbf{q}} \exp\left(-\frac{\|\tilde{\mathbf{B}}_{\mathbf{p}} - \tilde{\mathbf{B}}_{\mathbf{q}}\|^2}{\sigma^2 N_{\mathbf{p},\mathbf{q}}}\right)(1 - \mathcal{M}(\mathbf{q}))\, I(\mathbf{q})}{\sum_{\mathbf{q}} \exp\left(-\frac{\|\tilde{\mathbf{B}}_{\mathbf{p}} - \tilde{\mathbf{B}}_{\mathbf{q}}\|^2}{\sigma^2 N_{\mathbf{p},\mathbf{q}}}\right)(1 - \mathcal{M}(\mathbf{q}))}, \quad (16)$$

where $N_{\mathbf{p},\mathbf{q}}$ is the number of nonzero elements in the vector $(\mathbf{1} - \mathbf{R}_{\mathbf{p}}) \otimes (\mathbf{1} - \mathbf{R}_{\mathbf{q}})$. In other words, $N_{\mathbf{p},\mathbf{q}}$ counts the pixel locations, in which both $\mathbf{B}_{\mathbf{p}}$ and $\mathbf{B}_{\mathbf{q}}$ have rain-free pixels. Notice that the term $(1 - \mathcal{M}(\mathbf{q}))$ in (16) is also used to avoid using rainy pixels as nonlocal neighbors.

4. EXPERIMENTAL RESULTS

We evaluate the performance of the proposed algorithm on three rainy images "Mountain," "Bicycle," and "Obama" in Fig. 3. In all experiments, the size of the window $W_{\mathbf{p}}$ in (10) is 9×9, the size of the block $\tilde{\mathbf{B}}_{\mathbf{p}}$ or $\tilde{\mathbf{B}}_{\mathbf{q}}$ in (16) is 15×15, and the Gaussian parameter σ in (16) is 15. Also, we limit the search range for nonlocal neighbors to 50×50, in order to reduce the computational complexity.

Fig. 3 compares the deraining results of the proposed algorithm with those of the conventional nonlocal means filter [8] and the Kang *et al.*'s algorithm [7]. The nonlocal means filter cannot remove the structures of heavy rain streaks effectively. Moreover, it blurs restored images and loses detailed textures. For example, the nonlocal means filter cannot erase thick and strong rain streaks in the "Mountain" and "Bicycle" images and blurs the texture on the microphone in the "Obama" image. The Kang *et al.*'s algorithm removes rain streaks more effectively than the nonlocal means filter, but thick rain streaks are still observed in the restored "Mountain" image. Also, as shown at the bottom of Fig. 3(c), the Kang *et al.*'s algorithm distorts background textures since it regards most vertical patterns as rain streaks. Note that the grainy texture patterns at the bottom of Fig. 3(c) are not contained in the original image in Fig. 3(a). In contrast, we see that the proposed algorithm removes most rain streaks in all test images successfully, and at the same time preserves original textures faithfully. This is because the proposed algorithm selectively applies the adaptive nonlocal means filter to rainy pixels only.



(a) (b) (c) (d)

Fig. 3. Comparison of deraining results on the "Mountain," "Bicycle," and "Obama" images: (a) input rainy images and the restored images obtained by (b) the nonlocal means filter [8], (c) the Kang *et al*.'s algorithm [7], and (d) the proposed algorithm, respectively. The last row shows the magnified parts of the "Obama" image.

5. CONCLUSIONS

In this paper, we proposed an efficient single-image rain streak removal algorithm using the adaptive nonlocal means filter. We first identified the locations of rain streak regions by investigating the shape and the orientation of the elliptical kernel at each pixel location. Then, we removed the detected rain streaks by applying the adaptive nonlocal means filter, which excludes rainy pixels from the weight computation and the weighted averaging. Experimental results showed that the proposed algorithm can remove rain streaks more faithfully, without yielding visual artifacts, than the conventional algorithms [7, 8]. A future research issue is to extend the proposed algorithm to remove rain streaks in video sequences more efficiently, by employing the temporal information.

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