Postprint of an Adaptive Rain and Snow Removal Algorithm Based on Matrix Completion

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Abstract

Traditional deraining and desnowing methods typically do not consider parameter adaptivity. To improve the effectiveness of video rain and snow removal, an adaptive parameter is incorporated into the matrix completion model of Kim' s method, and an adaptive rain and snow removal algorithm based on matrix completion is proposed. First, the main contributions of Kim' s method are briefly described; second, the adaptive parameter is added to the second term of the classical Kim model; finally, the effectiveness and superiority of this parameter are validated using various rainy and snowy videos, and grid search is employed to identify the parameter that yields the optimal deraining effect. Experimental results demonstrate that the added adaptive parameter can effectively remove rain and snow from videos.

Full Text

Preamble

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Adaptive Deraining and Desnowing Algorithm Based on Matrix Completion

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Abstract: Traditional methods for removing rain and snow typically do not consider parameter adaptation. To improve the effectiveness of video deraining and desnowing, this paper adds an adaptive parameter to the matrix completion model of the Kim method and proposes an adaptive deraining and desnowing algorithm based on matrix completion. First, we briefly describe the main contributions of the Kim method. Second, the adaptive parameter is added to the second term of the classic Kim model. Finally, various rain and snow videos are used to verify the validity and superiority of the proposed parameter, and a grid search method is applied to find the parameter that yields the best rain removal performance. Experimental results demonstrate that the added adaptive parameter can effectively remove rain and snow from videos.

Keywords: video deraining and desnowing; rain streak removal; adaptive parameter; sparse representation; matrix completion

0 Introduction

Video deraining and desnowing represents an important research problem in digital image processing and computer vision, with widespread applications in video surveillance, intelligent transportation, and military reconnaissance. When acquiring video image information under adverse weather conditions, imaging systems are affected by fog, haze, rain, snow, and other atmospheric phenomena, leading to reduced image contrast, blurring, and loss of critical information. Consequently, the accuracy and reliability of subsequent video analysis and processing are compromised [?, ?]. In recent years, with improvements in computer hardware performance, the proliferation of big data, and the expansion of video image applications, an increasing number of researchers have focused on the application and study of video deraining and desnowing. A comprehensive survey of rain removal techniques in videos [?] describes numerous methods and research advances, demonstrating that video deraining has become a focal issue attracting widespread attention from the research community.

Kim et al. [?] proposed a video deraining and desnowing algorithm based on temporal correlation and low-rank matrix completion (hereinafter referred to as the Kim method for brevity). The Kim method can effectively detect and remove rain and snow streaks. Tian et al. [?] applied global and local properties of snowflake removal scenes to eliminate snow from videos, using correlation features of snowflakes to separate them from other moving objects, and proposed a snow removal method based on low-rank decomposition. Wei et al. [?] introduced a simple yet refined model for removing rain streaks from videos, encoding rain streaks as random knowledge and formulating the problem using patch-based mixture of Gaussians (P-MoG). The P-MoG model demonstrates good performance across various video deraining tasks. However, when test videos contain fast-moving objects, this method fails to remove all rain streaks and may even produce blurred results. Li et al. [?] extracted two intrinsic features of rain streaks: repetitive local patterns sparsely distributed at different locations in the video and multi-scale structures, and formulated these features as multi-scale convolutional sparse coding (MS-CSC). The MS-CSC model typically decomposes the rain layer into rain streaks at different levels with physical significance. The MS-CSC method is simple and effective for static scenes, but for videos with complex moving objects or significant camera shake, it can cause image blurring and reduced contrast.

Nevertheless, due to factors such as background complexity, morphological characteristics of rain and snow, motion speed, density of rain/snow streaks, and wind direction, video deraining and desnowing still faces many challenges in practical applications. Moreover, the dynamic complexity of adverse weather and variations in shooting scenes pose significant technical challenges for rain and snow removal. Consequently, numerous problems remain to be solved in the application research of video deraining and desnowing.

To address these issues, this paper proposes an adaptive deraining and desnowing algorithm based on matrix completion. This method improves upon the Kim method by specifically investigating the parameter adaptation problem that the original method neglected. In this paper, we use "rain" to denote both rain and snow, as the deraining algorithm is equally applicable to snow removal.

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1 Preliminary Knowledge

This paper adds an adaptive parameter to the classic Kim model and obtains initial and refined rain maps based on the principles of rain map extraction and optimization in the Kim method. First, an optical flow estimation algorithm [?] is used to obtain the initial rain or snow map, and sparse representation techniques [?] are applied to decompose the initial rain map into basis vectors. Then, an SVM classifier [?] categorizes these basis vectors into rain streaks and outliers. Finally, by removing outliers, the initial rain map is optimized, and input frames are marked as a binary matrix according to corresponding thresholds.

1.1 Initial Rain Map Extraction

The Kim method employs an optical flow estimation algorithm to obtain the initial rain map because optical flow can find dense motion fields between two consecutive frames [?]. The method then warps the previous frame to the current frame using the estimated optical flow field, thereby compensating for mismatched information between consecutive frames. Optical flow estimation is typically formulated as a minimization problem with the following energy function:

$$E_d = \int_{\Omega} \psi(|I_1(\mathbf{x}) - I_2(\mathbf{x} + \mathbf{u}(\mathbf{x}))|^2) d\mathbf{x} + \lambda \int_{\Omega} \psi(|\nabla u_1(\mathbf{x})|^2 + |\nabla u_2(\mathbf{x})|^2) d\mathbf{x}$$

where $\mathbf{u}$ is the optical flow field; λ is a regularization parameter, set to $\lambda = 1$ here; ψ is a penalty function with $\psi(\varepsilon^2) = \sqrt{\varepsilon^2 + 0.001}$; I_1 and I_2 are image frames; the first term is the data term measuring similarity between corresponding pixels in the source and target frames; and the second term is the smoothness term constraining neighboring pixels to be similar.

Given image frames I_{k-1}, I_k, and I_{k+1}, we can define the pre-warped frame $\tilde{I}_{\text{prev}}$ and post-warped frame $\tilde{I}_{\text{next}}$ using equations (2) and (3):

$$\tilde{I}_{\text{prev}}(\mathbf{x}) = I_{k-1}(\mathbf{x} + \mathbf{u}_{\text{prev}}(\mathbf{x}))$$

$$\tilde{I}_{\text{next}}(\mathbf{x}) = I_{k+1}(\mathbf{x} + \mathbf{u}_{\text{next}}(\mathbf{x}))$$

where $\mathbf{u}_{\text{prev}}(\mathbf{x})$ is the optical flow vector from frame I_{k-1} to I_k, and $\mathbf{u}_{\text{next}}(\mathbf{x})$ is the optical flow vector from frame I_k to I_{k+1}.

The Kim method attempts to select pixel values similar to the original pixel values in the current frame and describes this selection through a labeling process, assigning a binary label $l(\mathbf{x})$ to each pixel using equation (4):

$$l(\mathbf{x}) = \begin{cases} 0, & \text{if } |I_k(\mathbf{x}) - \tilde{I}_{\text{prev}}(\mathbf{x})| < |I_k(\mathbf{x}) - \tilde{I}_{\text{next}}(\mathbf{x})| \\ 1, & \text{otherwise} \end{cases}$$

Finally, the Kim method obtains the initial rain map R_k as the difference image between the current frame and the best warped frame using equation (5):

$$R_k(\mathbf{x}) = \max(I_k(\mathbf{x}) - \tilde{I}_{\text{prev}}(\mathbf{x}), 0)$$

1.2 Rain Map Optimization

To obtain a more accurate rain map, the Kim method optimizes the initial rain map by removing outliers. Optimizing the initial rain map before thresholding can effectively suppress outliers and reliably detect valid rain streaks. The method applies thresholding to the optimized initial rain map to obtain a binary rain mask, where different thresholds yield different binary masks.

The Kim method further optimizes the initial rain map using directional and morphological characteristics of rain streaks. Morphological Component Analysis (MCA) [**?**, **?**] decomposes a given signal into basis vectors based on sparse representation, then reconstructs the signal using only selected basis vectors. Sparse representation techniques can effectively eliminate overlapping outliers in rain streaks. Given an initial rain map R with n pixels, and considering a $p \times p$ block around each pixel, we construct an $m \times n$ matrix R where each column represents a block. Selected basis vectors can be sparsely represented through a dictionary by constructing an overcomplete dictionary $D \in \mathbb{R}^{m \times p}$

composed of p basis vectors of dimension m. The dictionary is then iteratively updated and sparse representation is solved [**?**]:

$$A^* = \arg \min_{A \in \mathbb{R}^{p \times n}} \frac{1}{2} \|R - DA\|_F^2 + \rho \|A\|_1$$

where A is the coefficient matrix. Assuming A is sparse, the Kim method obtains the optimal coefficient matrix A^* by solving optimization problem (7). Orthogonal Matching Pursuit [**?**] is used to find sparse coefficients by iteratively selecting basis vectors that produce the maximum inner product with the residual signal. After dividing basis vectors in dictionary D into rain streaks and outliers, the Kim method uses only rain streaks to reconstruct the rain-free image.

The Kim method applies kernel regression [**?**] to analyze block structures based on Singular Value Decomposition (SVD) and finds the best matching kernel for the intensity distribution in each block. The gradient values of pixel $\mathbf{x}_i$ are used to compute the covariance matrix C_i:

$$C_i = \begin{bmatrix} \sum_{\mathbf{x} \in W_i} g_h(\mathbf{x}) g_h(\mathbf{x})^T & \sum_{\mathbf{x} \in W_i} g_h(\mathbf{x}) g_v(\mathbf{x})^T \\ \sum_{\mathbf{x} \in W_i} g_v(\mathbf{x}) g_h(\mathbf{x})^T & \sum_{\mathbf{x} \in W_i} g_v(\mathbf{x}) g_v(\mathbf{x})^T \end{bmatrix}$$

where W_i is the block corresponding to the i-th basis vector in dictionary D; $g_h(\mathbf{x})$ and $g_v(\mathbf{x})$ represent the horizontal and vertical gradient values of pixel $\mathbf{x}$. SVD is applied to covariance matrix C_i to analyze the structure and orientation of the kernel:

$$C_i = V_i \begin{bmatrix} \cos\theta_i & -\sin\theta_i \\ \sin\theta_i & \cos\theta_i \end{bmatrix} \begin{bmatrix} \mu_i & 0 \\ 0 & \nu_i \end{bmatrix} \begin{bmatrix} \cos\theta_i & \sin\theta_i \\ -\sin\theta_i & \cos\theta_i \end{bmatrix} V_i^T$$

where θ_i is the rotation angle; μ_i and ν_i are the two eigenvalues representing kernel scales along the major and minor axes.

An SVM classifier is applied for classification. To train the SVM, the Kim method uses 3072 positive samples composed of valid basis vectors and 3072 negative samples composed of outlier vectors. After SVM classification, the initial rain map R is optimized to obtain a more accurate rain map $\hat{R}$. Following SVM classification, the Kim method replaces all outlier vectors in the original dictionary D with zero vectors to obtain a new dictionary $\hat{D}$. A new matrix $\hat{R}$ is then constructed by multiplying the new dictionary $\hat{D}$ with the optimal coefficient matrix A^*:

$$\hat{R} = \hat{D} A^*$$

Finally, the Kim method generates a binary rain mask $\hat{M}$ from the optimized rain map $\hat{R}$ using equation (11):

$$\hat{M}(\mathbf{x}) = \begin{cases} 1, & \text{if } \hat{R}(\mathbf{x}) > \xi \\ 0, & \text{otherwise} \end{cases}$$

1.3 Rain Streak Removal

The Kim method treats video deraining as a low-rank matrix completion problem. First, the current frame I_k is divided into disjoint blocks. For each block b_k^l, the method searches for L similar blocks from each of the four consecutive neighboring frames I_{k-2}, I_{k-1}, I_{k+1}, and I_{k+2}. Finally, an incomplete matrix B_k^l is constructed by concatenating the given block b_k^l in the current frame with its L most similar blocks from adjacent frames:

$$B_k^l = [b_k^l, b_{k-2}^{l_1}, b_{k-2}^{l_2}, \dots, b_{k+2}^{l_L}]$$

where b_k^l is any block after decomposition, and each column in matrix B_k^l represents a block.

A binary rain mask matrix M_k^l is defined for matrix B_k^l as:

$$M_k^l = [m_k^l, m_{k-2}^{l_1}, m_{k-2}^{l_2}, \dots, m_{k+2}^{l_L}]$$

where vectors in matrix M_k^l are composed of corresponding binary rain mask values from equation (11) and expressed as column vectors.

Low-rank matrix completion techniques [**?**, **?**, **?**] are applied to find a completed matrix X_k^l from the incomplete matrix B_k^l. The desired completed matrix X_k^l should minimize the nuclear norm subject to the following constraints:

$$\text{minimize} \quad \|X_k^l\|_* \quad \text{subject to} \quad P_\Omega(X_k^l) = P_\Omega(B_k^l)$$

where P_Ω is a projection operator that extracts elements from the input matrix at rain-free pixel locations and places elements from the current estimate X_k^l at rainy pixel locations.

An additional constraint is proposed: rain-free pixel values should be smaller than rainy pixel values. The following constrained matrix completion problem is formulated:

$$\text{minimize} \quad \|X_k^l\|_* \quad \text{subject to} \quad P_\Omega(X_k^l) = P_\Omega(B_k^l), \quad P_{\Omega^c}(X_k^l) \geq P_{\Omega^c}(B_k^l)$$

The Expectation-Maximization (EM) algorithm is applied to solve this constrained optimization problem. In the Expectation step (E-step) at iteration t, a completed matrix is constructed:

$$Y^{(t)} = P_\Omega(B_k^l) + P_{\Omega^c}(X^{(t)})$$

where the first term extracts elements from the input matrix at rain-free pixel locations, and the second term places elements from the current estimate $X^{(t)}$ at rainy pixel locations.

In the Maximization step (M-step), $X^{(t+1)}$ is updated as a low-rank approximation of $Y^{(t)}$ through singular value decomposition:

$$Y^{(t)} = V\Lambda W^T$$

where V and W are rotation matrices, and Λ is a diagonal matrix composed of singular values.

$X^{(t+1)}$ is updated as a low-rank approximation of $Y^{(t)}$:

$$X^{(t+1)} = \mathcal{H}_k(Y^{(t)}) = V\mathcal{H}_k(\Lambda)W^T$$

where $\mathcal{H}_k$ is an operator that truncates each singular value in Λ to 0 if it is smaller than threshold k.

The Kim method iterates between the E-step and M-step until the following stopping criterion is satisfied:

$$\frac{\|Y^{(t+1)} - Y^{(t)}\|_F}{\|Y^{(t)}\|_F} < \varepsilon$$

where $\varepsilon = 0.05$ represents the mean absolute difference between pixel values. The method uses elements from the resulting optimal completed matrix $\hat{X}_k^l$ to replace rain pixels in the input block b_k^l, thereby removing rain streaks from the video.

Since the Kim method does not consider parameter adaptation, this paper adds an adaptive parameter T to the second term of the Kim model (18) to obtain an improved matrix completion model:

$$\text{minimize} \quad \|X_k^l\|_* \quad \text{subject to} \quad P_\Omega(X_k^l) = P_\Omega(B_k^l), \quad P_{\Omega^c}(X_k^l) \geq T \cdot P_{\Omega^c}(B_k^l)$$

Experimental results demonstrate that the adaptive parameter T added to the second term of the Kim model significantly impacts video deraining performance.

2 Experiments and Results Analysis

The experiments in this paper are divided into three parts. The first part uses two synthetic datasets to verify the effectiveness of the added adaptive parameter and determine the optimal parameter search range. The search range for this experiment is 0.5-1.5 (determined through extensive preliminary experiments), with a step size of 0.1, using grid search. The second part uses two synthetic rain videos with different rain streak sizes to further verify the superiority of the adaptive parameter. Based on the first experiment, the optimal search range is determined to be 0.980-1.020, with a step size of 0.005, using grid search to find the parameter yielding the best deraining effect. The third part validates the effectiveness and superiority of the adaptive parameter on natural rain video sequences and snow video sequences extracted from TV dramas.

In these datasets, the natural rain video sequences were captured by moving cameras. The TV drama video sequences were extracted using video editing software. The synthetic video sequences were downloaded from http://www.changedetection.net/. The synthetic datasets include "Boats," "Highway," "Niagara," and "Port," where "Niagara" is from the Kim method' s dataset. Adobe After Effects [?] was used to synthesize different types of rain streaks. Natural video sequences and extracted TV drama sequences are named according to the characters appearing in them, while synthetic video sequences retain their original dataset names. After experiments, six Image Quality Assessment (IQA) metrics are used to evaluate the deraining effect after adding the adaptive parameter: PSNR [?], SSIM [?], MS-SSIM [?], VIF [?], FSIM [?], and UQI [?].

Figure 1 shows deraining results for the "Highway" sequence (with fast-moving vehicles) and the "Boats" sequence (with complex moving objects). As shown, different values of the adaptive parameter T produce different deraining results. When $T = 0.5$, almost no rain streaks are detected, and the image is covered by a grid pattern, resulting in poor removal. When $T = 1.0$, the image is somewhat blurred but essentially all rain streaks are removed. However, when $T = 1.5$, although all rain streaks are accurately detected, they are not removed from the image. Only results for $T = 0.5, 1.0, 1.5$ are shown here. To better demonstrate the effectiveness of our algorithm, detailed experimental results are presented as line charts showing the six evaluation metrics for different parameter values.

Figure 2 compares deraining results of the Kim method and our proposed method on the "Niagara" and "Port" sequences. The results show that images obtained with the adaptive parameter are closer to the ground truth. Although the Kim method removes most rain streaks, many remain in the image. This occurs because overlapping rain streaks in the input frame are relatively thick and have large pixel values, making them difficult to remove. Adding the adaptive parameter significantly improves deraining performance, leaving only a small number of rain streaks in the results. These experiments confirm that the adaptive parameter T substantially enhances video deraining effectiveness.

Figures 3 and 4 show deraining results for different adaptive parameters on "Highway" and "Boats," respectively, with corresponding metric values. Due to the large difference between PSNR values and the other five metrics, PSNR is shown separately to better demonstrate the algorithm' s effectiveness and superiority. The metric values for parameters sampled across the search range are compared with those of the input frame (marked as "Input" on the horizontal axis). The comparison reveals that different values of the adaptive parameter T yield different metric values, with PSNR showing the most significant variation. Therefore, experimental results on datasets "Highway" and "Boats" verify the effectiveness of the adaptive parameter T and establish its optimal search range as 0.980–1.020.

Figures 5 and 6 show deraining results for parameters within the optimal search range on "Niagara" and "Port," respectively. The six evaluation metric values for parameters sampled within this range are presented, along with comparisons to the input frame and the Kim method. The results show that metric values fluctuate only slightly within this range, essentially stabilizing. Deraining results on datasets "Niagara" and "Port" demonstrate that the optimal parameter value varies across different datasets, further validating the adaptability of T. It should be noted that results for $T = 1.000$ differ from the Kim method because rain maps are re-extracted and optimized for each parameter value in our experiments. If the same rain map were used, the results would be identical. This reflects the adaptability and broad applicability of the parameter in real-time applications.

To further verify the superiority of the adaptive parameter T, experiments were conducted on a set of real snow videos extracted from TV dramas and a set of natural rain videos captured by moving cameras. Due to advances in rain/snow synthesis technology, snow in TV dramas is almost indistinguishable from real snow. As shown in the input frames of Figure 7, the snow is heavy, with dense and overlapping snow streaks. The desnowing results show that after adding the adaptive parameter, almost all snow streaks are removed while faithfully preserving image information. Only some shallow snow marks remain in densely overlapped areas, but this does not affect image clarity or subsequent analysis. Figure 7 also shows a boy walking in the rain. The binary rain mask reveals very dense rain streaks. After adding the adaptive parameter, all rain streaks are removed from the input frame, and the derained image is very clear. These results demonstrate that the adaptive parameter can effectively remove rain and snow from videos.

3 Conclusion

This paper improves upon the classic Kim method by adding an adaptive parameter T to the second term of the Kim model and proposes an adaptive deraining and desnowing algorithm based on matrix completion. First, experiments verify the effectiveness of the added parameter, showing that different values of the adaptive parameter produce different deraining results, and the optimal parameter search range is determined. Second, grid search is applied to find the parameter yielding the best deraining effect and compare it with the Kim method. The derained results clearly show that adding the adaptive parameter effectively improves video deraining performance. Finally, various rain and snow videos are used to validate the effectiveness and superiority of the adaptive parameter. Extensive experimental results demonstrate that the added adaptive parameter is effective and significantly enhances video deraining and desnowing performance. The algorithm completely preserves image information while removing rain and snow and can be widely applied to various video image deraining and desnowing problems.

References

[1] Narasimhan S G, Nayar S K. Removing weather effects from monochrome images [C]// Proc of IEEE Computer Society Conference on Computer Vision and Pattern Recognition. Washington DC: IEEE Computer Society, 2001.

[2] Narasimhan S G, Nayar S K. Vision and the atmosphere [J]. International Journal of Computer Vision, 2002, 48(3): 233-254.

[3] Zhou Pucheng, Zhou Yuan, Han Yusheng. Review of rain removal techniques in videos and image [J]. Journal of Graphics, 2017, 38(5): 629-646.

[4] Kim J H, Sim J Y, Kim C S. Video deraining and desnowing using temporal correlation and low-rank matrix completion [J]. IEEE Trans on Image Processing, 2015, 24(9): 2658-2670.

[5] Tian Jiandong, Han Zhi, Ren Weihong, et al. Snowflake removal for videos via global and local low-rank decomposition [J]. IEEE Trans on Multimedia, 2018, 20(10): 2659-2669.

[6] Wei Wei, Yi Lixuan, Xie Qi, et al. Should we encode rain streaks in video as deterministic or stochastic [C]// Proc of the IEEE International Conference on Computer Vision. Washington DC: IEEE Computer Society, 2017: 2516-2525.

[7] Li Minghan, Xie Qi, Zhao Qian, et al. Video Rain Streak Removal By Multiscale Convolutional Sparse Coding [C]// Proc of IEEE Conference on Computer Vision and Pattern Recognition. Washington DC: IEEE Computer Society, 2018: 6644-6653.

[8] Liu Ce. Beyond pixels: exploring new representations and applications for motion analysis [D]. Cambridge, MA: Department of Electrical Engineering and Computer Science, MIT, 2009.

[9] Elad M. Sparse and redundant representations: From theory to applications in signal and image processing [M]. New York: Springer-Verlag, 2010.

[10] Chang C C, Lin C J. LIBSVM: a library for support vector machines [J]. ACM Trans on Intelligent Systems and Technology, 2011, 2(3): 27.

[11] Bruhn A, Weickert J, Schnörr C. Lucas/Kanade meets Horn/Schunck: combining local and global optic flow methods [J]. International Journal of Computer Vision, 2005, 61(3): 211-231.

[12] Starck J L, Elad M, Donoho D L. Image decomposition via the combination of sparse representations and a variational approach [J]. IEEE Trans on Image Processing, 2005, 14(10): 1570-1582.

[13] Fadili M J, Starck J L, Bobin J, et al. Image decomposition and separation using sparse representations: an overview [J]. Proceedings of the IEEE, 2010, 98(6): 983-994.

[14] Lin Jiayin, Zhan Yinwei. Fast dictionary learning method research based on proximal gradient [J]. Application Research of Computers, 2016, 33(5): 1566-1569.

[15] Wang Jian, Kwon S, Shim B. Generalized orthogonal matching pursuit [J]. IEEE Trans on Signal Processing, 2012, 60(12): 6202-6216.

[16] Takeda H, Farsiu S, Milanfar P. Kernel regression for image processing and reconstruction [J]. IEEE Trans on Image Processing, 2006, 16(2): 349-366.

[17] Okatani T, Yoshida T, Deguchi K. Efficient algorithm for low-rank matrix factorization with missing components and performance comparison of latest algorithms [C]// Proc of IEEE International Conference on Computer Vision. Washington DC: IEEE Computer Society, 2011: 842-849.

[18] Cai Jianfeng F, Candès E J, Shen Zuowei. A singular value thresholding algorithm for matrix completion [J]. SIAM Journal on Optimization, 2010, 20(4): 1956-1982.

[19] Shi Jiarong, Zheng Xiuyun, Wei Zongtian, et al. Survey on algorithms of low-rank matrix recovery [J]. Application Research of Computers, 2013, 30(6): 1601-1605.

[20] Adobe Systems Inc. After Effects CS6, San Jose, CA, USA, 2012.

[21] Sheikh H R, Sabir M F, Bovik A C. A statistical evaluation of recent full reference image quality assessment algorithms [J]. IEEE Trans on Image Processing, 2006, 15(11): 3440-3451.

[22] Wang Zhou, Bovik A C, Sheikh H R, et al. Image quality assessment: from error visibility to structural similarity [J]. IEEE Trans on Image Processing, 2004, 13(4): 600-612.

[23] Wang Zhou, Simoncelli E P, Bovik A C. Multi-scale structural similarity for image quality assessment [C]// Proc of the 37th Asilomar Conference on Signals, Systems & Computers. Piscataway, NJ: IEEE Press, 2003: 1398-1402.

[24] Sheikh H R, Bovik A C. Image information and visual quality [J]. IEEE Trans on Image Processing, 2006, 15(2): 430-444.

[25] Zhang Lin, Zhang Lei, Mou Xuanqin, et al. FSIM: a feature similarity index for image quality assessment [J]. IEEE Trans on Image Processing, 2011, 20(8): 2378-2386.

[26] Wang Zhou, Bovik A C. A universal image quality index [J]. IEEE Signal Processing Letters, 2002, 9(3): 81-84.

Note: Figure translations are in progress. See original paper for figures.