Perceptual Image Quality Enahncement for Solar Radio Image

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ABSTRACT

In solar radio observation, the visualization of data is very important since it can more intuitively and clearly deliver interest information of solar radio activities to astronomers. As to visualization, we highly expect good visual quality of images/videos in favor of the discovery of solar radio events recorded by observation data. The existing imaging system cannot guarantee good visual quality of solar radio data visualization. In this paper, an image quality enhancement algorithm is developed to improve solar radio extreme ultraviolet (EUV) images from Solar Dynamics Observatory (SDO). Firstly, the guided filter is employed to smooth image, which outputs an image with good skeleton and edges. Since the fine structures of solar radio activities are embedded in high frequency components of a solar radio image, we propose a novel structure preserving filtering to amplify the different signal of original input image subtracting smoothed one. Afterwards, fusing the amplified details and smoothed one together, the final enhanced image is generated. The experimental results prove that the image quality is significantly improved by using the proposed image quality enhancement algorithm.

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Index Terms—Solar radio astronomy, image enhancement, guided filter, perceptual visual quality

1. INTRODUCTION

The Solar Dynamics Observatory (SDO) [1] is a NASA mission, which was launched on Feb. 11, 2010. Its goal is to understand the influence of the Sun on the Earth and near-Earth space by studying the solar atmosphere on small scales of space and time, and in many wavelengths. The Atmospheric Imaging Assembly (AIA) aboard Solar Dynamics Observatory (SDO) produces high resolution and high dynamic range images of the corona in the extreme ultraviolet (EUV) channels. An image with 4096×4096 pixels is captured for each 12 seconds. The angular resolution can reach 0.6 second of arc. As such, AIA provides unprecedented views of the various phenomena that occur within the evolving solar outer atmosphere. AIA also records the movies of solar activities. These movies can be found on http://sdowww.lmsal.com/suntoday/.

Due to the interference of instruments and electromagnetic environment, the recorded movies may contain severe noises, including impulse noise, addictive Gaussian noise, and other kinds of noises, which impede human understanding about solar radio activities. Therefore, many algorithms were introduced or proposed to alleviate the noise and meanwhile improve image/video quality. Bilateral filter is one of the state-of-the-art techniques to remove noise and preserve edges at the same time. It was widely used in various tasks of image processing, including denoising [2], High Dynamic Range (HRD) image compression [3], multiscale detail decomposition [4], and image abstraction [5]. However, bilateral filter has some flaws. First, it has been noticed that the bilateral filter may suffer from "gradient reversal" artifacts. Second, the bilateral filter is concerning the issue of computational efficiency. A brute-force implementation is $O(Nr^2)$ time with kernel radius r. In [3], Durand *et al.* proposed a piece-wise linear model and enable FFT-based filtering to reduce computational complexity. In [6], Paris *et al.* formulates the gray-scale bilateral filter as a 3D filter to speed up if the Nyquist condition is approximately true.

From astronomy study, the most important information of solar radio activity is embedded in high spatial frequencies of an image. Usually, high spatial frequencies are the details of an image, and low frequencies are corresponding to image skeleton. The details of a solar radio image express critical information about solar radio activities. The traditional image denoising and enhancement algorithms on natural images do not satisfy the mission of solar radio image processing. In this paper, we employ the guided filter for solar radio image/video quality enhancement. Our task is to remove the impulse noise in solar radio movies of AIA SDO and meanwhile improve perceptual image/video quality, especially the details of images which usually undergo noises and low contrast. The guided filter removes possible noises during the process of smoothing image, and also preserves edges of objects. The output of guided filter shows a good image skeleton, and the difference between original image and filtered one contains image details which express fine structures of solar radio activities. The details are enhanced by multiplying an amplification factor. The final enhanced image is the combination of the output of guided filter the amplified details. Besides, we observe the severe impulse noise in the movies. Therefore, the median filter is employed to remove impulse noise before the guided filter.

The remaining content of this paper is arranged as follows. Section 2 reviews the related work on edge-preserving image filtering methods. Section 3 presents the proposed image enhancement algorithm for processing images and videos of AIA SDO. Experimental results are provided in Section 4. Finally, the conclusion is given in Section 5.

2. RELATED WORK

A number of image filtering methods have been proposed to process images with noises, low contrast, and some other problems degrading the human visual perception. A good image filtering method is expected to well preserve critical edges of image while removing noises, which was named edge-preserving filtering.

The bilateral filter [7] is the simplest and most intuitive one among the weighted-average filters. For each pixel, it computes the average of neighboring pixels, weighted by the Gaussian of both spatial and intensity distance. The benefit of bilateral filter lies in the consideration of intensity distance, which makes it different from general Gaussian and Laplacian filters, and therefore presents the ability of edge-preserving. The bilateral filter can help smooth the image while preserve edges, which is widely used in noise reduction [2], HDR compression [3], multiscale detail decomposition [4], image abstraction [5], and so on. In [8], a joint generalized bilateral filter is proposed, where the weights are computed from another guidance image rather than the filtering input, which can be further employed for flash/no-flash denoising [8], image upsampling [9], image deconvolution [10], stereo matching [11], etc. However, the bilateral filter may suffer from the "gradient reversal" artifacts, as discussed in [3], [12] and [13]. On one hand, a pixel has few similar pixels around it. As such, the Gaussian weighted average may be unstable. In this case, the results may exhibit unwanted and unpleasant profiles around the edges. On the other hand, the efficiency of the bilateral filter needs to be considered.

Another thread of work treats the image filtering as an inverse problem by an inverse matrix process, such as the haze removal in [19]. Moreover, the weighted least squares filter in [13] further adjusts the matrix affinities according to the image gradients and produces halo-free edge-preserving smoothing. However, solving the linear system is time-consuming, even though these optimization-based approaches can produce high quality results. More specifically, the direct solvers, such as Gaussian elimination, are not practical due to the memory-demanding "filled in" problem [20], [21], while iterative solvers, such as conjugate gradients [20] are too slow to converge.

3. THE PROPOSED IMAGE ENHANCEMENT

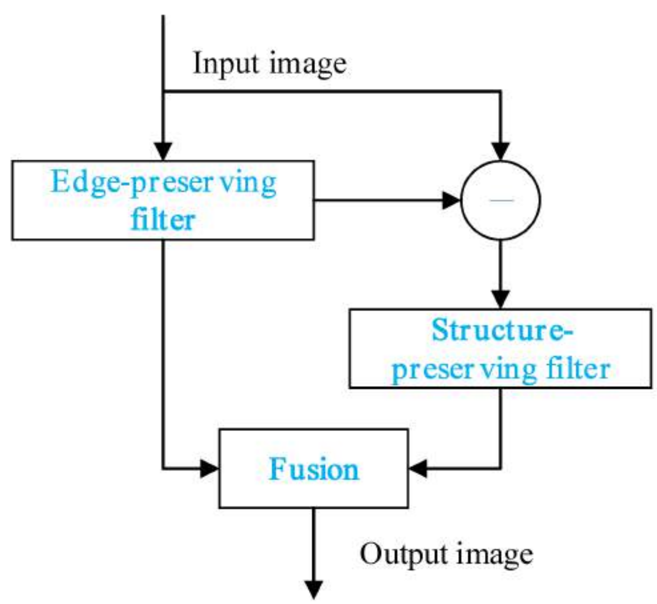


Fig. 1 The flowchart of the proposed image enhancement algorithm

The proposed image enhancement composes of three components: edge-preserving filtering, structure-preserving filtering and fusion of these two outputs. The algorithm flowchart is illustrated in Fig. 1. The input image is firstly filtered by an edge-preserving filter, specifically guided filter in this paper. Then, the detail signal deriving from the difference between original input image and filtered output of edge-preserving filter is further filtered by using a structure-preserving filter stated in section 3.2. Finally, the outputs of the two filters are fused to generate the final enhanced image.

3.1 Guided Filtering

A general explicit weighted-average filter is defined by

$$q_i = \sum_j W_{ij}(I) p_j \,, \tag{1}$$

q_i represents filtering output at a pixel i, p is input image for filtering, I is guidance image, and W represents filter kernel which is a function of guidance image I. The guidance image and input image could be identical. From (1), the filter is linear with respect to p. An example of such a filter is the joint bilateral filter [8].

An implicit weighted-average filter is to resolve a linear system in the form:

$$Aq = p \tag{2}$$

where q and p are N-by-1 vectors concatenating $\{q_i\}$ and $\{p_i\}$, respectively, and A is an N-by-N matrix only depends on I. The solution of (2) is $q = A^{-1}p$, which has the same form as (1).

A key assumption for guided filter is a local linear relation between the guidance I and the filtering output q. It is assumed that q is a liner transform of I in a window ω_k centered at the pixel k:

$$q_i = a_k I_i + b_k, \forall i \in \omega_k \,, \tag{3}$$

where a_k, and b_k are model coefficient assumed to be constant in ω_k which is a square window of a radius r.

To determine the linear coefficients in (3), we need constraints from the filtering input p. It is assumed that the input p is the output q contaminated by the noise n: $p=q+n$. Then, we seek a solution that minimizes the difference between q and p while maintaining the linear model (3). Specifically, we minimize the following cost function in the window ω_k:

$$E(a_k, b_k) = \sum_{i \in \omega k} ((a_k I_i + b_k - p_i)^2 + \varepsilon a_k^2) \tag{4}$$

where ε is a regularization parameter penalizing large a_k. (4) is the linear ridge regression model [26][27], and its solution is given in [24] by

$$a_k = \frac{\frac{1}{|\omega|}\sum_{i \in \omega_k} I_i p_i - \mu_k k \overline{p}_k}{\sigma_k^2 + \varepsilon} \tag{5}$$

$$b_k = \overline{p}_k - a_k \mu_k$$

where μ_k and σ_k^2 are the mean and variance of I in ω_k, $|\omega|$ is the number of pixels in ω_k, and $\overline{p}_k$ is the mean of p in ω_k. Since a pixel i is involved in all the overlapping windows that cover I, so q_i is not identical when it is computed by (3) in different windows. The filtering output is to average all the possible values of q_i, so (3) is rewritten as

$$q_i = \frac{1}{|\omega|} \sum_{k | i \in \omega_k} \left(a_k I_i + b_k \right) \tag{6}$$

Noticing that $\frac{1}{|\omega|} \sum_{k | i \in \omega_k} a_k = \frac{1}{|\omega|} \sum_{k \in \omega_i} a_k$ due to the symmetry of the box window, (6) is rewritten as

$$q_i = \overline{a}_i I_i + \overline{b}_i \tag{7}$$

where $\overline{a}_i = \frac{1}{|\omega|} \sum_{k \in \omega_i} a_k$ and $\overline{b}_i = \frac{1}{|\omega|} \sum_{k \in \omega_i} b_k$ are the average coefficients of all windows overlapping i.

3.2 Structure Preserving Filtering

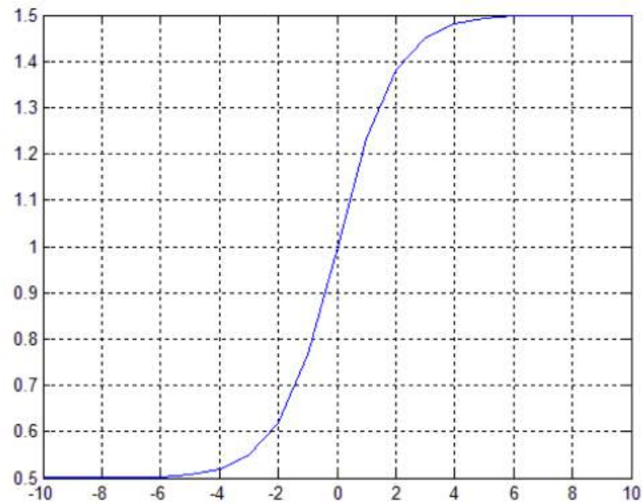


Fig. 1. The profile of scale factor used for enlarging detail signal

After guided filtering, the detail signal representing fine structures of an image is obtained by original image subtracting guided-filtered one. To enhance the fine structures while suppressing noises, we process the details differently by using different scale factor. We divide detail signal into three categories: high, median and low variance/contrast areas. For low variance, it possibly contains noises, for high variance indicate good contrast, and it does not need enhance. We enlarge the median variance, which is assumed to be with important details. An image enhancement strategy is design as follows: 1) a threshold for dividing high, median and low variance areas is given by the parameter of guided filter ε: the variance less than ε is regarded to be noise.

In principle, we enlarge the areas with variance near ε, and suppress others. The reason is that low variance area possibly contains noises, and high variance area is already with good contrast. Observing the picture of sigmoid function shown in Fig. 1, it satisfies our purpose. So a scale factor is defined as

$$s(x) = 0.5 + \frac{1}{1+\exp(-x+\varepsilon)} \ . \tag{8}$$

The parameter ε is given in (4), it makes the inflection point of $s(x)$ is at 0. Imposing (8) on the detail signal $d_i = p_i - q_i$, the contrast of median variance areas would be enhanced; the contrast of low and high variances areas would be compressed proportionally.

3.3 Fusing Smoothed Image and Enhanced Details

The outputs of the two filters mentioned above are fused to give the final enhanced image. We employ the simplest fusion, i.e., weighted summation as

$$f_i = q_i + K \times s(d_i) \times d_i ; \ \ d_i = p_i - q_i \ , \tag{9}$$

where K is the enhancement strength given by users. The value of K ranges from 4 to 16 for most applications. In addition, it is highly related with specific application, so it is designed to be an input parameter in the proposed algorithm.

4. EXPERIMENTAL RESULTS

For evaluating the proposed algorithm for good performance on edge preserving and quality improvement. We realized it using Matlab. In addition, a friendly interface as shown in Fig. 2 is designed for testing more conveniently.

We test the proposed algorithm on images of AIA. The original image, filtered output of guided filter, and final enhancement image are shown in Fig. 3. In Fig. 3, the left column shows original image, the middle column is the output of guided filter. It can be observed that the smoothed image is obtained by guided filter. In addition, the edges are preserved well by guided filter. It can be observed that the skeleton of objects in image can be preserved well by using guided filter. For this reason, guided filter also was integrated into softwares used to beautify pictures. The right column gives the final enhanced images. It can be observed that the fine structure of solar radio burst can be figured out more clearly. For enhancing fine details of images, the straightforward way is to enlarge the detail signal which is the difference between original images and filtered ones.

For the images of solar radio bursts, the fine structures contained in images are usually around the solar disk and bright points representing violet solar radio bursts. These fine structures are interested by the researchers. To enhance the fine structures while suppressing noises, we process the details differently by using a scale factor stated in (9). We divide detail signal into three categories: high, median and low variance/contrast areas. For low variance, it possibly contains noises. The high variance already has good contrast, and it does not need to be enhanced. We enlarge the median variance areas, which is assumed to be with important details. The parameter ε is given by the input of guided filter: the variance less than ε is regarded to be noise, where the parameter ε indicates how much signal is considered to be noises. As shown in Fig. 2, this parameter is given by users. In practice, users can regulate it to see how is the performance, and then decide the best one for a specific task.

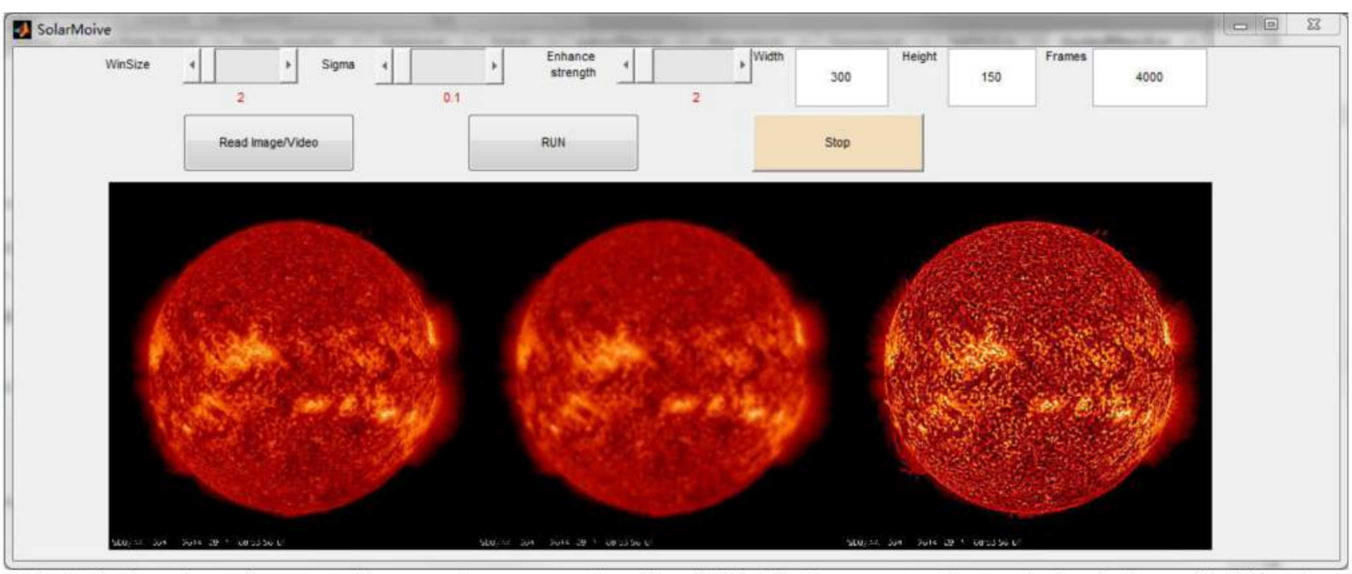
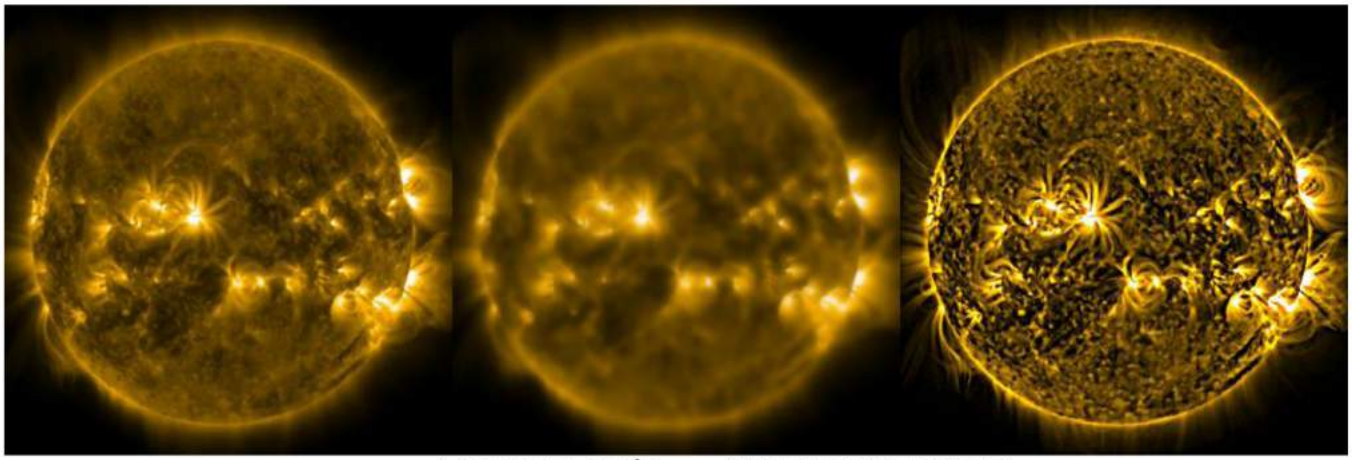
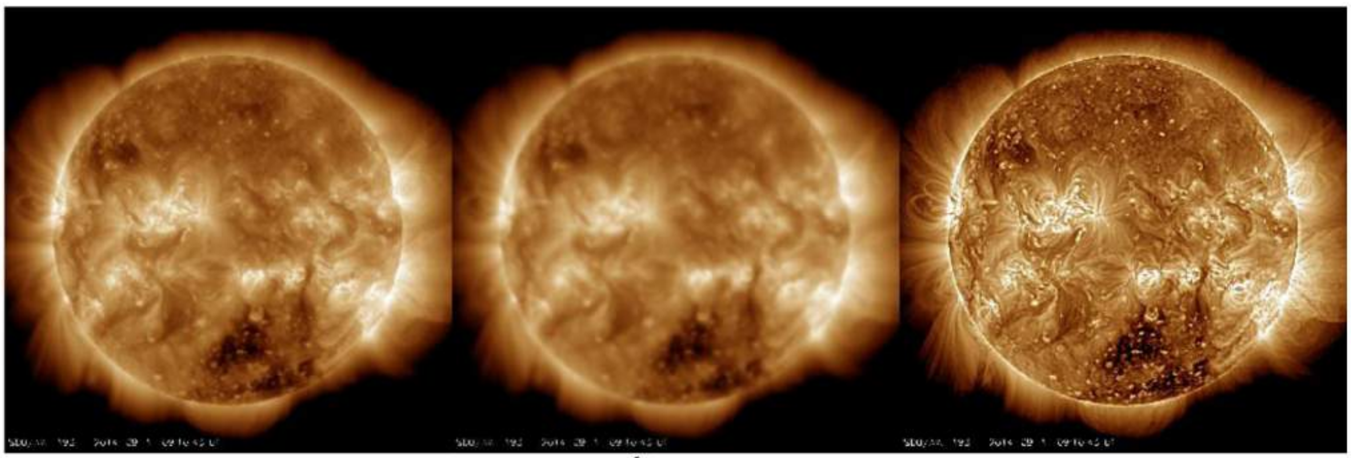


Fig. 2 The interface of proposed image enhancement algorithm ("WinSize" represents the patch size during guided filtering, "Sigma" is the input parameter of guided filter ε, "Enhancement Strength" is a scale factor to enlarge the strength of detail signal, which is denoted as K in (9), "Width" and "Height" represent the resolution of input image/video, "Frames" is the number of frames of input video)



(a) SDO AIA 171Å image (2014-09-17 09:11:36 UT)



(b) SDO AIA 193Å image (2014-09-17 09:10:43 UT)

(c) SDO AIA 171Å video

(d) Supernovae in universe (A picture from Internet)

Fig. 3 The guided filtering image and enhanced image (For comparison, original image is shown in the left column, the median column shows the result of guided filtering, and the right column gives the enhanced image by using the proposed algorithm)

5. CONCLUSIONS

This paper presented a guided filter based image enhancement algorithm for solar radio image processing. By using guided-filter, the images of solar radio observation can be better smoothed. To enhance details of signal, the difference signal is enlarged by using an adaptive scale guided by a given threshold. The better subjective image quality is obtained by the proposed method.

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REFERENCES

[1] http://sdo.gsfc.nasa.gov/

[2] C. Liu, W.T. Freeman, R. Szeliski, and S.B. Kang, "Noise Estimation from a Single Image," Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2006.

[3] F. Durand and J. Dorsey, "Fast Bilateral Filtering for the Display of High-Dynamic-Range Images," Proc. ACM Siggraph, 2002.

[4] R. Fattal, M. Agrawala, and S. Rusinkiewicz, "Multiscale Shape and Detail Enhancement from Multi-Light Image Collections," Proc. ACM Siggraph, 2007.

[5] H. Winnemo ¨ller, S.C. Olsen, and B. Gooch, "Real-Time Video Abstraction," Proc. ACM Siggraph, 2006.

[6] S. Paris and F. Durand, "A Fast Approximation of the Bilateral Filter Using a Signal Processing Approach," Proc. European Conf. Computer Vision, 2006.

[7] C. Tomasi and R. Manduchi, "Bilateral Filtering for Gray and Color Images," Proc. IEEE Int'l Computer Vision Conf., 1998.

[8] G. Petschnigg, M. Agrawala,H. Hoppe, R. Szeliski, M. Cohen, and K. Toyama, "Digital Photography with Flash and No-Flash Image Pairs," Proc. ACM Siggraph, 2004.

[9] J. Kopf, M. Cohen, D. Lischinski, and M. Uyttendaele, "Joint Bilateral Upsampling," Proc. ACM Siggraph, 2007.

[10] L. Yuan, J. Sun, L. Quan, and H.-Y. Shum, "Progressive Inter-Scale and Intra-Scale Non-Blind Image Deconvolution," Proc. ACM Siggraph, pp. 74:1-74:10, 2008.

[11] K.-J. Yoon and I.S. Kweon, "Adaptive Support-Weight Approach for Correspondence Search," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 28, no. 4, pp. 650-656, Apr. 2006.

[12] S. Bae, S. Paris, and F. Durand, "Two-Scale Tone Management for Photographic Look," Proc. ACM Siggraph, 2006.

[13] Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski, "Edge-Preserving Decompositions for Multi-Scale Tone and Detail Manipulation," Proc. ACM Siggraph, 2008

[14] R. Fattal, "Edge-Avoiding Wavelets and Their Applications," Proc. ACM Siggraph, 2009.

[15] E.S.L. Gastal and M.M. Oliveira, "Domain Transform for Edge- Aware Image and Video Processing," ACM Trans. Graphics, vol. 30, no. 4, pp. 69:1-69:12, 2011.

[16] L. Grady, "Random Walks for Image Segmentation," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 28, no. 11, pp. 1768- 1783, Nov. 2006.

[17] A. Levin, D. Lischinski, and Y. Weiss, "Colorization Using Optimization," Proc. ACM Siggraph, 2004.

[18] A. Levin, D. Lischinski, and Y. Weiss, "A Closed Form Solution to Natural Image Matting," Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2006.

[19] K. He, J. Sun, and X. Tang, "Single Image Haze Removal Using Dark Channel Prior," Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2009

[20] Y. Saad, Iterative Methods for Sparse Linear Systems. SIAM, 2003.

[21] R. Szeliski, "Locally Adapted Hierarchical Basis Preconditioning," Proc. ACM Siggraph, 2006.

[22] W.L. Briggs, V.E. Henson, and S.F. McCormick, A Multigrid Tutorial, second ed. SIAM, 2000.

[23] M. Elad, "On the Origin of the Bilateral Filter and Ways to Improve It," IEEE Trans. Image Processing, vol. 11, no. 10, pp. 1141- 1151, Oct. 2002

[24] K. He, J. Sun, and X. Tang, "Guided image filtering," IEEE Trans. Pattern Anal. Mach. Intell., vol. 6311, no. 1, pp. 1-14, 2010.

[25] A. Zomet and S. Peleg, "Multi-Sensor Super Resolution," Proc. IEEE Workshop Applications of Computer Vision, 2002.

[26] N. Draper and H. Smith, Applied Regression Analysis, second ed. John Wiley, 1981.

[27] T. Hastie, R. Tibshirani, and J.H. Friedman, The Elements of Statistical Learning. Springer, 2003.