

Real-Time Spatially Adaptive Image Restoration Using Truncated Constrained Least Squares Filter

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Abstract-- A finite impulse response (FIR) filter design method is presented by truncating the constrained least squares filter for real-time, spatially adaptive image restoration. The proposed method truncates the original constrained least squares image restoration filter using the Maxwell-Boltzmann distribution kernel. For the edge preserving image restoration, the orientation of local edge is analyzed based on the covariance matrix, and the edge orientation-adaptive restoration filters are generated. The reduced size of the FIR type restoration filter makes hardware implementation easier for real-time image enhancement. Experimental results show that the proposed method provide more detail and less restoration artifacts than existing methods. As a result, the proposed restoration filter can be applied to real-time image enhancement systems, such as high-definition televisions and video surveillance systems.

I. INTRODUCTION

Recently, real-time image restoration has been used in various applications including digital televisions and video surveillance systems, which have inherent image degradation problems such as motion blur, out-of-focus blur, and noise in the image acquisition process. Various image restoration algorithms have been proposed in literatures to solve these image degradation problems. While sophisticated image restoration algorithms are developed in the frequency domain or in the iterative manner, they are not suitable for low-cost, compact consumer imaging devices.

Image restoration algorithms in the frequency domain are conceptually simple, and easy to implement by software simulation because of the special characteristics of the Fourier transform. However, they usually exhibit ringing artifacts since abrupt changes at the edge of an image do not satisfy the periodic assumption of the discrete Fourier transform (DFT). Multiple frame-based and iterative type image restoration algorithms can provide better restored results including spatially adaptive enhancement functions at the cost of the indefinite processing time for the iterative minimization of the pre-defined energy function.

To combine advantages of both the frequency-domain and iterative-type image restoration algorithms, a novel finite impulse response (FIR) image restoration filter design method is presented by truncating the constrained least squares (CLS) filter [1]. The truncated constrained least squares (T-CLS)

filter can restore image details in the spatially adaptive manner. The FIR structure of the proposed restoration filter is particularly suitable for consumer imaging devices because of its real-time implementation without any high-cost frame memories.

II. THE PROPOSED DESIGN METHOD FOR FIR IMAGE RESTORATION FILTER

This section describes the process of designing FIR filter using CLS filter. A point spread function (PSF) is assumed to be known.

The CLS filter is truncated by various kernels in order to reduce energy loss in the middle and to smooth out the surroundings of the filter. Although the traditional Gaussian kernel has a higher energy loss in the middle of the CLS filter than the cosine kernel, it has lower ringing artifacts because of the smooth truncation around the filter. On the other hand, the traditional cosine kernel has a higher ringing than the Gaussian kernel, but it has a lower energy loss in the middle of the filter [1]. This paper proposes the Maxwell-Boltzmann distribution kernel that has all the advantages of the traditional kernel.

The proposed two-dimensional kernel is defined as

$$K(x, y) = \frac{1}{1 + \exp\left(\frac{x^2 + y^2 - d^2}{\sigma}\right)}, d = \alpha\mathcal{N}, \sigma = \beta(\mathcal{N} - 2d), (1)$$

where \mathcal{N} represents the filter size. σ controls the slope gradient of the kernel. As the standard deviation increases, the slope gradient gets lower. d controls the position of the median value of slopes. The two ranges: $0.35 < \alpha < 0.50$ and $0.8 < \beta < 1.0$ have optimal σ and d to minimize energy loss in the middle of the filter and to truncate around the filter smoothly. Fig. 1 shows the shape of the proposed kernel according to changes of σ and d .

The proposed kernel in Fig. 1 is found to have a less energy loss in the middle of the filter than the traditional cosine kernel, and at the same time it is smoothly truncated around the filter like the one in the traditional Gaussian kernel.

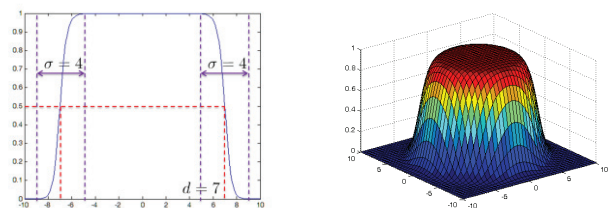


Fig. 1. The proposed kernel.

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III. EDGE PRESERVING IMAGE RESTORATION

This section describes the edge preserving image restoration algorithm to estimate the local orientation. When images are restored with the directional adaptive method, edges are naturally restored.

The directional kernel is created by estimating the local orientation using the covariance matrix [2]. The directional T-CLS filter is created by performing the convolution of the directional kernel and the T-CLS filter is proposed in section 2.

The Gaussian-based directional steering kernel is defined as

$$K_S(x, y) = \frac{\sqrt{\det(W)}}{2\pi\sigma^2} \exp\left(-\frac{(\mathbf{x}_m - \mathbf{x})^T W (\mathbf{x}_m - \mathbf{x})}{2\sigma^2}\right), \quad (2)$$

where m -th $\mathbf{x} = [x_m, y_m]^T$, and σ is the smoothing parameter which controls the Gaussian distribution. The covariance matrix W can be decomposed into three components as follows

$$W = \gamma U_\theta \Lambda U_\theta^T, U_\theta = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}, \Lambda = \begin{bmatrix} q & 0 \\ 0 & q^{-1} \end{bmatrix}, \quad (3)$$

where U_θ is the rotation matrix, and Λ is the elongation matrix. γ , θ , and q respectively, control elongation, rotation, and scale for calculating the covariance matrix [2].

Denote the local estimate of the gradient of image $f_L(x, y)$ by

$$\nabla f_L(m) = [\partial f_L(x_m, y_m)/\partial x, \partial f_L(x_m, y_m)/\partial y]^T. \quad (4)$$

The gradient field is divided into local blocks to estimate the local orientation [3].

$$G = [\nabla f(1) \quad \nabla f(2) \quad \cdots \quad \nabla f(M)]^T, \quad (5)$$

where M is the number of pixels in local blocks, and G is the $M \times 2$ matrix. γ , θ , and q are obtained by performing the singular value decomposition (SVD) on the matrix G in order to calculate the covariance matrix [4]. Fig. 2 shows the directional T-CLS filter created by convolution of the estimated directional kernel and the T-CLS filter.

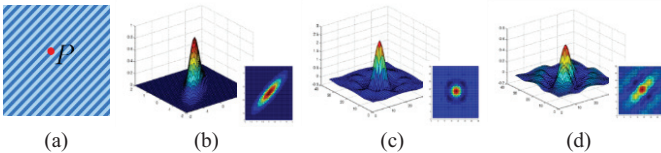


Fig. 2. (a) An image of the diagonal pattern, (b) the directional kernel on point P of the image (a), (c) the T-CLS filter, (d) the directional T-CLS filter.

IV. EXPERIMENTAL RESULTS

Overall, these experiments show the advantages of the proposed technique compared to the traditional method. The original image was degraded by Gaussian PSF in order to show that the proposed method is more reliable for restoration.



Fig. 3. Image restoration with T-CLS filters using (a) the Gaussian kernel [1] (PSNR: 26.21, SSIM: 0.9005), (b) the cosine kernel [1] (PSNR: 27.73, SSIM: 0.9204), and (c) the proposed kernel (PSNR: 28.29, SSIM: 0.9271).

Fig. 3 shows the experimental results restored by using the traditional kernels and the proposed kernel with the Maxwell-Boltzmann distribution. The size of the T-CLS filter is 13×13 , and the standard deviation of the Gaussian distribution PSF is set to 1.5.

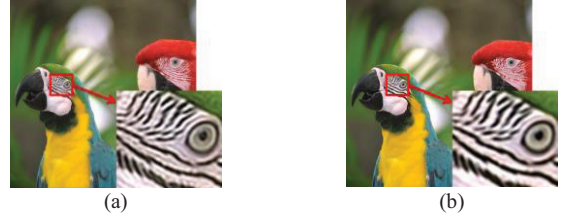


Fig. 4. Image restoration using (a) the T-CLS filter (PSNR: 30.61, SSIM: 0.9176), (b) the proposed directional T-CLS filter (PSNR: 31.73, SSIM: 0.9309).

The performance of the T-CLS filter and directional T-CLS filter is compared as shown in Fig. 4. The size of T-CLS filter is 11×11 . It can be found that the edges are more natural in Fig. 4(b) than Fig. 4(a).

V. CONCLUSION

The Maxwell-Boltzmann distribution kernel is used to truncate the original CLS image restoration filter. The proposed truncation method preserves a set of main lobes from the original CLS filter given a finite filter support. Various versions of the T-CLS filter are also presented for directionally adaptive image restoration using the local covariance matrix. Spatially selective application of the multiple-direction T-CLS filters can restore the edge details in the input image in real-time. Experimental results demonstrate that the proposed set of FIR T-CLS restoration filters outperform the existing restoration methods in the sense that they can restore edge details and provide applicable efficiency.

REFERENCES

- [1] S. Kim, S. Jun, E. Lee, J. Shin, and J. Paik, "Real-time bayer-domain image restoration for an extended depth of field (EDoF) camera," *IEEE Trans. Consumer Electronics*, vol. 55, no. 4, pp. 1756-1764, November 2009.
- [2] H. Takeda, S. Farsiu, and P. Milanfar, "Kernel regression for image processing and reconstruction," *IEEE Trans. Image Processing*, vol. 16, no. 2, pp. 349-366, February 2007.
- [3] X. Feng and P. Milanfar, "Multiscale principal components analysis for image local orientation estimation," *Proc. 36th Asilomar Conf. Signals, Systems and Computers*, vol. 1, pp. 478-482, November 2002.
- [4] J. Jeon, I. Yoon, D. Kim, J. Lee, and J. Paik, "Fully digital auto-focusing system with automatic focusing region selection and point spread function estimation," *IEEE Trans. Consumer Electronics*, vol. 56, no. 3, pp. 1204-1210, August 2010.