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A Novel method for Unified Blind motion Deblurring of single / multi image / video using blur Deconvolution

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Abstract— A unified blind method for single/multi image blur deconvolution and super-resolution of the images or videos. This paper proposes a method based on alternating minimization (AM) with respect unknown high-resolution (HR). Edge-emphasizing smoothing operation supports blur estimation process, to enhance strong soft edges and filtering out weak structures which improves the quality of blur estimation. In every iteration, parameters are updated, so that all salient edges are used to increase blur estimation. Filtering domain is used rather than pixel domain to improve blur estimation. Processing time of super-resolution is comparatively increased by separating upsampling and registration process.

Keywords— Blur decovolution, High resolution, Edge emphasizing, Blur estimation, Filtering domain.

I. INTRODUCTION

Image capturing devices with lack of sensitivity is failing to capture high resolution images. High resolution images are widely popular in many applications such as photography, astronomy, medical imaging, etc,. Present days we have cameras to capture high resolution images but they are very expensive. Computational imaging systems are in contrast with traditional imaging system, which combines the power of digital processing with data gathering. Blurring, aliasing and noise may affect spatial resolution which can be visually determined.

Imaging system uses two methods Blur deconvolution (BD) and Super-resolution (SR) to increase resolution. BD removes blurring and noise, where as SR reduces effect of aliasing. SR also increases size of the image. Super-resolution (SR) is a technique that enhances the resolution of an imaging system. It is a process of combining multiple low resolution images to form a high resolution image. Fig.1 shows how original image resolution is increased.

Fig. 1. Example for Superresolution.

In image processing, a **kernel**, **convolution matrix**, or **mask** is a small matrix useful for blurring, sharpening, embossing, edge-detection, and more. This is accomplished by means of convolution between a kernel and an image. Fig.(2) and (3) Blur deconvolution is a process used to reverse the effects of convolution.

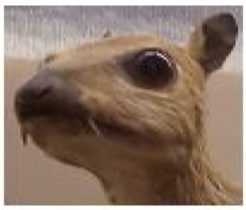
Original	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	

Fig. 2. Matrix of an original image

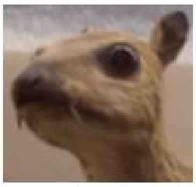
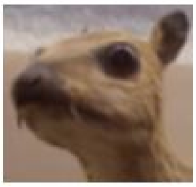
Blur*	$\begin{bmatrix}1 & 2 & 1\\ 2 & 4 & 2\\ 1 & 2 & 1\end{bmatrix}$	
	$\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$	

Fig. 3. After applying convolution matrix, image blurred.

II. RELATED WORKS

Image captured by adjusting the quality of the reconstructed image according to its information [1]. Multi-image super-resolution (MISR) methods reconstructs one HR image by fusing multiple LR images [2]-[3]. Single-image super-resolution (SISR) proposed small spatial patches in the input LR image are replaced by similar higher resolution patches which are previously extracted from a number of HR images.

SISR methods do not require motion and blur estimation processes, but have a lower performance compare to MISR [5]. Most BD reconstructed from a single image (SIBD). However, Multi image BD (MIBD) is used to improve the reconstruction performance. Most of the publications on BD/SR are non-blind. Non-blind method considers blur identification explicitly during reconstruction. Most of the methods assume PSFs are prior known. Few other works considers amount of blur can be ignored and can be omitted from the reconstruction. These assumptions are impractical in real world. Based on two categories these papers are classified as: method which considers blur identification and image restoration as different process [6],[7],[8],[9], and method which combines these two methods as unified process, e.g. alternating minimization (AM) [10], [11]-[15].

In this paper, unified approach is proposed for blind SR, SIBD, and MIBD reconstructions. Huber-Markov random field (HMRF) model is used prior for cost function of output HR image. This prior suppress noise, while edges and structures are preserved without causing noticeable ringing. In the proposed blur (kernel) estimation there are three important facts: 1) In blur estimation edges and their neighboring edges are more useful; 2) Blur estimation is more accurate to start with few salient edges and allow more and more progressively contribute; 3) Blur estimation is more efficient in filtering domain than pixel domain.

III. PROPOSED METHOD

For all SR, LR images are assumed to be having identical PSF's and noise:

$$g_k = D_k H S_k f + n_k \qquad \textbf{(1)}$$

Where, H is block circulant matrix with circulant blocks (BCCB). While PSF is assumed linear space-invariant (LSI) and periodic boundary conditions are assumed. Product of H and are commutable for all the pixels. In Non-linear interpolation images are reconstructed my scaling up LR image size to original image. Every LR image has different PSF's (Point Spread Function) due to dissimilar camera parameters. Original image PSF's are estimated to analyse the pixel location.

Edge emphasizing operation applied o\n estimated images. Blur(s) are estimated by adjacent pixels and salient edges, so that weak edges are smoothed out. Edge emphasizing method is applied in all iterations of AM. This method is more effective than other existing method. Experimentally it is proved that Blur is estimated by filtering domain using the gradients of HR and LR images produces accurate results than pixel domain [6]. Fig.4 (b) shows blurred image.

Hence, for the blur estimation following cost is used:

$$J(h^n) = \sum_{k=1}^{N}\sum_{i=1}^{2}\left\| C iz - C i S^n h_k^n \right\|^2 + \gamma \sum_{k=1}^{N}\sum_{j=1}^{4}\left\| Bj\ h_k^n \right\| \qquad \textbf{(2)}$$

Here $\mathbf{C}_1$ and $\mathbf{C}_2$ are the convolution matrices of the gradient in filtering domain. These c_1 and c_2 are in the horizontal and vertical directions, and S_n is the convolution matrix of S^n. In (2) γ is fixed for every AM iterations

(a) (b) (c)

Fig. 4. (a) Ground-truth image. (b) Blurred image. (c) Reconstruction of image from proposed method.

Where $k = 1, \ldots, N$, $F(.)$, and $F^{-1}(.)$ denote FFT and inverse-FFT operations, and $(\cdot)$ is the complex conjugate operator. We use the MATLAB function edgetaper $(\cdot)$to avoid boundary artifacts. After applying few AM iterations at each level, Bilinear interpolation is used to up sample the estimation results. This increases speed of processing.

IV. PROPOSED METHOD RESULTS

Performance of the proposed method is increased on both synthetic and real-life image sets. The gk is represented by Signal-to-noise ratio which defines severity of noise in the kth LR image.

$$SNR_{dB}^{k} = 10log_{10}\left(\frac{\sigma_{gk}^{2}}{\sigma_{nk}^{2}}\right) \qquad (4)$$

For deconvoution of the image, Fourier domain is used as:

$$= F^{-1}\left(\left[\sum_{l=1}^{2}\overline{[F(C_l)\times F\times(S^n)]}\times[F(C_l)\times F(z)]\right] / \left[\sum_{l=1}^{2}\left|F(C_l)\times F(S^2)\right|^2+\gamma\sum_{j=1}^{4}\left|F(b_j)\right|^2\right]\right) \qquad (5)$$

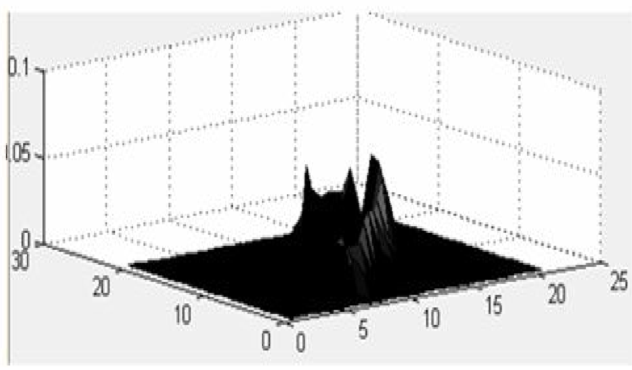


Fig.5. Original image PSF's

Here σ_{gk}^2 and σ_{nk}^2 are the variances of kth LR image and noise, respectively. The image restoration is measured by the peak signal-to-noise ratio (PSNR) between the ground-truth and reconstructed HR images. For an image with a

$$NMSE(\tilde{h}) = \frac{\|h - \tilde{h}\|^2}{\|h\|^2} \qquad (6)$$

$$PSNR(\hat{f}) = 10log_{10}\left(\frac{255^2}{\frac{1}{N_f}\|f - \hat{f}\|^2}\right) \qquad (5)$$

maximum intensity level of 255, this metric is defined as: Also, the quality of PSF restoration is evaluated by the normalized mean squared error (NMSE) between the true and estimated blurs: A few important points should be considered from these metrics. First, the above two metrics are not computable for real blurry images, because ground-truth images are only accessible in synthetic experiments. Second, even if the exact blur function is known, some fine structures are permanently removed by the blur function and not recoverable by no means. As a result the value of PSNR for images which has many fine structures would be lower than for images which have only smooth regions. Third, in generally, a good algorithm is categorized by high PSNR and low NMSE.

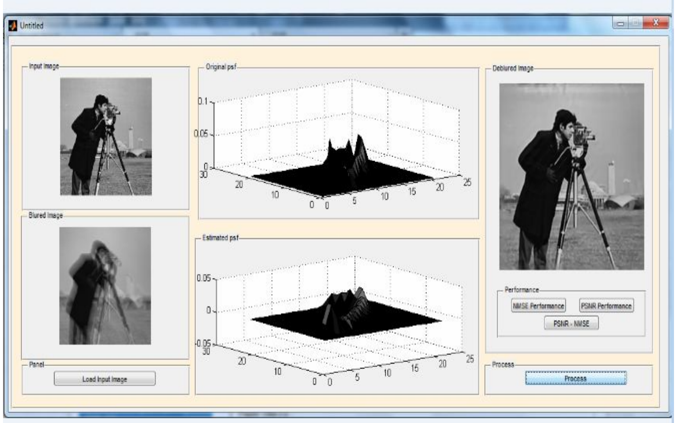


Fig.6. GUI of the proposed method.

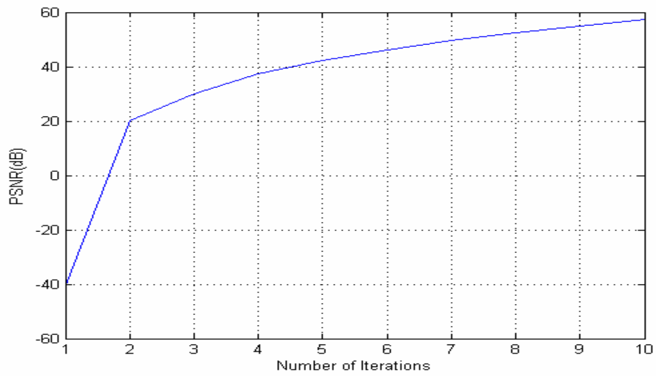


Fig.7. Variations of image PSNR.

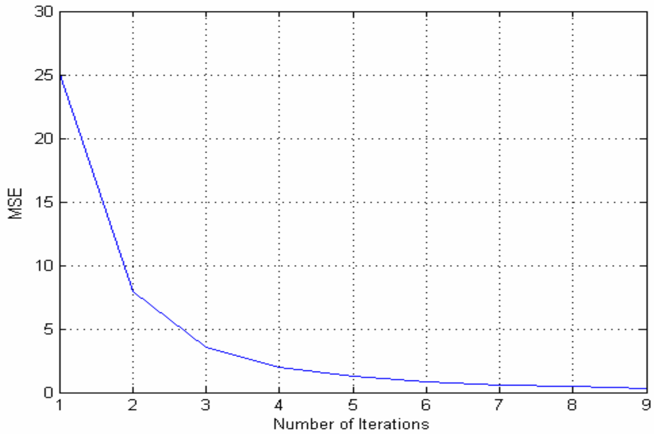


Fig.8. Blur-NMSE over iterations.

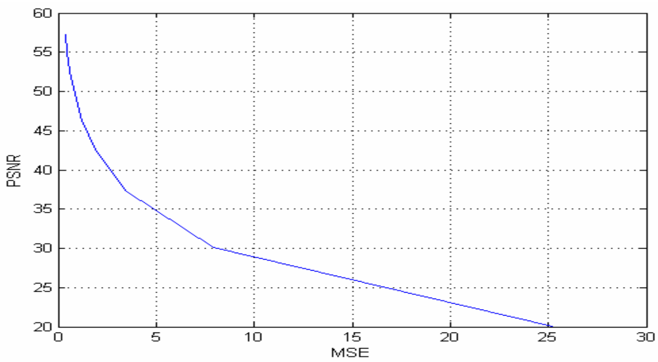


Fig.9. Variations of image-PSNR versus NMSE.

V. Conclusion

A novel blind method is presented for multi-image super-resolution (MISR), single/multi image blur deconvolution (S/MIBD). MIBD accepts multiple LR images with different blurs, without spatial displacements. In the proposed MISR method accepts number of LR images from a video with subpixel displacement but the same blur function and noise parameters used. The proposed blur estimation method preprocesses the estimated HR image by applying edge emphasizing operation. In every iteration parameters are altered so that more salient edges contributed in blur reconstruction. For blur estimation filtering domain is used which improves the performance. The future enhancement would be on video deblurring.

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References

[1] M. P. Christensen, V. Bhakta, D. Rajan, T. Mirani, S. C. Douglas, S. L. Wood, and M. W. Haney, “Adaptive flat multiresolution multiplexed computational imaging architecture utilizing micromirror arrays to steer subimager fields of view,” Appl. Opt., vol. 45, no. 13, pp. 2884–2892, May 2006.J. Breckling, Ed., The Analysis of Directional Time Series: Applications to Wind Speed and Direction, ser. Lecture Notes in Statistics. Berlin, Germany: Springer, 1989, vol. 61.

[2] S. Farsiu, M. Robinson, M. Elad, and P. Milanfar, “Fast and robust multiframe super resolution,” IEEE Trans. Image Process., vol. 13, no. 10, pp. 1327–1344, Oct. 2004.

[3] R. Schultz and R. Stevenson, “Extraction of high-resolution frames from video sequences,” IEEE Trans. Image Process., vol. 5, no. 6, pp. 996–1011, Jun. 1996.

[4] W. Dong, L. Zhang, G. Shi, and X. Wu, “Image deblurring and superresolution by adaptive sparse domain selection and adaptive regularization, IEEE Trans. Image Process., vol. 20, no. 7, pp. 1838–1857, Jul. 2011.

[5] F. Šroubek and P. Milanfar, “Robust multichannel blind deconvolution via fast alternating minimization,” IEEE Trans. Image Process., vol. 21, no. 4, pp. 1687–1700, Apr. 2012.

[6] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, “Removing camera shake from a single photograph,” ACM Trans.Graph., vol. 25, pp. 787–794, Jul. 2006.

[7] S. Cho and S. Lee, “Fast motion deblurring,” ACM Trans. Graph. (SIGGRAPH ASIA), vol. 28, no. 5, p. 145, 2009.

[8] M. Chang, A. Tekalp, and A. Erdem, “Blur identification using the bispectrum,” IEEE Trans. Signal Process., vol. 39, no. 10, pp. 2323–2325, Oct. 1991.

[9] N. Nguyen, P. Milanfar, and G. Golub, “Efficient generalized crossvalidation with applications to parametric image restoration and resolution enhancement,” IEEE Trans. Image Process, vol. 10, no. 9, pp. 1299–1308, Sep. 2001. pp. 996–1011, Jun. 1996.

[10] Q. Shan, J. Jia, and A. Agarwala, “High-quality motion deblurring from a single image,” ACM Trans. Graph. (SIGGRAPH), vol. 27, no. 3, pp. 73:1–73:10, Aug. 2008.

[11] Y. Guo, H. Lee, and C. Teo, “Blind restoration of images degraded by space-variant blurs using iterative algorithms for both blur identification and image restoration,” Image Vis. Comput., vol. 15, no. 5, pp. 399–410, May 1997.

[12] T. Chan and C.-K. Wong, “Total variation blind deconvolution,” IEEE Trans. Image Process., vol. 7, no. 3, pp. 370–375, Mar. 1998.

[13] Y.-L. You and M. Kaveh, “A regularization approach to joint blur identification and image restoration,” IEEE Trans. Image Process., vol. 5, no. 3, pp. 416–428, Mar. 1996.

[14] Y.-L. You and M. Kaveh, “Blind image restoration by anisotropic regularization,” IEEE Trans. Image Process., vol. 8, no. 3, pp. 396–407, Mar. 1999.

[15] F. Sroubek, G. Cristobal, and J. Flusser, “A unified approach to superresolution and multichannel blind deconvolution,” IEEE Trans. Image Process, vol. 16, no. 9, pp. 2322–2332, Sep. 2007.