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Single-image full-focus reconstruction using depth-based deconvolution

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Abstract. In contrast with traditional extended depth-of-field approaches, we propose a depth-based deconvolution technique that realizes the depth-variant nature of the point spread function of an ordinary fixed-focus camera. The developed technique brings a single blurred image to focus at different depth planes which can be stitched together based on a depth map to output a full-focus image. Strategies to suppress the deconvolution's ringing artifacts are implemented on three levels: block tiling to eliminate boundary artifacts, reference maps to reduce ringing initiated by sharp edges, and depth-based masking to mitigate artifacts raised by neighboring depth-transition surfaces. The performance is validated numerically for planar and multidepth objects. © 2016 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.OE.56.4.041302]

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1 Introduction

Conventional optical systems have a limited imaging capability beyond their depth-of-field (DOF) set by the numerical aperture of the optics and the pixel pitch of the focal plane array. Researchers have traditionally invested in the imaging optics and the acquisition mechanism to extend the DOF by making an imaging system that holds a depth-invariant point spread function (PSF). This has been accomplished either by reducing the imaging aperture,¹ stacking multiple images taken at different focus distances,² sweeping the focus during the image acquisition,³ performing a joint spatiotemporal optimization on a defocused video pair,⁴ or utilizing diffusion or wavefront coding photography.^{5,6} However, the insertion, modification, or even translation of optical elements may result in longer acquisition time, larger physical size, and additional monetary cost.

To avoid many of the hardware-based limitations, software-based deblurring approaches have been developed to output an all-in-focus scene from a single image captured by ordinary cameras, trading off the hardware complexity for the computational cost. This has been achieved by multiscale deconvolution,⁷ two-phase processing for edge and texture restoration,⁸ blur map estimation with sharp edge prior and guided image filter,⁹ edge detection and focus map estimation with blind deconvolution,¹⁰ and adaptive local regularization to impose edge and smoothness priors.^{11,12} Most such techniques imprecisely approximate the PSF as a two-dimensional (2-D) depth-invariant entity which leads to suboptimal restorations with ringing artifacts especially when objects included in the captured scene belong to a broad range of depth planes.

Ordinary fixed-focus cameras, such as low-end hand-held cameras, smartphone cameras, and surveillance cameras, have a depth-variant PSF that can be visualized as double

cones when focusing at finite distances or as a single cone when focusing at infinity with apex at the on-axis in-focus point located at the hyperfocal distance. Objects become progressively more defocused as their distance to the lens gets smaller than half of the hyperfocal distance.¹³ The prior knowledge of the volumetric PSF can be utilized effectively to deblur the captured image at different depth planes.

Image deconvolution is a computational technique that undoes the optical blurring to retrieve the true scene. Deconvolution, in its simplest implementation, can be carried out by a division between the captured image and the blurring kernel in the Fourier domain.¹⁴ However, several factors can inevitably cause a boost in noise and ringing artifacts in the deconvolution process: the missing boundary information that participated in the blurring process, the discontinuity between the image boundaries, the distortion of high-frequency components of the sharp edges, the division by weak kernel values in the Fourier domain (due to PSF profiles of large support when deblurring close objects for instance), and the unmatched depth planes between the image regions and the deconvolving PSF kernels. Besides the ringing artifacts, traditional deconvolution techniques also narrow the DOF as they usually blindly approximate the PSF as a 2-D depth-invariant entity.

To bypass the noninvariance PSF problem in traditional deconvolution techniques, researchers considered blending multiple deconvolutions with the invariance PSF assumption but for different profiles using evolutive merging masks.¹⁵ Some also suggested a three-dimensional (3-D) block-based restoration approach that approximates the spatial-variant imaging of thick samples using orthonormal basis decomposition of multiple PSF profiles computed at block vertices.¹⁶ Others derived the maximum-likelihood estimator based on the expectation-maximization formalism for the depth-varying image formation.¹⁷

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In this paper, we contribute to the software-based full-focus restoration literature by a single-image nonblind depth-based deconvolution technique that realizes the depth-variant nature of PSF. The developed technique computationally brings a captured blurred scene to focus at different depth planes by deconvolving it with axial slices of a precharacterized PSF volume. A full-focus image is then formed by merging the focused details across all axially deconvolved images based on a depth map prior. In addition, we contribute by a depth-based masking approach to suppress artifacts initiated by neighboring depth-transition surfaces. To our knowledge, this paper is the first to address this type of ringing artifact. In addition, we implement an efficient block tiling approach and adaptive deconvolution method to eliminate boundary artifacts and sharp edge ringing, respectively. Comparison analyses using single-depth (SD) and multi-depth (MD) objects reveal the goodness of the implemented anti-ringing strategies.

2 Depth-Based Deconvolution Technique

A 3-D object f is blurred by an imaging PSF kernel h to form an image g that is captured along with noise n . Here, h acts as a 3-D-to-2-D mapping operator as shown in the following imaging process:

$$g(x_i, y_i) = \int dz_o \iint dx_o dy_o h(x_i, y_i, x_o, y_o, z_o) f(x_o, y_o, z_o) + n(x_i, y_i),$$

where o and i subscripts denote object and image coordinates, respectively.

Realizing the depth-dependent nature of the PSF, a computational depth-based deconvolution technique is developed, shown in Fig. 1. The technique inputs the single blurred image g , the multidimensional PSF h , and a depth map, and outputs a fully focused image I . First, the blurred image is padded by interpolated smoothed blocks to eliminate the boundary artifacts. Next, the PSF volume is sliced axially into various depth planes z_d (where $d = 1, 2, \dots, N$) and fed along with the padded blurred image into an iterative adaptive nonblind deconvolution stage. The algorithm iterates to get a better estimate of the reference maps η_d

employed to locally regularize a smoothing prior, which in turns balances the suppressible ringing and the resolvable details in the deconvolved images I_{z_d} associated with the applied axial PSF slice h_{z_d} . The details in each axial deconvolved image are only brought to focus if they are located at the exact depth plane correspondent to the applied deblurring PSF slice. Finally, after an adequate number of iterations, these focused points are extracted from I_{z_d} and stitched together according to a depth map to form a full-focus image I , giving the ordinary camera an extended DOF capability. Methods such as gradient-domain fusion and graph-cut optimization¹⁸ may also be implemented to produce a seamless stitching appearance.

Note that there exist other deconvolution techniques such as depth from defocus,¹⁹ 2.5-D deconvolution,²⁰ and 3-D deconvolution techniques^{21,22} which operate on a stack of images and perform deconvolution with the PSF volume as a whole resulting in a heavy computational load. This is not the case in our developed depth-based deconvolution technique since deconvolving a single blurred image by 2-D axial PSF profiles is a highly parallelizable process and has a light computational weight. In addition, it also outputs refocused images from a single-image without any further processing steps.

3 Addressing the Ringing Artifacts

Tackling various ringing artifacts associated with the deconvolution process such as boundary artifacts, edges ringing, and depth-transition artifacts requires better understanding of their nature and they can be addressed separately.

3.1 Tackling the Boundary Artifacts

Deconvolution is simply a division in the Fourier domain between the image and the blurring kernel. However, the discrete Fourier transform assumes data periodicity which is not present within the captured images. Moreover, parts of the scene beyond the field of view (FOV) participate in the blurring process but are missing in the captured images. These cause the boundary artifacts to propagate through the deconvolved images, and the artifacts become more severe when the PSF profile is of a large support (usually for close objects that are far from the hyperfocal plane).

Fig. 1 Block diagram of the computational depth-based deconvolution technique.

Constrained image extrapolation, smoothing gradients, and block tiling^{12,23} may be applied to achieve periodicity without introducing discontinuities or sharp edges at the borders that may additionally contribute to the ringing artifacts. The content of each tiled block is computed by solving a regularized least square problem which imposes smooth transitions within the block itself and with the neighboring blocks' boundaries as well.²³ Since solving the optimization problem can be computationally heavy when large images are being processed, we approximate the content of the tiled blocks by a simple linear interpolation between the given boundary values, followed by adaptively blurring incrementally toward the center of the tiled blocks to impose smoothness. We found that these simple preprocessing steps are sufficient to eliminate the boundary artifacts with a light computation load.

3.2 Tackling the Edge Artifacts

Ringing initiated by the image content is typically controlled by various regularization techniques such as Tikhonov regularization,²⁴ iteratively reweighted least squares technique,²⁵ Gaussian scale mixtures²⁶ with conjugate gradient optimization, total variation²⁷ with Laplacian prior, and adaptive sparse priors²⁸ imposing smoothness via first- and second-order derivative filters. However, these techniques may also over-smooth the image, require hundreds of iterations to converge, or assume priors that may not exactly fit the image gradients. The image gradients of real-world scenes usually follow distributions of heavy tails that may be better approximated by hyper-Laplacian priors^{29,30} even though solving for them is probably much slower than the Gaussian and Laplacian priors.

Assuming a Gaussian noise model and hyper-Laplacian prior, the maximum *a posteriori* estimator after computing the negative log becomes a minimization problem^{11,30} given as

$$\min_f \sum_{j=1}^{\text{#Pixels}} \{ (h * f - g)_j^2 + \eta [|(\delta_x * f)_j|^\alpha + |(\delta_y * f)_j|^\alpha] \},$$

where $*$ denotes a convolution, j indexes the image's pixels, η is a scalar regularization, α is the hyper-Laplacian order, and δ_x and δ_y represent the horizontal and vertical gradient operators.

Now by accounting for the depth-variant nature of the PSF and deconvolving the captured image g with the axial slices h_{Z_d} to output the deconvolved images I_{Z_d} , we can rewrite the above minimization as follows:

$$\min_{I_{Z_d}} \sum_{j=1}^{\text{#Pixels}} \{ (h_{Z_d} * I_{Z_d} - M_d g)_j^2 + \eta_d [|(\delta_x * I_{Z_d})_j|^\alpha + |(\delta_y * I_{Z_d})_j|^\alpha] \},$$

where M_d is the depth-based masking operation (described in Sec. 3.3). Also note that this minimization is actually being applied on a block-tiled version of g to eliminate the boundary ringing, hence, the resulted deconvolved images I_{Z_d} have to be untiled before the stitching step.

Giving η_d a higher value means favoring more ringing smoothing over edge sharpening in the whole image, and vice versa. To gain a better control, local regularization based on a reference map^{11,12} can adaptively assign larger

Fig. 2 Sketch illustrating the developed depth-based masking approach for planar USAF target set at the three depth planes utilized in the simulation study.

weights to the smooth regions where ringing suppression is of interest and smaller weights for the sharp edges where maximizing the details is desired. In this context, η_d becomes a 2-D matrix representing the reference map which is being estimated initially from the input blurred image and updated continuously from the axially deconvolved image I_{Z_d} (one

reference map η_d per depth plane) through an iterative deconvolution process, as shown in Fig. 1. The reference maps are found through calculating the edge strength at each pixel in the image by applying gradient filters in the horizontal and vertical directions on multiresolution levels, binarizing them given a preselected threshold, and finally accumulating their

Fig. 3 USAF (first row) and cameraman (second row) images captured at various object distances. The associated axial PSF profile of 64×64 pixels is shown at the bottom-right corner of each USAF image.

Fig. 4 Stitching planar regions according to a depth map (left) to form MD objects for USAF (center) and cameraman (right).

Fig. 5 Blurred images after preprocessing the boundaries with various techniques: zero padding (left), edge taper (center), and block tiling (right) for USAF (first row) and cameraman (second row) objects captured at 100-mm distance.

Fig. 6 Comparison of deblurred images under various boundary preprocessing techniques using adaptive regularization for planar USAF (first row) and cameraman (second row) objects at 100-mm distance. The SSIM values are shown to the left of each image.

Fig. 7 Visual comparison of different deconvolution techniques for USAF target at different depth planes when deconvolved with the corresponding axial PSF profiles. The last row shows the final reference maps used as local regularizers in Tsai's technique. The SSIM values are shown to the left of each image.

weights across the levels which in turn results in assigning lower weights to the texture regions and higher weights to the smooth regions. A detailed mathematical description of the estimation procedure for the reference map can be found in Ref. 11.

Solving the minimization problem can be done efficiently in the frequency domain through an alternating minimization procedure,^{31,32} and analytical derivations can be found for certain α values (e.g., 1/2, 2/3),³⁰ reducing the computational effort.

3.3 Tackling the Depth-Transition Artifacts

In the case of MD objects, samples are shown in Fig. 4, surfaces belonging to different depth planes will be blurred uniquely with their corresponding blurring kernels. Deconvolving these blurred surfaces by unmatched axial PSF profiles will result in ringing denoted here as depth-transition artifacts.

Tackling such artifacts requires prior knowledge about the depth map, which can be acquired from a depth sensor or a stereo system. The depth map provides the masking information needed to prevent simultaneous processing of surfaces belonging to different depth planes, hence eliminating the source of such artifacts. Figure 2 shows the depth-based masking steps proposed to suppress the depth-transition artifacts. First, the masking information is extracted from the depth map and applied to the raw blurred tiled image to output N masked images. The masked-out (black) areas are then filled by bilinear interpolation to maintain continuity with the mask's boundaries. We use scattered data interpolation³³ so masked-out regions of any shape for complex scenes can be inpainted. Afterward, the interpolated areas are blurred with the exact PSF profile to be used at the deconvolution step. This step will assure smoothness in the interpolated regions and guarantee matching with the deconvolving kernel so no depth-transition artifacts are induced. Finally, the N masked interpolated blurred images are adaptively deconvolved by

		100 mm		200 mm		400 mm
Lucy	0.16		0.169		0.188	
Fortunato	0.411		0.614		0.51	
Krishnan	0.386		0.572		0.323	
Tsai	0.615		0.723		0.752	
Ref. map						

Fig. 8 Visual comparison of different deconvolution techniques for cameraman image set at different depth planes when deconvolved with the corresponding axial PSF profiles. The last row shows the final reference maps used as local regularizers in Tsai's technique. The SSIM values are shown to the left of each image.

the corresponding PSF profiles using reference maps which have also been masked accordingly (so interpolated areas are considered smooth regions during the regularization) to produce N axially deconvolved images to be merged later based on the depth map to form the full-focus image.

4 Simulation Results

A ray-tracing program, OpticStudio by Zemax, is utilized to simulate the imaging of planar objects placed at different depth planes through an off-the-shelf fixed-focus objective lens (4.5-mm focal length, 2.4 f-number, and 1.5 m hyper-focal distance) to a focal plane array of resolution 600×800 pixels with pitch size $1.4 \times 1.4 \mu\text{m}^2$. The blurring kernels have been similarly estimated by calculating the Huygens PSF³⁴ of on-axis points placed at the desired depths. The 1951 U.S. Air Force (USAF) resolution test target and cameraman image are chosen to assess the ringing artifacts and the resolved details achieved by the proposed deconvolution technique. The blurred images along with their associated axial PSF profiles, shown in Fig. 3, show the variation in FOV, magnification, and amount of blur as the depth varies.

To imitate MD objects, different regions of planar objects traced at various depth planes, shown in Fig. 3, are stitched together according to a customized depth map, shown in Fig. 4.

The adaptive deconvolution technique,¹¹ reported here, operates using the regularization parameters: three iterations, three scaled levels, hyper-Laplacian with $\alpha = 2/3$, threshold $T = 0.1 \times \max$ value of the reference map, and $\eta_d \in [10^{-5}, 10^{-3}]$. Note that in the case of color images, the deconvolution is applied to the luminance channel only, which is afterward recombined with the chrominance channels. The deconvolution numerical errors are quantified using the structural similarity index measure (SSIM)³⁵ which mimics the human visual system to extract information based on structure, luminance, and contrast and identify how similar they are to those in the reference image where $\text{SSIM} = 1$ means the best match. For illustration purposes, the various ringing artifacts are addressed one at a time through the following simulation scenarios.

4.1 Impact of Preprocessing the Boundaries of the Blurred Images

The impact of preprocessing the image boundaries is evaluated in three scenarios: zero padding by 32 pixels (i.e., half size of the blurring kernel) along each boundary, edge tapering by blurring the boundaries with the exact PSF profile to be used for deconvolution, and block tiling to impose continuity and smoothness across the boundaries. The blurred images for close USAF and cameraman objects after preprocessing the boundaries are shown in Fig. 5, and their

Fig. 9 Visual comparison of deconvolution results for MD USAF and cameraman images without any depth processing (first two rows) and with depth-based masking approach (last two rows) when deconvolved with different axial PSF profiles (sorted column-wise). The SSIM values are shown to the left of each image.

deblurred results using adaptive regularization¹¹ are shown in Fig. 6.

Figure 6 shows how a simple zero padding (and similarly in the case of no boundary preprocessing) can boost ringing all over the deconvolved images especially when the PSF has large support. Tapering the boundaries can help reduce the ringing, but rippling can still be observed near boundaries (see both USAF and cameraman deblurring results in Fig. 6). These results demonstrate that the block tiling approach is superior with the highest SSIM values and barely noticeable boundary artifacts.

4.2 Impact of Adaptive Regularization for Planar Objects Set at Different Depth Planes

To study the impact of adaptive regularization at different depth planes, we deconvolved the planar objects shown in Fig. 3, captured at various depth planes by their corresponding axial PSF profiles. We evaluated four deconvolution techniques: the Lucy–Richardson Bayesian-based iterative

method^{36,37} with 100 iterations, Fortunato’s deconvolution using sparse adaptive priors²⁸ with weighting vector (0.001, 20, 0.033, and 0.05), Krishnan’s method with hyper-Laplacian prior³⁰ of $\alpha = 2/3$ and scalar regularization $\lambda = 10^4$, and Tsai’s adaptive deconvolution¹¹ with the regularization parameters defined at the beginning of Sec. 4. The parameters are chosen so the deconvolution techniques can resolve the same level of details (as quantified by USAF) so the ringing appearance can be fairly judged between them. The visual reconstructions and numerical errors for USAF and cameraman images are shown in Figs. 7 and 8, respectively. The regularizing reference maps of Tsai’s algorithm are shown at the last row of each figure, where the white regions represent the areas to be smoothed and the black regions represent the edges to be preserved.

A visual and numerical comparison of the reconstruction results in Figs. 7 and 8 show the effectiveness of Tsai’s adaptive deconvolution over other techniques in suppressing the edge artifacts and the noisy appearance while maximizing

Fig. 10 Visual comparison of final full-focus deconvolution results after stitching based on a depth map for USAF and cameraman images showing reference MD objects (first row), deblurring results when considering SD objects followed by stitching to mimic MD object (second row), deblurring results of MD object without any depth processing (third row), and deblurring results of MD object with depth-based masking approach (last row). The SSIM values are shown to the left of each image.

the image details and sharpness. This becomes more noticeable as the objects get far from the DOF range (e.g., 100 mm). Note that the adaptive deconvolution results in a higher structural similarity (SSIM) as compared with others.

4.3 Impact of the Depth-Based Masking Approach

Given the depth map, shown on the left in Fig. 4, the regions belonging to different depth planes can be masked out according to the procedure described in Sec. 3.3. To evaluate the effectiveness of depth masking, bilinear interpolation, and blurring by the associated axial PSF profile, the resulting axially deconvolved images (last two rows in Fig. 9) are compared against deblurring results when no depth processing is implemented (first two rows in Fig. 9). It is clear from the visual restorations, in addition to the high SSIM values, that many of the depth-transition ringing artifacts are successfully filtered out by the depth-based masking approach.

4.4 Comparison of Full-Focus Deconvolution Results After Stitching

The final step to form a full-focus image is merging the axially deconvolved images according to a given depth map prior, shown on the left in Fig. 4. To completely isolate the depth-transition artifacts, raw planar SD images, shown in Fig. 3, are block tiled, adaptively deconvolved by Tsai's technique with their corresponding PSF profiles, and finally stitched according to the depth map (see second row in Fig. 10) to mimic the MD deconvolution scenario. On the other extreme, the depth-transition artifacts can dominate the MD deconvolution results if no special processing is involved (see third row in Fig. 10). The depth-based masking approach can help a lot in reducing such artifacts (see last row in Fig. 10), although it is not fully restoring some of the image details (e.g., compare the vertical bars on the right of restored USAF images between the depth-based masking case and the SD deblurred case).

5 Conclusion and Future Work

This paper introduces a computational depth-based deconvolution technique that equips ordinary cameras with an extended depth-of-field capability. The developed technique acknowledges the depth-variant nature of the PSF by deconvolving the captured blurred scene with axial PSF profiles which bring it to focus at different depth planes. Afterward, the focused features from the axially deconvolved images are stitched together based on a depth map prior to form a full-focus image. The developed technique can accomplish the tasks of image refocusing and full-focus imaging simultaneously.

The ringing artifacts have been analyzed and addressed on three levels. The boundary artifacts are eliminated by adopting a block-tiling approach that imposes continuity and smoothness along the boundaries. The edge artifacts are adaptively controlled by iteratively-updated reference maps which penalize the ringing in the smooth regions and favor the details in the textured regions. Finally, artifacts initiated by depth-transition surfaces are suppressed by a depth-based masking approach to isolate processing surfaces belonging to different depth planes simultaneously, hence eliminating the source of such artifacts over a wide depth range. The

effectiveness of the proposed ringing suppression process is demonstrated for planar objects and MD objects.

Future work will experimentally validate the performance of the developed deconvolution technique on continuous MD objects captured by a real camera. Also, we will explore other schemes to deal with depth-transition artifacts that can relax the need for a depth map as an extra prior. Moreover, to eliminate the need for frequent calibration as the depth-variant PSF volume varies with time, temperature, or due to mechanical shock, a hybrid deconvolution scheme will be investigated to combine the adaptive depth-based deconvolution with iterative blind deconvolution techniques so the PSF volume is kept updated with minimal calibration effort.

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