Dual Domain Filters based Texture and Structure Preserving Image Non-blind Deconvolution

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Image deconvolution methods can be broadly divided into two classes. The first class of methods apply a regularized inversion of the blur, followed by a denoising procedure. Various denoising methods have been used for this task: for instance, wavelet transform [1], and a block matching with 3D-filtering kernel regression (BM3D) [2]. The TV model[3] and SURE-LET[4] belong to the second category, which is based on a variational optimization problem where the desired solution minimizes a criterion composed of fidelity and penalty terms. In recent works, the sparsity and the self-similarity of natural images are usually combined to achieve better performance [5]. Lately, low-rank modeling based approaches have also achieved great success in image restoration[6].

We show in this paper how a patch-less image deconvolution method can be implemented, integrating a rolling guidance filter [7] and a short-time Fourier transform(STFT) technique into the same framework. We propose an efficient iterative algorithm consists of two parts: debluring and denoising. The deblurring step amplifies and colors the noise, and corrupts the image information. Hence, in the denoising step, we use the rolling guidance filter to obtain a high-contrast image, and the residual image (texture and noise) is denoised in the short-time Fourier transform domain using energy shrinkage.

One of the most challenging problems in image deconvolution is how to preserve the fine scale texture structures while removing blur and noise. The rolling guidance filter is in essence a joint bilateral filter (JBF) that effectively removes texture while preserving structure, which the standard bilateral filter often fails to do. But rolling guidance filter can not preserve low-contrast detail like textures without introducing noise. STFT shrinkage on the other hand results in good detail preservation, but suffers from ringing artifacts near steep edges. We integrate these two methods to produce a new deconvolution approach which outperforms many current state-of-the-art schemes. Apart from operating in different domains, the rolling guidance filter and the STFT shrinkage are very alike; hence, we call our method dual-domain filters (**DDFs**) based image deconvolution.

In our approach, we minimize the following energy function to estimate the noise-free image u.

$$\min_u \| y - h * u \|^2 + \lambda \| u - \mathtt{DDFs}(u) \|^2 \tag{1}$$

where y is a blurry image and h is a PSF, both y and h are given.

Directly minimizing this energy is hard because $\mathtt{DDFs}(\cdot)$ is highly non-linear. We found that iterating the following two steps yields a good result in practice:

$$\begin{aligned} v^{k+1} &= \arg\min_u \| y - h * u \|^2 + \lambda^{k+1} \| u - u^k \|^2 && (2)\\ u^{k+1} &= \mathtt{DDFs}(v^{k+1}) && (3) \end{aligned}$$

Considering that Eq.(2) is a simple least squares problem, we can update v with its analytic solution. The regularization parameter λ^k strikes a balance between the data fidelity and regularity. In practice, for an image of $N \times N$ size and the k-th step, we compute the parameters λ^k using following method:

$$\begin{aligned} \lambda^0 &= \frac{N^2\sigma^2}{\| y - E(y) \|_2^2 - N^2\sigma^2} \\ \lambda^{k+1} &= \beta\lambda^k && (4) \end{aligned}$$

where $E(y)$ denotes the mean of y, β is update factor.

To suppress the amplified noise and artifacts introduced by Eq.(2), we plan to apply the dual domain transform to denoise the estimate image v^k (**DDFs**(v^k)). We observe that spatial domain methods excel at denoising high-contrast images while transform domain methods excel at low-contrast images. We therefore separate the image into two layers, and denoise them separately. The rolling guidance filter is appropriate for this decomposition. The high-contrast layer is the rolling guidance filtered image, and the low-contrast layer (texture and noise) is the residual image. Since the high-contrast image is already denoised, it only remains to denoise the low-contrast image in the transform domain using STFT shrinkage.

In the **first step**, we calculate the denoised high-contrast value using a rolling guidance filter. We use rolling guidance filter to filter the noisy image v^k, and obtain a filtered image v_r^k.

In the **second step**, we prepare for the energy shrinkage in the transform domain by extracting the low contrast images and performing the STFT. The STFT is a discrete Fourier transform (DFT) preceded by multiplication of the signal with a window function to avoid boundary artifacts. In this work, we choose the spatial Gaussian of the bilateral kernel as the window function and shrinkage the residual image $v^{k+1} - v_r^{k+1}$ in the short-time Fourier domain to extract the low contrast image st^k.

In the **last step**, the original image can be approximated by the sum of the two denoised layers as: $\tilde{u}^k = v_r^k + st^k$ The resulting image st^k usually contains a special form of distortions and introduce additional visual artifacts. Since bilateral filter can effectively remove the edges of small magnitudes caused by these artifacts, we utilize it to suppress visual artifacts and leave the edges and texture of large magnitudes intact:

$$u^k = JBF(v^k, \tilde{u}^k, \sigma_s, \sigma_r) \tag{5}$$

where σ_s and σ_r control the spatial and range weights respectively.

Implementation details of this method is described in the paper, as are the details of STFT shrinkage. Our conclusion is that the effectivity of the deconvolution method with the decouple of deblurring and denoising steps, makes it a useful model to preserve the texture and structure of restored image.

[1] R. Neelamani, H. Choi, and R. G. Baraniuk. ForWaRD: Fourier-wavelet regularized deconvolution for ill-conditioned systems. *IEEE Trans. Signal Process.*, 52(2):418–433, 2004.

[2] K. Dabove, A.Foi, V.Katkovnik, and K.Egiazarian. Image restoration by sparse 3D transform-domain collaborative filtering. In *Soc. Photo-Optical Instrumentation Engineers*, volume 6812, page 6, 2008.

[3] L. Rudin, S. Osher, and E. Fatemi. Nonlinear total variation based noise removal algorithms. *Physica D*, 60:259–268, 1992.

[4] F. Xue, F.Luisier, and T.Blu. Multi-Wiener SURE-LET Deconvolution. In *IEEE T-Image Process*, 22(5):1954–1968, 2013

[5] W. Dong, L. Zhang, G. Shi, and X. Wu. Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization. *IEEE T-Image Process*, 20(7):1838–1857, 2011.

[6] W. Dong, G. Shi, and X. Li. Nonlocal image restoration with bilateral variance estimation: A low-rank approach. *IEEE T-Image Process*, 20 (2):700–711, 2013.

[7] Q.Zhang, X.Y.Shen, L.Xu, and J.Y.Jia. Rolling guidance filter. In *Proc. ECCV*, 2014.

This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.