IMAGE DECONVOLUTION USING MULTIGRID NATURAL IMAGE PRIOR AND ITS APPLICATIONS

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ABSTRACT

The natural image prior has been shown as a powerful tool for image deblurring in recent work, while its performance against noise and various applications have not been thoroughly studied. In this paper, we present a multigrid natural image prior for image deconvolution that enhances its robustness against noise, and furnish three applications of image deconvolution using this prior: deblurring, super-resolution and denoising. The prior is based on a remarkable property of natural images that derivatives with different resolutions are subject to the same heavy-tailed distribution with a spatial factor. It can serve in both blind and non-blind deconvolutions. The performances of the proposed prior in different applications are demonstrated by corresponding experimental results.

Index Terms— Image deblurring, natural image prior, super-resolution, image denoising

1. INTRODUCTION

Image deconvolution is a common and important problem with consistently intensive attentions in image processing and computational photography. While people from different fields have different focuses on this problem, we are mainly interested by the recent progress in image deblurring using the natural image prior [1, 2, 3, 4], which refers to the heavy-tailed distribution of image gradient magnitudes. Nevertheless, it still remains challenging and hard to understand in many respects [5].

Recently, the natural image prior has been successfully applied to a variety of applications in image processing and computational photography. The intrinsic property of this prior is that, most pixels of natural images have very small gradient magnitudes, while only a few pixels have large gradient magnitudes. The strength of this prior lies in its remarkable consistency over various types of natural images. This prior penalizes pixels with great gradient magnitudes in such a way to reduce ringing and preserve sharp edges. There are some representations appearing in the previous work [1, 2, 3], where we found that the sparse prior [2] is concise and effective, which is also referred as the hyper-Laplacian prior in [4]. Due to a recent evaluation of deconvolution algorithms [5], the sparse prior has been shown to achieve the best performance in the non-blind deconvolution process.

In this paper, we propose a new multigrid prior that embodies the hyper-Laplacian priors in multi-resolutions, which inherits the advantage of natural image prior on artifacts control, and enhances the robustness of deconvolution against noise. We apply this prior to deconvolution-based methods working on three problems: deblurring, super-resolution and denoising. In the experiments, we compare our method only with deconvolution-based methods, as we are focusing on improve the performance of image deconvolution. An exception can be found in the experiment of denoising, since the convolution kernel here is degenerated to a delta function.

2. DECONVOLUTION WITH MULTIGRID NATURAL IMAGE PRIOR

2.1. Multigrid natural image prior

Natural images have an intrinsic property on the statistics of their gradient magnitudes, i.e., the "heavy-tailed" distribution. In our observation, magnitudes of multi-resolution gradients are also subject to this property. Fig. 1 shows two natural images and their statistical responses of three derivative filters with different resolutions, which are selected from 1-ring (red), 2-ring (blue) and 3-ring (green) neighbors of the central pixel (black). It illustrates that the responses of derivative filters within a certain size of local neighborhood (7 × 7 in this example) have the similar distributions. Moreover, the tails of response distribution become lighter when the distance of derivative filter increases, which indicates that the space variation affects the distribution of filter outputs.

Inspired by the above observations, we propose a new prior in image deconvolution based on a series of derivative filters: $\{F_d\}$ with $(d = 1, ..., n_w)$ which computes the multigrid discrete derivatives of a pixel in its $w \times w$ neighborhood,

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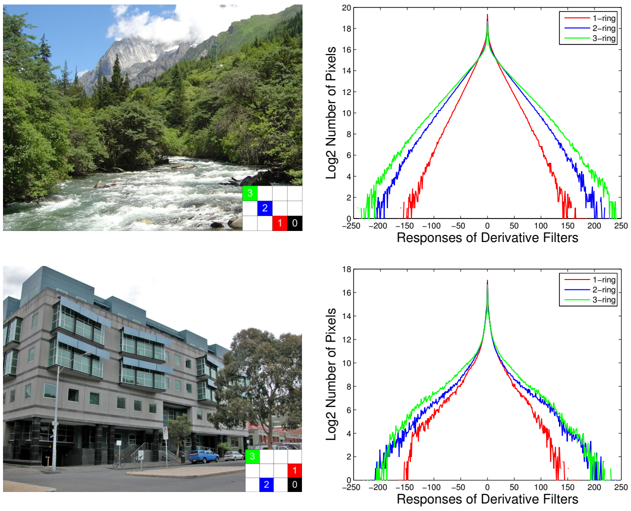


Fig. 1. Two natural images and their statistical responses of three derivative filters with different resolutions, which are selected from 1-ring (red), 2-ring (blue) and 3-ring (green) neighbors of the central pixel (black). The patterns of these three filters are shown at the down-right of left images.

given by

$$p(x) = \prod_{d=1}^{n_w} e^{-\phi(F_d, x)}, \tag{1}$$

where $n_w = \frac{w \times w - 1}{2}$ is the number of filters, and $\phi(F_d, x)$ is the potential function. We adopt the hyper-Laplacian prior for representation of the natural image prior, and embody a spatial factor s_d in the potential function to reflect spatial affects, which yields

$$\phi(F_d, x) = s_d |F_d * x|^{\alpha}, \tag{2}$$

where $*$ is the convolution operator, and α is a positive exponent value set in the range of [0.5, 0.8] as suggested by [2, 4]. The spatial factor of a filter F_d is given by

$$s_d = \frac{1}{|F_d|^2}, \tag{3}$$

where $|F_d|$ is the distance of two non-zero elements of F_d. This prior reflects the intrinsic characteristic of natural images with concise expression.

2.2. Bayesian image deconvolution

Here we consider the process of image convolution as a latent image x convolves a shift-invariant kernel k with additive noise n, written by

$$y = k * x + n. \tag{4}$$

And the goal of non-blind deconvolution is to restore latent image x with known kernel k from blurred image y.

The Bayesian probability model is adopted by popular approaches of image deconvolution, given by

$$p(x|y, k) \propto p(y, k|x)p(x), \tag{5}$$

where the marginal probability $p(x)$ is defined in Eq. (1) in our method. The likelihood term $p(y, k|x)$ is defined as

$$p(y, k|x) = e^{-(k*x-y)^2}, \tag{6}$$

subject to the assumption of Gaussian noise. The solution can be found by the Bayesian inference, and a straightforward strategy is the maximum a posteriori (MAP), which is equivalent to minimizing an objective function. By taking the negative logarithm of posteriori, we can get the objective function as

$$E(x) = (k * x - y)^2 + \lambda \sum_{d=1}^{n_w} s_d |F_d * x|^{\alpha}, \tag{7}$$

where λ is a coefficient of the image prior. To solve this non-convex minimization problem, we adopt the iterative re-weighted method in [2] by defining a weight function as

$$w_d(x) = s_d |F_d * x|^{\alpha - 2}, \tag{8}$$

and substitute it into the Eq. (7). Then the remaining problem can be solved by the conjugate gradient method for a given weight w_d. As an iterative re-weighted strategy, the weight $w_d(x)$ will be updated after x is estimated in each iteration, and so on and so forth.

3. APPLICATIONS AND EXPERIMENTS

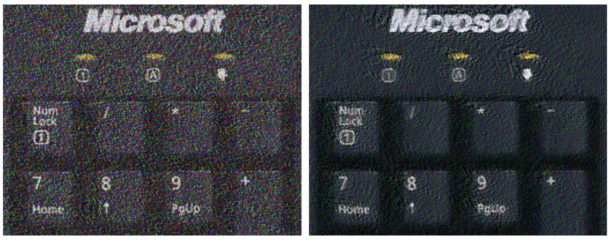
3.1. Deblurring

Image blur is very common in photography, which occurs when the camera shake emerges due to long exposure, or the fast-moving object. The blur is usually modeled by image deconvolution with shift-invariant kernel, where our deconvolution method can be directly applied. For known blur kernels, e.g., coded aperture in [2], the application is straightforward. For unknown blur kernels, our method requires an estimation of blur kernel, which can be provided by blurred/noisy image pairs [6] or Fergus's method [1].

Particularly, we consider the noise in deconvolution, which comes from many sources such as photon noise, quantization error and kernel estimation error. It is thoroughly different with conventional image denoising, because the noise will be exaggerated and cause artifacts during deconvolution. Fig. 2 shows different strategies running on a blurred image with Gaussian noise ($\sigma = 0.03$). The sperate usage of deblurring [2] and denoising [7] with different orders are shown in (c) and (d) with PSNR 16.41dB and 21.36dB. Our method tends to enhance the robustness of deconvolution against noise, as shown in (b) with PSNR 27.55dB. The experiemntal results of image deblurring are shown in Fig. 3, where our results contain fewer ringing artifacts and noise than the results by the sparse prior [2].

Fig. 3. More deblurring results, from left to right: original images, blurred images with Gaussian noise ($\sigma = 0.03$), results by sparse prior [2], and our results.

(a) blurred image with noise (b) our method



(c) deblur-then-denoise (d) denoise-then-deblur

Fig. 2. Comparison of different strategies for image deconvolution with noise. The blurred image is corrupted by Gaussian noise ($\sigma = 0.03$). The PSNR values for (b-d) are 27.55dB, 16.41dB, 21.36dB, respectively.

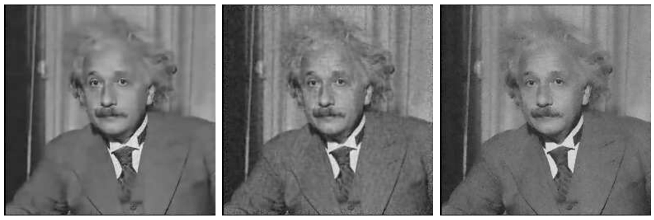
3.2. Super-resolution

In recent work of image/video upsampling by deconvolution [8], a low-resolution image L is expressed by convolution:

$$L = (f * H) \downarrow^d, \tag{9}$$

where f denotes the discretized PSF, H is the high-resolution image and $\downarrow^d$ is a decimating (subsampling) operator with factor d. The PSF is commonly approximated by a Gaussian filter.

A single low-resolution image is first upsampled by bicubic interpolation, which will blur the image. Then a deconvolution with Gaussian kernel is applied, to obtain a sharp high-resolution image. We adopt the setting of Gaussian kernel in [8], which depends on the factor of upsampling. Fig. 4 shows some results of super-resolution. We add 1% random noise on input low-resolution images. Shan's deconvolution [3] generates a lot of artifacts, and exaggerates the noise level. In their super-resolution [8], they use the same deconvolution method iteratively to refine the upsampling result. Hence, their results (third column in Fig. 4) are smoothed. Our method only performs deconvolution with the multigrid prior, and have sharper results without artifacts. The "zigzag" artifacts indicate that it may not be the best way to perform super-resolution by deconvolution. As a fast and effective approach, our method, however, can sharpen the high-resolution image, and enhance the robustness of deconvolution-based super-resolution.



PSNR: 30.65dB (a) FoE | PSNR: 31.48dB (b) GSM FoE | PSNR: 31.16dB (c) our method

Fig. 5. Denoising result on the "Einstein" image [9] compared with the FoE and GSM FoE models.

3.3. Denoising

Image denoising is also active in image processing. Image deconvolution has been applied to denoising, by taking it as a

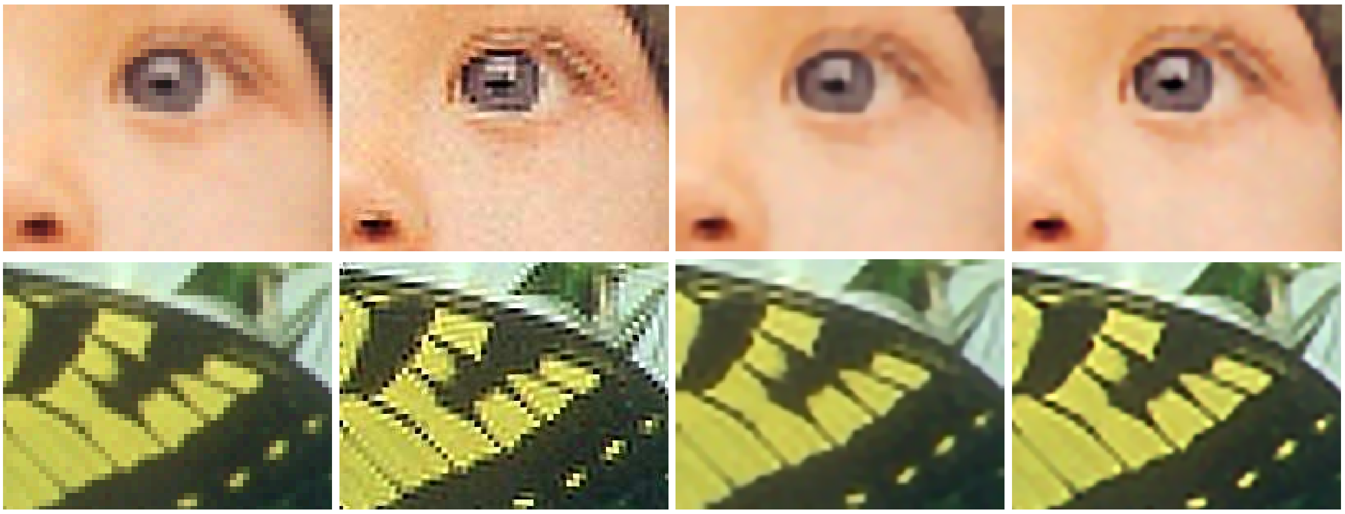


Fig. 4. Super-resolution (4 times) results of noisy images, from left to right: low resolution images with 1% random noise, results by Shan's deconvolution [3], results by Shan's super-resolution [8], and our results.

degeneracy of deconvolution with kernel as a delta function. Therefore Eq. (7) can be reduced to:

$$E(x) = (x - y)^2 + \sum_{d=1}^{n_w} w_d |F_d * x|^2, \qquad (10)$$

with weight w_d defined as in Eq. (8). This is similar with previous Field of Experts (FoE) models [10] and Gaussian Scale Mixture (GSM) FoE models [9]. In contrast to previous work using nonintuitive trained filters, we exploit a series of multigrid derivative filters, which is much faster to compute and achieves competitive performance. Fig. 5 shows a denoising result on the "Einstein" image from [9] compared with the FoE and GSM FoE models. Our method achieves competitive PSNR value, but takes about $1/20$ running time of the FoE and GSM FoE models.

4. CONCLUSION

We have proposed a multigrid natural image prior that enhances the robustness of image deconvolution against noise. This prior follows an intrinsic property of natural images, with a special effect on anisotropic smoothing. Three applications of deconvolution with our multigrid natural image prior are given in this paper: deblurring, super-resolution and denoising. Experimental results show that our method enhances the robustness of deconvolution against noise. In the future, we will continue to study good priors for image deconvolution, and the evaluation of visual quality.

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