Restoring focus in photographs: extraction of the point-spread function

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1 Introduction

Out-of-focus images are the bane of the modern photographer. While error in exposure, cropping, and color can often be easily fixed in post-processing, errors in focus are not so simple to erase. The most common approach to dealing with an out-of-focus image is to use a tool like "unsharp mask," which increases the apparent sharpness of the photo but does not correct the fundamental focusing mistake. This is because the unsharp mask procedure increases the acutance (essentially, the edge contrast) instead of reversing the blur. Fortunately, a technique that applies deconvolution can recover the latent sharp image from the observed blurry picture.

Formally, we can represent the captured (blurred) image B with the equation

$$B = L \star P + N \tag{1}$$

where L represents the latent sharp (unblurred) image, P represents the point-spread function (discussed below), $\star$ is the convolution operator, and N represents noise. We will assume that the noise term N models the collective sensor noise, quantization noise, and compression noise.

The point-spread function (PSF) is, by definition, a model of how a point source of light is modified and distorted by an optical system, such as a camera lens. This is particularly visible in terrestrial photos as the image of the aperture (typially a circle or a polygon) that is visible in out-of-focus images of bright lights. For most terrestrial cameras with wide-open apertures, the PSF appears as a large fuzzy disc. The PSF is also related to the quality of the image *bokeh*, which is the pleasant blurring of the background that can be produced by a lens with a large aperture. It can model more than just out-of-focus blur; the PSF can also model motion blur (caused by a moving object or moving camera) and atmospheric distortion (often observed by ground-based telescopes).

There are two classes of deconvolution: blind and non-blind. In non-blind deconvolution, the PSF is known but the latent sharp image is unknown. The noise may or may not be characterized. In blind deconvolution, both the PSF and the latent sharp image are unknown, and the user is left to recover one or both of them. Since it is generally impractical to measure directly the PSF of an optical system without access to specialized equipment, we will focus on the blind case.

This paper discussed a method to recover the PSF from a blurry image, minimizing the number of scope of assumptions about the PSF, the latent sharp image, and the blurry image.

2 Related Work

Many methods have been proposed for recovering the sharp image and the PSF. Some operate by estimating the latent sharp image directly and then comparing the estimate to the observed blurry image to infer the PSF. Others operate by doing statistical analysis, modeling the blurry image, latent sharp image, and PSF in probabalistic terms.

One of the oldest techniques, still in use today, is the Richardson-Lucy algorithm, which iteratively arrives at a solution by alternately optimizing the latent image estimate and the PSF estimate. Richardson-Lucy saw extensive use in the astronomy community, and it is still the default blind deconvolution method in Matlab. However, it is poorly suited to terrestrial images.

Recent work by Shan et al. (2008) solves for the latent image and the PSF using probability models of the image, noise, and PSF. These results have been demonstrated to be particularly useful when applied to motion-blurred images. However, the assumptions about the nature of the PSF, namely that it is sparse, might not be applicable to images blurred due to focus errors.

Fergus (2006) describes a similar method using natural image priors. They attempt to recover the PSF for an image using a variational Bayesian framework, which allows them to solve for the PSF directly.

There has also been some work in better applying the recovered PSF. In particular, Levin et al. (2007) discusses methods of restoring focus to particular objects in a scene using subject-identification techniques and focus-error-estimation methods. These concepts should be amenable to a variety of PSF recovery and deconvolution techniques.

3 Our approach

We attempt to extract the unknown PSF for a blurred image using natural image statistics. This is similar to the approach of Fergus (2006).

Natural images, such as photographs of landscapes and people, tend to have statistical similarities. One such area is in the distribution of gradients within the image.

Sharp natural images tend to have heavy-tailed gradient densities (such as 1), but blurry natural images tend to have gradient densities with small tails (such as 2). Intuitively, this means that the sharp images have more high- and mid-frequency components than blurry images.

Our algorithm attempts to find the PSF that, when used during the deconvolution of the observed blurry image, produces a sharp image with a gradient density most similar to this heavy-tailed ideal. No additional assumptions are placed on the images and PSF.

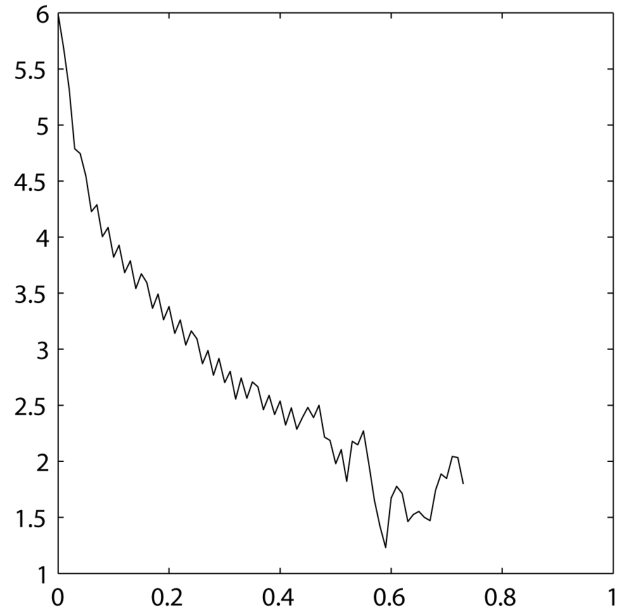


Figure 1: Plot of absolute value of $\log_{10}$-density of ∇L, the density of a sharp image. Note the heavy tail.

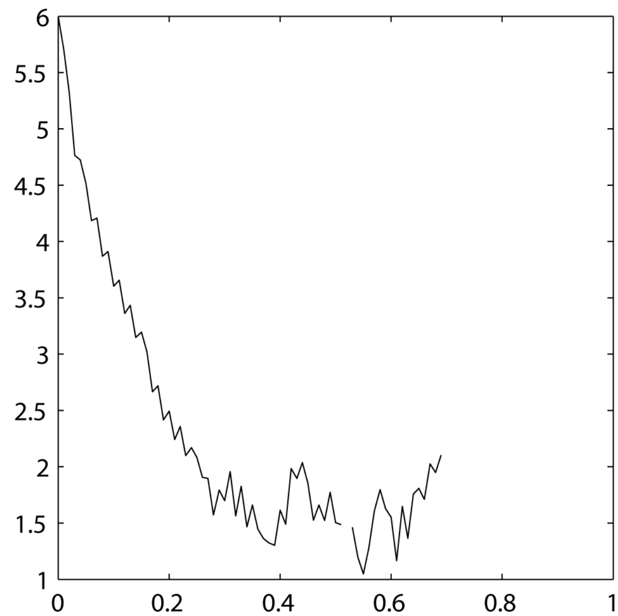


Figure 2: Plot of absolute value of $\log_{10}$-density of ∇B, the density of a blurry image. Note the lack of a heavy tail.

4 Implementation

The PSF recovery algorithm was implemented in Matlab. For the deconvolution function, we chose to use the `deconvL2_frequency` function developed by Levin et al.[4], due to its fast performance, good results, relative immunity to noise. We tuned the weights required by this algorithm to provide the best results for the image being processed, as were the other parameters needed by the algorithm described above.

A sample of natural images were used to tune the parameters used for the gradient match. The two parameters of particular interest were the inflection points in the log gradient density curves. Empirically, the first point corresponds with the point at which the blurry image curve diverges from the sharp image curve. The second point corresponds with the upper bound of the “smooth” gradient curve, beyond which there is a sharp falloff and noise dominates.

The PSF was calculated iteratively. A delta function (a single non-zero pixel in the PSF, located at the center) was used for the starting PSF. Then, using stochastic gradient descent, the algorithm iteratively optimized each pixel of the PSF to minimize the cost function. As alluded to earlier, the cost function was a least-squares measure of the difference between the modeled “ideal” gradient density for a sharp photo and the observed gradient density, calculated by deconvolving the current iteration of the PSF with the observed blurry image.

In order to decrease running time, we chose to operate on progressively larger versions of the original observed blurring image. This allowed us to start with a small image, for which the processing time is short, and generate a good estimated starting point for the next-larger image size.

A summary of the algorithm follows:

1. Estimate gradient density of the latent image based on the characteristics of natural images and the observed blurred image.

2. Resize the blurry image and the working PSF size to be smaller

3. Iterate through all of the pixels of the PSF, updating using stochastic gradient descent

4. Repeat Step 3 until the cost function (the difference between the estimated gradient density and the gradient density obtained by deconvolving the blurred image with the current iteration of the PSF)

5. After convergence, resize the blurry image and working PSF to the next larger step size

6. Repeat until the blurry image is at its original size

7. Output the full recovered PSF

Once the PSF was inferred, we extracted the latent sharp image using the same `deconvL2_frequency` function that was used in the algorithm. The image statistics on the recovered image were then plotted, and the image was evaluated subjectively for sharpness.

Figure 3: Ground truth (sharp) version of the sample image.

5 Results

Images with two types of blur were tested: those with out-of-focus blur (such as the sample image in Figure 4), and those with motion-blur. In both cases, the images were real photos captured with a DSLR camera. The images were cropped so that the entire image expressed nearly identical blur, which eliminated the need to solve for spatially varying PSFs.

The algorithm successfully converged on PSFs that minimized the cost function: images deconvolved with the derived PSF exhibited gradient-density functions with the desirable heavy-tailed characteristics. The improvement in this metric is clearly visible in Figure 7 for the sample image. In that sense, the algorithm was very successful.

For the blurry sample image, the algorithm recovered the PSF shown in Figure 6. This PSF is generally consistent with the expected shape of a PSF for out-of-focus images: a fuzzy disc. However, there are two faint vertical lines on the left side of the PSF that are both unexpected and of unknown origin. Vertical lines in PSFs are typically associated with vertical motion blur, but no such distortion was present in the observed image.

Unfortunately, the algorithm was very slow to converge, especially for larger images or PSFs. This due to both the `deconvL2_frequency` function, which uses several fast-Fourier transforms, and the need to iterate over every pixel in the PSF, which grows exponentially on every size increase. As such, the run time was extremely sensitive to the parameter specifying the upper bound on the PSF size. With

Figure 4: Observed version of the sample image, with out-of-focus blur, captured in a different frame than the ground truth sharp image. Note the fuzzy appearance of the lines on the lens box.

Figure 5: Recovered latent sharp image, derived using the inferred PSF. While the image is not perfect, it is perceptibly sharper, especially around the eyes of the plush doll.

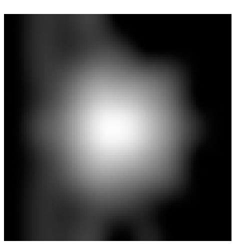
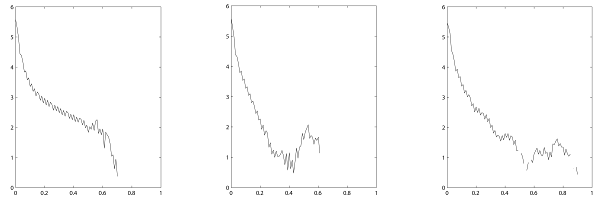


Figure 6: Recovered PSF, enlarged and contrast-enhanced for publication clarity.



(a) (b) (c)

Figure 7: The absolute values of the densities of the log-gradients for the ground truth sharp image (a), the observed blurry image (b), and the sharp image recovered with the inferred PSF (c). Note the improved weight of the tail in (c) compared to (b).

1.0-megapixel images and 15x15 pixel maximum PSF sizes, run times on the order of 15-20 minutes were not uncommon.

Once the algorithm converged, the resulting PSF was still suboptimal. Visual artifacts (e.g., ringing) indicated that the level of fit between the true (unknown) PSF and the inferred PSF was not as good as it could have been.

Most apparent was the remaining blurriness in the recovered latent images. Clearly, the resulting images, such as the example in Figure 5 would be considered "sharper" but not "sharp," especially when compared to the ground truth sharp images, such as Figure 3. Experience suggests that the recovered PSF needs to be larger and have sharper edges in order to provide a better representation of the true (unobserved) PSF.

6 Conclusion

From the results we observed, we conclude that recovering the PSF based solely on attempting to match natural image gradient distributions leads to a suboptimal end. It is unclear if making use of additional natural image characteristics, such as color data, would, all else being equal, lead to a better outcome.

Based on the work of others, we suspect that the performance would be improved if the algorithm placed constraints on the PSF, such as enforcing sparseness or limiting gradients.

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