Image processing

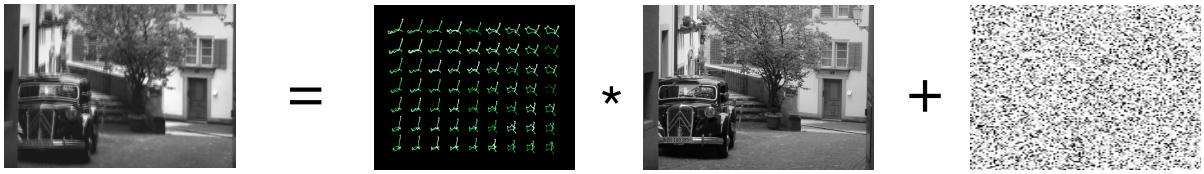


Figure 0.1: Generative model for camera shake.

Real-world images suffer from various distortions: photographs in low light can be blurred by camera shake and affected by high noise. Using probabilistic generative models of the imaging process (Figure 0.1), our research aims to recover the most likely original image given a low-quality image, or image sequence.

Spatially varying blurs: our work on blind deconvolution of astronomical image sequences [5] can recover sharp images through atmospheric turbulence, but is limited to relatively small patches of the sky, since the image defect is modeled as a space-*invariant* blur. Images that cover larger areas require a convolutional model allowing for space-*variant* blur. In [7] we proposed such a model based on an overlap-add, called *Efficient Filter Flow (EFF)*. Deconvolution based on EFF successfully recovers a sharp image from an image sequences distorted by air turbulence (Figure 0.2).

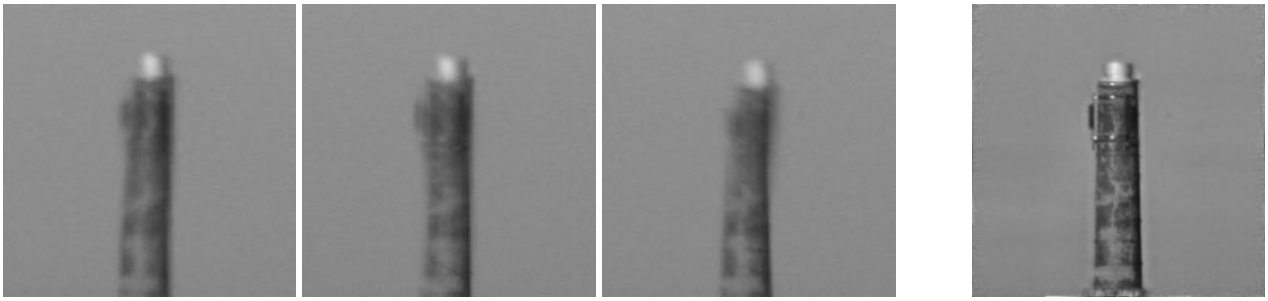
Removing camera shake: photographs taken with long exposure times are affected by camera shake creating smoothly varying blur. Real hand-held camera movement involves both translation and rotation, which can be modeled with our EFF framework for space-variant blur [4]. We were also able to recover a sharp image from a single distorted image, using sparsity-inducing image priors and an alternating update algorithm. The algorithm can be made more robust by restricting the EFF to blurs consistent with physical camera shake [6]. This leads to higher image quality (Figure 0.3) and computational advantages. To foster and simplify comparisons between different algorithms removing camera shake, we created a public benchmark dataset and an initial comparison of current methods [8].

Correcting lens aberration: even good lenses exhibit optical aberration off the center when used with wide apertures. Similar to camera shake, this creates a certain type of blur that can be modeled with our EFF framework; but optical aberrations affects each color channel differently (chromatic aberration). We measured these effects with a robotic setup and corrected them using a non-blind deconvolution based on the EFF framework [9]. We were also able to implement a *blind* method rectifying optical aberrations in single images [10] (Figure 0.4). The key was to constrain the EFF framework to rotationally symmetric blurs varying smoothly from the image center to the edges. Such aberration corrections might lead to new approaches in lens design.

Dark frame denoising: in astronomical imaging, dim celestial objects require very long exposure times, which causes high sensor noise. It is common to subtract a *dark frame* from the image – an image taken with covered lens, containing only sensor noise. The difficulty with this is that the sensor noise is stochastic, and image information is not taken into account. We studied the distribution of sensor noise generated by a specific camera sensor and proposed a parameterized model [2]. Combined with a simple image model for astronomical images, this gives superior denoising.

Multi-scale denoising: most denoising methods process small image patches, limiting themselves to recovering high-frequencies. This is valid in low noise situations, but not for large amounts of noise which also affect low frequencies. Most existing denoising methods can be improved for this high noise setting by applying them in a multi-scale fashion [1].

Denoising as a learning problem: denoising can be also seen as a non-trivial mapping from noisy to clean images. In [3] we showed how a multi-layer perceptron (MLP) can be trained to learn such a mapping, leading to the new state-of-the-art denoising method.



example frames from an image sequence with air turbulence | reconstructed image

Figure 0.2: Deconvolution based on efficient filter flow (EFF) can recover a sharp image (right) from image sequences distorted by air turbulence (left, shown are three example frames).

original image with camera shake | reconstructed image

Figure 0.3: Recovering a sharp image (right) from a single image that is distorted by camera shake (left).

original image with lens aberration | reconstructed image

Figure 0.4: Recovering a sharp image (right) from a single image that is distorted by lens aberration (left).

Publications

Articles in Conference Proceedings

[1] HC Burger and S Harmeling. Improving denoising algorithms via a multi-scale meta-procedure. In R Mester and M Felsberg, editors, *Pattern Recognition*, pages 206–215, Frankfurt a.M., Germany, 9 2011. Springer. 1

[2] HC Burger, B Schölkopf, and S Harmeling. Removing noise from astronomical images using a pixel-specific noise model. In H Lensch, SL Narasimhan, and ME Testorf, editors, *IEEE International Conference on Computational Photography (ICCP 2011)*, Pittsburgh, PA, USA, 4 2011. IEEE. 1

[3] HC Burger, CJ Schuler, and S Harmeling. Image denoising: Can plain neural networks compete with BM3D? In *25th IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2012)*, pages 2392 – 2399, Providence, RI, USA, 6 2012. 1

[4] S Harmeling, M Hirsch, and B Schölkopf. Space-variant single-image blind deconvolution for removing camera shake. In J Lafferty, CKI Williams, J Shawe-Taylor, RS Zemel, and A Culotta, editors, *24th Annual Conference on Neural Information Processing Systems (NIPS)*, pages 829–837, Vancouver, BC, Canada, 2010. Curran. 1

[5] S Harmeling, M Hirsch, S Sra, and B Schölkopf. Online blind deconvolution for astronomical imaging. In *First IEEE International Conference on Computational Photography (ICCP 2009)*, pages 1–7, San Francisco, CA, USA, 4 2009. IEEE. 1

[6] M Hirsch, CJ Schuler, S Harmeling, and B Schölkopf. Fast removal of non-uniform camera shake. In DN Metaxas, L Quan, A Sanfeliu, and LJ Van Gool, editors, *13th IEEE International Conference on Computer Vision (ICCV 2011)*, pages 463–470, Barcelona, Spain, 11 2011. IEEE. 1

[7] M Hirsch, S Sra, B Schölkopf, and S Harmeling. Efficient filter flow for space-variant multiframe blind deconvolution. In *Proceedings of the 23rd IEEE Conference on Computer Vision and Pattern Recognition*, pages 607–614, San Francisco, CA, USA, 6 2010. IEEE. 1

[8] R Köhler, M Hirsch, B Mohler, B Schölkopf, and S Harmeling. Recording and playback of camera shake: Benchmarking blind deconvolution with a real-world database. In A Fitzgibbon, S Lazebnik, P Perona, Y Sato, and C Schmid, editors, *12th European Conference on Computer Vision (ECCV 2012)*, pages 27–40, Florence, Italy, 2012. Springer. 1

[9] CJ Schuler, M Hirsch, S Harmeling, and B Schölkopf. Non-stationary correction of optical aberrations. In DN Metaxas, L Quan, A Sanfeliu, and LJ Van Gool, editors, *13th IEEE International Conference on Computer Vision (ICCV 2011)*, pages 659–666, Barcelona, Spain, 11 2011. IEEE. 1

[10] CJ Schuler, M Hirsch, S Harmeling, and B Schölkopf. Blind correction of optical aberrations. In A Fitzgibbon, S Lazebnik, P Perona, Y Sato, and C Schmid, editors, *12th IEEE European Conference on Computer Vision (ECCV 2012)*, pages 187–200, Florence, Italy, 2012. Springer. 1