

Poisson Noise Removal for Image Demosaicing

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Abstract

With increasing resolution of the sensors in camera detector arrays, acquired images are ever more susceptible to perturbations that appear as grainy artifacts called ‘noise’. In real acquisitions, the dominant noise model has been shown to follow the Poisson distribution, which is signal dependent. Most color image cameras today acquire only one out of the R, G, B values per pixel by means of a color filter array in the hardware, and in-built software routines have to undertake the task of obtaining the rest of the color information at each pixel through a process termed demosaicing. The presence of the Poisson noise can significantly degrade the output of a demosaicing algorithm. In this paper, we propose and compare two dictionary learning methods to remove the Poisson noise from the single channel images by directly solving a Poisson likelihood problem or performing a variance stabilizer transform prior to demosaicing. Experimental results on simulated noisy images as well as real camera acquisitions, show the advantage of these methods over approaches that remove noise subsequent to demosaicing.

1 Introduction

Images acquired by digital cameras often exhibit grainy artifacts, called ‘noise’. This is especially under poor ambient lighting, in which case the detector arrays of the camera receive relatively fewer photons. This leads to a poor signal to noise ratio. While the image quality can be controlled by allowing larger exposure times, this can potentially lead to motion blur artifacts due to changes in the scene or hand tremor during the exposure period. The image quality can also be improved by using a higher ISO setting in the camera, to improve the detector sensitivity. This increased sensitivity, however, can further exacerbate the noise. In certain cases, one may use the camera flash to actively improve the lighting, but this option is saddled with the danger of changing the color or appearance of some regions, and is also not feasible in many applications such as security or wildlife photography. Under such conditions, it is advisable to resort to software-based routines to enhance the image appearance by removing the noise. Empirical studies have revealed that the dominant noise distribution in acquired digital images is Poisson [19], which is a signal dependent noise model with a variance that varies spatially and is exactly equal to the mean of the underlying ‘true’ signal.

The images acquired by digital cameras or scanners are first stored in a detector (CCD) array. For color (RGB) images, three separate detector arrays are infeasible due to extra cost

and spatial misalignment between the three acquired single-channel images. Hence most cameras or scanners acquire the color image on a single detector array by means of a color filter array (CFA), the most common pattern being the Bayer pattern. Thus each detector pixel measures only one out of the R,G,B values producing what is termed a ‘CFA image’ or ‘mosaic image’, and it is the responsibility of a software routine built in the camera to obtain the missing color information by means of an interpolation procedure called ‘demaicing’. There are two approaches for performing demosaicing: (1) denoising the CFA image followed by demosaicing, or (2) demosaicing followed by denoising the color image. The latter approach (as we also show in the experiments) is theoretically unprincipled because the demosaicing approach alters the noise statistics as the mutually independent noise values in the mosaic image now become inter-dependent.

The contribution of this paper is to present and compare two principled approaches to denoise the CFA image by adhering to the properties of the Poisson distribution and also exploiting the non-local similarity of CFA images produced by periodic CFA patterns. The denoised CFA image can be given as input to any off-the-shelf demosaicing routine to generate the full RGB image from noise-free CFA data. Experiments are performed on simulated noisy images as well as noisy real camera acquisitions with excellent results. Although the experiments in this paper are performed on the Bayer pattern, which is the most commonly used CFA pattern, it also in principle works with any periodic CFA pattern such as CYYM or CYGM¹. We emphasize that while image demosaicing is a well-researched topic, this paper takes care of the *Poisson* nature of the noise in the *raw* images in a principled manner *without requiring any prior training*.

This paper is organized as follows. Related literature is summarized and critiqued in Section 2. Our main theoretical approach is described in Section 3 and experimental results are presented in Section 4. A conclusion and discussion follows in Section 5.

2 Related Work

While there is no dearth of literature on demosaicing algorithms [10], many existing methods process noise-free CFA images which is not a realistic assumption. There exist several approaches which either perform joint denoising and demosaicing, or which denoise the CFA data prior to demosaicing, for example as in [2, 5, 8, 15, 20]. Studies in [19] have demonstrated that the noise in raw images is dominated by the Poisson distribution. However these methods do not fully account for the Poisson nature of the noise in the raw CFA images. For example, [5] assumes a Gaussian model with a signal-dependent spatially varying standard deviation, whereas [12, 15, 20] assume an i.i.d. signal independent Gaussian noise model with a constant variance in each channel. The approach in [8] applies different variants of a median filter to the CFA data before demosaicing, and shows that this produces better results than applying similar median filters to the demosaiced image obtained by interpolating the noisy CFA image. On the other hand, the approach in [2] approximates the Poisson noise distribution by a generalized Gaussian (hyper-Laplacian) distribution whose variance is proportional to the mean of the samples. We emphasize that this is an *approximation* as the mean of the samples can be a noisy estimate, and vary from one region of the image to another. Moreover this leads to a non-convex cost function for inferring sparse codes given a dictionary, unlike the two approaches presented in this paper. Recently an approach to joint

¹https://en.wikipedia.org/wiki/Color_filter_array

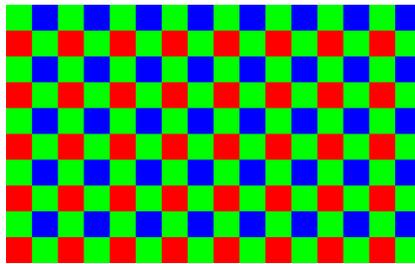


Figure 1: Bayer CFA Pattern

denoising and demosaicing using regression tree fields was proposed in [9], which learns a regression model on a training set of clean RGB images and their corresponding CFA images corrupted by a realistic Poisson-based model. However the learned model may depend on the training set as well as on the resolution of images used. As opposed to this, the approaches presented in this paper infer a dictionary-based model *directly* from the noisy CFA image *in situ*. There also exists some recent work which treats image demosaicing as a (possibly noisy) compressed sensing problem [13]. While this method works excellently for a variety of CFA patterns, it is not best suited to the Bayer pattern, because the sensing matrix derived from the Bayer pattern does not obey sufficient conditions for compressive recovery - such as incoherence, or a small restricted isometry constant. Moreover, this approach does not account for the Poisson noise in the CFA images.

3 Theory

In this section, we develop two approaches for removal of Poisson noise from the CFA image. The first approach, which we call as the ‘Poisson Penalty Approach’, is based on the direct minimization of an energy function which is the sum of the negative log likelihood of the Poisson noise model and a weighted sparsity-promoting term. The second approach is indirect and is inspired by the literature on variance stabilization transforms to convert the Poisson noise to Gaussian noise with a fixed variance, followed by Gaussian denoising and an inverse transform. We term this approach the ‘Variance Stabilizer Approach’. Both these approaches are based on inferring dictionaries *in situ* from the noisy CFA data, without requiring any prior training. Before we describe these two approaches in detail, we first briefly review the structure of the Bayer pattern.

3.1 Structure of the Bayer Pattern

The Bayer pattern consists of repeated 2×2 patterns with GB in one of the rows and RG in the other (or circular shifts thereof), as seen in Figure 1. The sampling of the green channel is denser than those of the red or blue channel in keeping with the greater sensitivity of the human eye to the green color. While newer CFA patterns have emerged, the Bayer pattern remains the most common one. In both the approaches outlined below, the periodicity of the Bayer pattern allows for efficient denoising of the CFA image. Given the denoised CFA image, the same periodic nature allows for efficient demosaicing by means of edge-directed interpolation.

3.2 Poisson Penalty Approach

Consider an image Y which is a Poisson-corrupted version of an underlying ‘clean’ image X , *i.e.* $Y \sim \text{Poisson}(X)$. Let \mathbf{y}_i be a small $n \times n$ sized patch (reshaped to form a vector) at location i from Y , which is the noisy manifestation of a patch \mathbf{x}_i of the same size from the same location in image X , *i.e.* $\mathbf{y}_i \sim \text{Poisson}(\mathbf{x}_i)$. Now assuming independent noise at each pixel of \mathbf{y}_i , the likelihood of \mathbf{y}_i given \mathbf{x}_i is given as:

$$p(\mathbf{y}_i|\mathbf{x}_i) = \prod_{j=1}^{n^2} \frac{x_{ij}^{y_{ij}} e^{-x_{ij}}}{y_{ij}!}. \quad (1)$$

We assume that each of the unknown underlying patches \mathbf{x}_i can be expressed as sparse or compressible linear combinations of the columns of a *common* dictionary $\mathbf{D} \in R^{n^2 \times K}$, *i.e.*

$$\mathbf{x}_i = \mathbf{D}\mathbf{s}_i = \sum_{k=1}^K \mathbf{d}_k s_{ik} \quad (2)$$

where $\mathbf{s}_i \in R^K$ is a sparse/compressible vector and \mathbf{d}_k denotes the k^{th} column of \mathbf{D} . The inference of all patches $\{\mathbf{x}_i\}_{i=1}^{N_p}$ given $\{\mathbf{y}_i\}_{i=1}^{N_p}$ involves the inference of \mathbf{D} and $\mathbf{s} = \{\mathbf{s}_i\}_{i=1}^{N_p}$ where N_p is the total number of (possibly overlapping) patches. Given the non-negative nature of most naturally occurring images and hence each patch \mathbf{x}_i , we impose the constraint that all elements of \mathbf{D} and $\{\mathbf{s}_i\}_{i=1}^{N_p}$ are non-negative. To impose sparsity on each \mathbf{s}_i , we assume it is a sample from a generalized Gaussian distribution with shape parameter $q \leq 1$. Taking all this into account, we can infer \mathbf{D} and \mathbf{s} by minimizing the following objective function which is the sum of the negative Poisson log likelihoods of all the patches given these unknown variables, and the negative logs of the prior probability of the sparse coefficient vectors:

$$\mathcal{E}(\mathbf{D}, \mathbf{s}) = \sum_{i=1}^{N_p} \sum_{j=1}^{n^2} (-y_{ij} \log(\mathbf{D}\mathbf{s}_i)_j + (\mathbf{D}\mathbf{s}_i)_j) + \lambda \sum_{i=1}^{N_p} \|\mathbf{s}_i\|_q \text{ s. t. } \mathbf{D} \succeq 0, \mathbf{s} \succeq 0, \forall k \|\mathbf{d}_k\|_2 = 1 \quad (3)$$

where λ is a parameter that is a trade-of between the likelihood and sparse regularizer terms. In our experiments, we set $q = 1$, although in principle this method works for any $q \in (0, 1]$. Since the representation in Equation 2 has inherent scaling ambiguities, we impose a unit norm constraint on the columns of the dictionary. The actual optimization starts with a random initial guess for \mathbf{D} and \mathbf{s} followed by an alternating minimization - a projected gradient descent (with adaptive step size) on \mathbf{s} keeping \mathbf{D} fixed, and a projected gradient descent (with adaptive step size) on the columns of \mathbf{D} keeping \mathbf{s} fixed.

The model presented here is essentially inspired from non-negative sparse coding [7] but with a Poisson likelihood. There exist two other models to impose the constraint of non-negativity on \mathbf{x}_i : (i) using exponential functions, *i.e.* $\mathbf{x}_i = \exp(\mathbf{D}\mathbf{s}_i)$ [3, 4, 17], and (ii) using the form $\mathbf{x}_i = \mathbf{D}\mathbf{s}_i$ subject to $\mathbf{D}\mathbf{s}_i \succeq 0$. The model (i) inherently expresses the element-wise logarithm of the patch intensities as a sparse linear combination of dictionary columns, which is somewhat less intuitive and faces problems at intensity values approaching 0. The model (iii) is difficult from an optimization point of view, especially if \mathbf{D} is overcomplete, *i.e.* $K > n^2$. This is because the constraint $\mathbf{x}_i = \mathbf{D}\mathbf{s}_i \succeq \mathbf{0}$ is imposed by setting all negative values that appear in \mathbf{x}_i (in the gradient descent step) to 0. Fitting an optimal \mathbf{s}_i to such a modified \mathbf{x}_i is a non-trivial problem if $K > n^2$. On the other hand, the model used in this

paper differs from model (iii) in that we impose both $\mathbf{D} \succeq \mathbf{0}$ and $\mathbf{s} \succeq \mathbf{0}$ which is easier in terms of the optimization.

Global and Local Dictionaries: The dictionary \mathbf{D} can be learned in two ways. In the first approach, a single \mathbf{D} is learned for the entire set of patches from the complete image. This is called the ‘global dictionary’. In the second approach, a small window of size $w \times w$, $w > n$ is considered around any given patch (called as a ‘reference patch’), and a single dictionary is learned using patches only from this window. Thus, a separate dictionary is learned for each such reference patch. This approach is termed the inference of spatially varying or ‘local dictionaries’. The global dictionary approach is preferred in case of images that are homogeneous or in case of single texture images, whereas spatially varying dictionaries are preferred in case of images with varying structural content.

3.3 Variance Stabilizer Approach

Given a Poisson distributed random variable y with mean x , it is well known that if $z = 2\sqrt{y + 3/8}$, then z is approximately distributed as $\mathcal{N}(0, 1)$. This approximation is called the Anscombe transform [1] and it stabilizes the variance, *i.e.* makes it equal all over the image. The approximation is known to be fairly accurate for mean values greater than or equal to four. Indeed, as per [1], the variance of z is approximately $1 + \frac{1}{16x^2}$ which is approximately equal to 1 for $x \geq 1$. For most applications in photography or scanning, it is rare to encounter images with a significant number of pixels with intensity values less than 1, and hence the Anscombe transform is very useful for our purposes. To denoise a CFA image Y using this approach, we first compute $Z = 2\sqrt{Y + 3/8}$, denoise Z using an image denoiser suited to Gaussian noise with a fixed, known variance (which equals 1 in this case), and obtain the final image as $W = Z^2/4 - 3/8$. The specific denoiser we use is the spatially varying PCA approach with Wiener filter as outlined in [14]. It can be shown that this method is the solution to the following optimization problem [3, 14]:

$$\mathcal{E}'(\mathbf{D}, \mathbf{s}) = \sum_{i=1}^{N_p} \|\mathbf{y}_i - \mathbf{D}\mathbf{s}_i\|_2^2 + \rho \|\mathbf{s}_i\|_2^2 \quad (4)$$

where ρ is dependent upon the noise variance. It should be noted that the approach in [20] also uses spatially varying PCA for denoising the CFA images prior to demosaicing, but it does *not* consider Poisson noise, *i.e.* there is no variance stabilization step.

4 Experimental Results

We have performed extensive experiments on both synthetic and real data, which we describe in this section. The denoising was performed using 8×8 patches with 41×41 windows around the reference patch for the local dictionaries. The patches were sampled with a step-size of 2 in both X and Y directions, since the size of the smallest repeating element in a Bayer pattern is 2×2 . For the Poisson penalty approach, the number of dictionary columns was $K = 100$ whereas for the Variance Stabilizer approach, we set $K = 64$ since the dictionary here is the standard PCA basis. Given the denoised CFA image, the final demosaiced image was generated by using the ‘demosaic’ function in MATLAB which implements an edge-directed interpolation algorithm from [11], which is well suited to the Bayer pattern.

Synthetic Images: For this, CFA images were generated in software from existing color images with different peak intensity values, and Poisson noise was simulated. The denoising results followed by demosaicing are compared for the following methods at each peak value: Poisson Penalty Global with $\lambda = 0.1$, Variance Stabilizer Local (similar to the approach in [20] but preceded by the Anscombe transform) and a commercially available software called NeatImage² for which demosaicing was performed directly on the noisy CFA image followed by denoising of the color image. NeatImage provides an interactive plugin to be used within Photoshop which asks the user to select a homogeneous region within the image, followed by execution of its denoising engine. The results are shown in Figure 2 show comparable performances of the Poisson Penalty and Variance Stabilizer approaches. The advantages over NeatImage are clear as it exhibits color artifacts absent in the our more principled approaches. Note that we chose only those methods for comparison, whose software was available and which account for the noise in the CFA images.

Real Images: An actual camera acquires CFA images in a 16-24 bit raw format. The acquired images go through a pipeline of various pre-processing steps, very neatly documented in [18]:

- **Linearization:** The aim of this step is to undo the non-linear operations that a camera applies to raw data for storage purposes.
- **Offset Correction:** Each camera has a ‘black level’ and a ‘saturation level’. An affine transformation needs to be performed on the raw data to normalize it to the [0,1] range. Due to sensor noise, data outside the range from black to saturation needs to be clipped.
- **White Balance:** This involves removing unwanted color casts by multiplying the red and blue channels by scaling factors (the scaling factor for green is set to 1 by default).
- **Demosaicing:** This uses any inbuilt routine in the camera.
- **Color space conversion:** The intensity values in the image so far are in a color coordinate system of the camera. These values need to be converted to the sRGB color space by means of a linear transformation which depends upon the specific type of camera.

Our experiments were performed on raw CFA images (.CR2 format) acquired by a Canon EoS Rebel T2i 550D camera under high ISO setting (6400) under low to moderate lighting. No linearization step was required for the Canon camera. Important meta-data such as black and saturation values and white balance scaling factors were extracted from the raw images using the publicly available ‘dcrw’ software³. The matrix for color space conversion (post-demosaicing) for the Canon 550D camera was obtained from an online source⁴.

The results of our experiments are shown in Figure 3 and comparisons are drawn between the noisy image displayed by the camera (after in built demosaicing), the Poisson Penalty approach (Local) with $\lambda = 1$, Variance Stabilizer (Local) and NeatImage. The results on NeatImage are distinctly inferior with color artifacts. We noticed that the Poisson penalty (local) approach with $\lambda = 0.2$ produced results superior to the Variance Stabilizer approach with the noise variance $\sigma = 1$ after the Anscombe transform. Hence we altered the noise variance to $\sigma = 5$ to improve the results of the Variance Stabilizer approach. This could

²<https://ni.neatvideo.com/>

³<http://www.cybercom.net/~dcoffin/dcrw/>

⁴http://www.brucelindbloom.com/index.html?Eqn_RGB_XYZ_Matrix.html

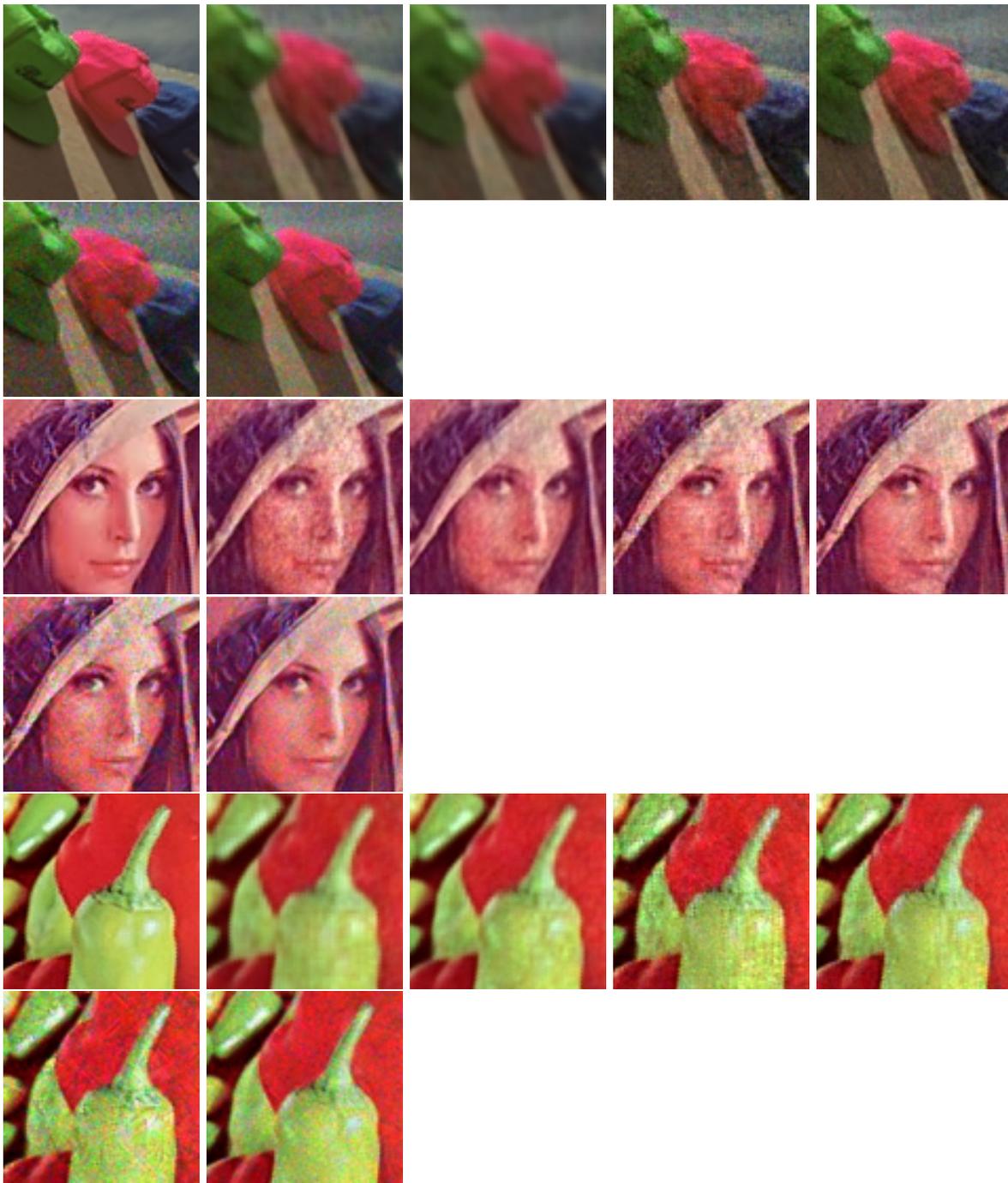


Figure 2: In each group of 7 images, left to right: original image, output of Poisson Penalty method at peaks 50 and 100 respectively, output of Variance Stabilizer method at peaks 50 and 100 respectively, output of NeatImage at peaks 50 and 100 respectively. Zoom into the pdf file or refer to the supplemental material for a clearer view.

point out to the presence of additional noise during the reading of the data or quantization errors.

Taking all the results in account, a note comparing the Poisson Penalty and Variance Stabilizer methods is in order. The former approach is computationally more expensive as the dictionary and coefficients do not have closed form expressions, unlike the latter case where they are expressed as eigenvector and eigencoefficients respectively. The former approach also requires the choice of a regularizer parameter λ , which however gives it greater flexibility since the λ can be interpreted as a creative user choice and makes the method more robust if imperfections creep in the assumed Poisson noise model, *e.g.* due to sensor or quantization noise. Similar flexibility can be achieved in the Variance Stabilizer approach, by adjusting the σ after the Anscombe transform.

5 Conclusion

We have presented two methods to demosaicing of CFA images corrupted by Poisson noise, the dominant source of noise in raw digital images. Both methods are derived from properties of the Poisson noise model, and make use of the prior that patches from natural CFA images can be expressed as sparse or compressible linear combinations of a dictionary, which can in fact be inferred from the noisy data. The results produced are superior to those by commercially available software such as NeatImage. We emphasize that our methods take care of the Poisson noise model during demosaicing in a principled manner without requiring any prior training. Since our methods are primarily aimed to denoising the CFA image prior to demosaicing, they can work in conjunction with any demosaicing algorithm. As such, our experiments have been performed on Bayer patterns, but our methods can work with any periodic CFA pattern including panchromatic ones [6, 13], though other demosaicing algorithms (instead of [11]) would need to be employed. There remains the issue of *joint* denoising and demosaicing. We tested this in our experiments by giving dictionaries learned from denoised and demosaiced color images back to the CFA denoising algorithm for inference of just the sparse codes. However this did not noticeably improve the results. We also experimented with approaches inspired from blind compressed sensing [16] for joint inference of the dictionary and sparse codes from the CFA images. While these proved to be computationally expensive, the results were far from satisfactory since they failed to exploit the periodicity of the Bayer pattern, and possibly because the Bayer pattern does not obey the coherence or restricted isometry properties sufficient for good compressive recovery.

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Figure 3: In each row, left to right: noisy image acquired by camera (post in-built demosaicing), output of NeatImage, output of Poisson Penalty approach with $\lambda = 0.2$ and $\lambda = 1$, output of local Variance Stabilizer approach with $\sigma = 5$. Zoom into the pdf file or refer to the supplemental material for a clearer view.

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