Poisson Noise Removal for Image Demosaicing

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Most color image cameras today acquire only one out of the R, G, B values per pixel by means of a color filter array (CFA) in the hardware producing the so called 'CFA image'. In-built software routines are required to undertake the task of obtaining the rest of the color information at each pixel through a process termed demosaicing. The most common CFA pattern is the well-known Bayer pattern which consists of repeating 2×2 filter sub-arrays. Studies in [2] have demonstrated that raw CFA images captured by a camera are corrupted predominantly by Poisson noise. This noise adversely affects the results of a demosaicing algorithm. While there exist several approaches in the literature to perform demosaicing, most of them do not fully account for the Poisson nature of the noise in the raw CFA images. In this paper, we present two simple but principled methods that infer dictionaries *in situ* from the noisy CFA images, both taking into account the Poisson nature of the noise. These dictionaries are used to denoise the noisy CFA images prior to demosaicing by exploiting the patch-level non-local similarity present in CFA images formed under periodic patterns such as the Bayer pattern and the sparsity of the coefficients of a linear combination of dictionary elements to express these patches. The denoised CFA image can be given as input to any off-the-shelf demosaicing routine to generate the full RGB image from the denoised CFA data.

Our first approach, which we term the 'Poisson Penalty Approach' (PPA), 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. Patches from the noisy CFA image are expressed as a non-negative sparse linear combination of dictionary columns, also constrained to be non-negative. Here, the dictionary as well as the sparse coefficients are learned *in situ* from the noisy patches in the CFA image. This minimization produces a denoised CFA image.

Our second approach is termed the 'Variance Stabiliser Approach'. It is well known that the so-called Anscombe transform [1] stabilizes the variance of Poisson distributed random variables of different mean values (and hence different variances), *i.e.* the transform makes these variances approximately equal. To denoise a Poisson corrupted CFA image Y using this approach, we first compute its Anscombe transform given by $Z = 2\sqrt{Y + 3/8}$, denoise Z using a dictionary-based image denoising algorithm suited for the Gaussian noise model 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 denoising algorithm we use is the spatially varying PCA approach with a Wiener filter.

We have performed extensive experiments on both synthetic and real data. Some results on real data captured using a Canon camera are shown in Figure 1 and comparisons are drawn between the noisy image displayed by the camera (after in-built demosaicing without denoising), the Poisson Penalty Approach, the Variance Stabilizer Approach, and a commerically available tool called NeatImage which denoises the RGB image after demoisaicing the noisy CFA image. Both the approaches clearly outperform the results obtained using NeatImage. Our methods have been tested on Bayer pattern CFA images but would work equally well on any other periodic CFA pattern.

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

[1] F. J. Anscombe. The transformation of poisson, binomial and negative-binomial data. *Biometrika*, 35(3/4):246–254, 1948.

[2] H. J. Trussell and R. Zhang. The dominance of poisson noise in color digital cameras. In *ICIP*, pages 329–332, Sept 2012.