Practical Deep Raw Image Denoising on Mobile Devices: Supplementary Material

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In this supplementary material, we provide a detailed derivation of k-Sigma Transform and more visual denoising results.

1 k-Sigma Transform Derivation:

1.1 The k-Sigma Transform

Our Poisson-Gaussian noise model is:

$$x \sim k\mathcal{P}(\frac{x^*}{k}) + \mathcal{N}(0, \sigma^2), \tag{1}$$

where x is the value read from sensor, x^* is the ground-truth value, k and σ^2 are sensor noise parameters. This can be written as

$$\begin{cases} x &= x_0 + n, \\ \frac{x_0}{k} &\sim \mathcal{P}(\frac{x^*}{k}), \\ n &\sim \mathcal{N}(0, \sigma^2). \end{cases} \tag{2}$$

By applying the k-Sigma transform to Eqn. (2), we have

$$f(x) = \frac{x_0}{k} + \frac{n}{k} + \frac{\sigma^2}{k^2}. \tag{3}$$

Based on the properties of Gaussian and Poisson distribution, we derive that

$$\frac{x_0}{k} \sim \mathcal{P}(\frac{x^*}{k}) \approx \mathcal{N}(\frac{x^*}{k}, \frac{x^*}{k}), \tag{4}$$

$$\frac{n}{k} + \frac{\sigma^2}{k^2} \sim \mathcal{N}(\frac{\sigma^2}{k^2}, \frac{\sigma^2}{k^2}). \tag{5}$$

Therefore, $f(x)$ can be approximately treated as Gaussian, written as:

$$f(x) \sim \mathcal{N}(\frac{x^*}{k} + \frac{\sigma^2}{k^2}, \frac{x^*}{k} + \frac{\sigma^2}{k^2}). \tag{6}$$

The approximation Eqn. (4) is accurate when $\frac{x^*}{k}$ is sufficiently large. In our application, we find that when $\frac{x^*}{k}$ is small, the Gaussian-part of $f(x)$, $\frac{n}{k} + \frac{\sigma^2}{k^2}$ dominates the distribution of $f(x)$, and Eqn. (6) is still enough accurate.

We verify Eqn. (6) by numerical simulation. We use the noise parameters of IMX586 sensor, setting ISO values to 400, 1600, 3200 and 6400, and x^* values to 1, 10, 50, 500. For each setting, we generate 1e6 samples from both Possion-Gaussian distribution according to Eqn. (2) and Eqn. (3) and pure Gaussian distribution Eqn. (6), and plot the histograms of the samples in Fig. 1. The statisitcal results show that the Gaussian approximation Eqn. (6) is quite accurate even if x^* is set to the smallest possible value.

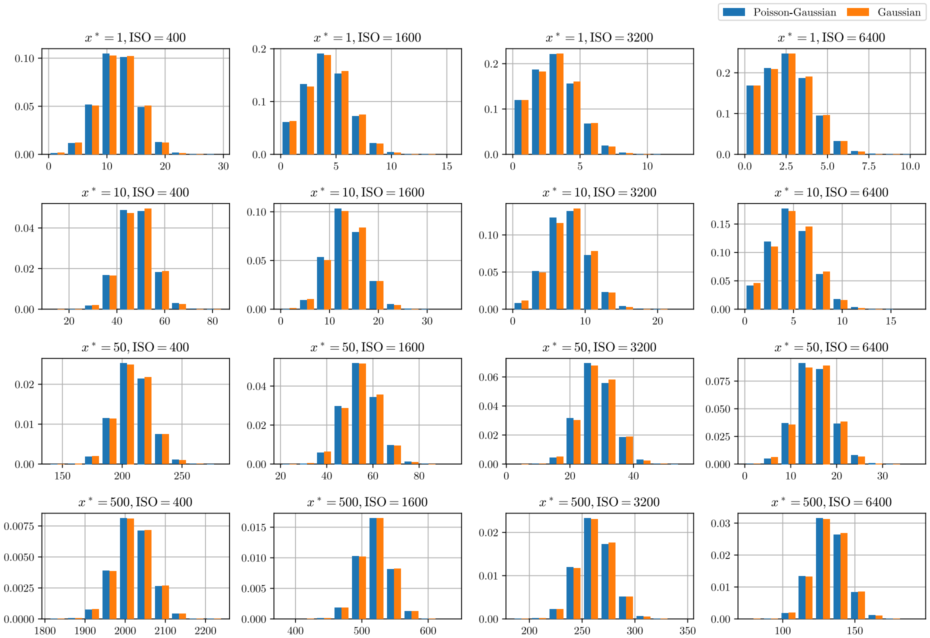

Fig. 1: Numerical simulated comparison of $f(x)$'s distribution and its Gaussian approximation. From top to bottom, x^* is respectively 1, 10, 50, 100; and from left to right, ISO is respectively 400, 1600, 3200, 6400. The statisitcal distributions of Possion-Gaussian and pure Gaussian model of $f(x)$ are almost the same.

2 More Results

Fig. 2: More visual results on our real dataset. From left to right: input image; ground truth; result based on BM3D [1]; result based on method in [2]; our result. Compared with [1] and [2] which generates blurred areas, our method can efficiently reduce the noise as well maintain underlying details.

References

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