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A Simple Model for Characterizing and Simulating Dark Noise in CMOS Sensors

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Abstract

Gaussian distribution models are widely used for characterizing and modeling noise in CMOS sensors. Although it provides simplicity and speeds needed in real-time applications, it is usually not a very good representation of dark current characteristics observed in real devices. The statistical distribution of CMOS sensor dark noise is typically right-skewed with a long tail, i.e. with more "hot" pixels than described in a normal distribution. Furthermore, the spatial distribution in real devices typically exhibit a 1/f-like power spectrum instead of a flat spectrum from a simple Gaussian distributions model. When simulating sensor images, for example generating images and videos for training and testing image processing algorithms, it is important to reproduce both characteristics accurately. We propose a simple convolution-type algorithm using seed images with a log-normal distribution and randomized kernels to more accurately reproduce both statistical and spatial distributions. The convolution formulation also enables relatively easy GPU acceleration to support real-time execution for driving simulation platforms.

Introduction

Imaging system simulations is increasingly being used in a wide range of industrial and consumer applications, for example electronic gaming, virtual/augmented reality, advertising, and designing camera system for mobile phone and automotive use. There are two main motivations in industrial applications: (1) camera applications software can be developed from simulated images before the hardware becomes available to reduce time to market, and (2) training data for machine learning algorithms can be generated from simulation in order to reduce the time and cost of having a fleet of drivers to acquire them in the physical world. For these applications in particular, it is important to apply noise models that closely match the characteristics of real sensors, as the simulated images are used as input for developing image signal processors (ISP) and training autonomous driving algorithms. The latter application is most crucial as incorrect noise characteristics can potentially lead to significantly different object detection performances and in worst cases compromise vehicle safety in the real-world operation.

When modeling CMOS sensor noise, it is important to consider both statistical and spatial distributions, as well as their dependence on operating parameters such as temperature and gain settings. With most camera simulators, noises are typically modeled with Gaussian statistical distribution with a simple mean and standard deviation parameters [1, 2]. Their spatial properties are not specifically considered, thus resulting a random distribution with a flat power spectrum. Dark noise in real sensors behave differently from this simple description as we shall discuss in more detail in the following section.

Furthermore with modern high dynamic range (HDR) sensors that uses multiple capture channels, it is also important to model each channel's distinct noise characteristics to produce simulated image that accurately reproduce real sensors' performances. For example, the latest generation of CMOS sensors for advanced driver-assistance systems (ADAS) from major sensor manufacturers, such as OMNIVISION's OX08D and Sony's IMX728, use multiple channels with dual conversion gains, multiple exposure times, and an additional lateral overflow integration capacitor (LOFIC) [3] to achieve a combined dynamic range of over 120 dB. Each of these channels have different noise characteristics and dependence on temperature. Since automotive sensors often must operate at over 100°C, an accurate noise model of each channel and their evolution with temperature change is critical to simulate these HDR sensors' performance characteristics throughout their dynamic range.

We report a dark noise model that attempts to match both the statistical distribution and spatial distribution of real sensors dark current. The goal is to provide simulated images with better fidelity than the commonly used Gaussian noise model while maintaining computational performance to support real-time applications.

CMOS Sensor Noise Distribution

We first briefly examine some dark noise properties of CMOS sensor. Figure 1 shows the dark noise distribution of a typical sensor from a raw image captured with no light exposure. Three images were captured first with dead pixel correction (DPC) turned off, then turned on, and finally with a more aggressive de-noise function activated. The power spectra of these 3 images are also plotted. Without any de-noise, the noise distribution is right-skewed with a long tail, indicating significantly more "hot" pixels than a Gaussian distribution would predict. Therefore the simple Gaussian model will generally underestimate the amount of hot pixels. Application of de-noise functions filters out most of the hot pixels, but at some cost of impacting the high-resolution features. It's worth noting that multiple peaks may be observed in some sensor samples. This is often an indication of processing imperfections and it's less common in state-of-the-art sensors.

In addition to statistical distribution, the spatial distribution of noise is also important. A simple Gaussian model will lead to a random spatial distribution with a flat power spectrum. However the dark image power spectrum of a raw sensor image generally exhibits a $1/f$-like spatial frequency dependence, particularly at low-frequency end and often become flat at high-frequency end. As DPC is applied, the high-frequency components is suppressed, and stronger high-frequency suppression results when a more aggressive de-noise process is applied.

It's also interesting to observe the temperature dependence of the power spectrum shown in Figure 2. At low temperatures, below

65℃ in this example, the power spectra show an almost exact $1/f$-like behavior. As temperature increases, the high-frequency components increasingly becomes flat, indicating the additional thermal noise follow a random spatial distributions. The effect of high spatial frequency suppression from the DPC function also becomes more prominent as more hot pixels are identified and corrected by the algorithm.

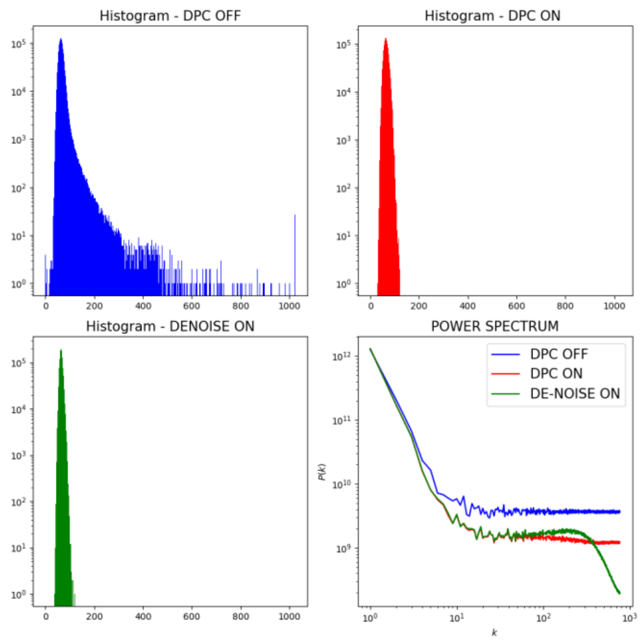

Figure 1. *Noise distribution of a typical CMOS sensor. Upper left: the raw output. Upper right: with DPC turned on. Lower left: with more aggressive de-noise function turned on. Lower right: power spectrum of the 3 images.*

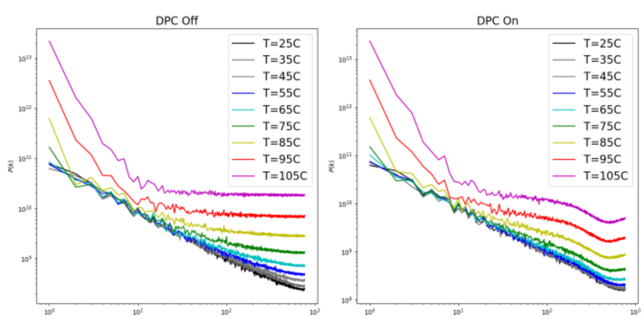

Figure 2. *Power spectrum of a CMOS sensor without DPC (left) and with DPC applied (right) at temperatures between 25℃ and 105℃.*

A sensor simulation model should ideally reproduce both the statistical and spatial distributions of a real sensor. There have been several models introduced to characterize and simulate these properties in detail [4, 5], but this work proposes a more simplified convolution-type algorithm that is able to closely approximate both characteristics and can also be easily implemented with GPUs for real-time execution, for example on autonomous driving platforms.

It is also interesting to note such a power spectra series acquired at different temperatures also provides a simple way to detect the application of de-noise algorithms in a sensor by observing how much the high-frequency components deviate from a simple random distribution at different temperatures. Although it is difficult to quantify how aggressive the algorithm is, it nevertheless provides an insight into noise performance and suppression of high-frequency features when comparing multiple sensors. Hence a comprehensive sensor evaluation criterion and process should take these factors into account.

Approach and Results

We use convolution-like algorithm with a seed image and randomized kernel to simulate CMOS sensor dark noise. A random two-dimensional seed images $f(x,y)$ is first generated using a simple Gaussian distribution with mean μ and standard deviation δ. With the commonly used Gaussian noise model, this seed image would be used as the actual noise image. But to reproduce the asymmetric profile of the noise distribution in Figure 1, we apply an exponential to each element of the seed image. With the proper choice μ and δ, this new image $e^{f(x,y)}$ would reproduce the right-skewed statistical distribution matching the captured image, and potential negative values in the Gaussian distribution is eliminated. However, the spatial distribution still has a flat spectrum because the noise values are randomly distributed spatially.

To modify this spatial distribution, we construct a kernel for each pixel consisting of a constant part and a randomly varying part. For example, a 3×3 kernel could be constructed as:

$$g(x,y) = \begin{bmatrix} \phi & \phi & \phi \\ \phi & 1-8\phi & \phi \\ \phi & \phi & \phi \end{bmatrix} + \begin{bmatrix} \epsilon_1 & \epsilon_2 & \epsilon_3 \\ \epsilon_4 & \epsilon_5 & \epsilon_6 \\ \epsilon_7 & \epsilon_8 & \epsilon_9 \end{bmatrix}$$

where ϕ is a constant and the ϵ values are generated with normal distribution with zero mean and stand deviation σ. The exponential noise image is then convolved with the kernel to generate the final noise image:

$$h(x,y) = \sum_{i=1}^{3} \sum_{j=1}^{3} e^{f(x+i-2,y+j-2)} g(i,j)$$

The kernel can be roughly interpreted as a crosstalk function that affect both the statistical and spatial distributions. The simulated noise images are controlled by 4 parameters μ, δ, ϕ, and σ. Among them, μ and δ primarily control the peak value of the noise distribution and its right-skewed tail, while ϕ and σ modify the distributions at local scales. It is straightforward to manually adjust these values to match simulated results to captured sensor data and an iterative algorithm is being developed to optimize them automatically.

Figure 3 shows a noise image simulated with this approach. The seed image and noise images show significantly different appearance although they have similar mean and standard deviation measures. The statistical distribution shows a similar right-skewed pattern as the measurement from a real CMOS sensor shown in Figure 1 and the power spectrum shows a similar $1/f$ spatial frequency dependence as in Figure 2 at low temperatures.

The comparison from Figure 3 is a good illustration of the importance of accurate noise modeling for image simulation, especially for modern HDR sensor where multiple channels, each with different noise characteristics, are combined to create a final image. If any channel's simulated noise properties differ too much from the real sensors, it may mislead the image processing algorithms and misguide the autonomous driving system training, costing time and effort to rework the algorithms and in worse cases leading to safety issues with the vehicle.

The process we use is similar to the autoregressive algorithm often used in sensor noise generation but simplified for easy CUDA implementation for high-speed calculations. The current code is written in python and a C++/CUDA version is being developed for real-time execution in OVT's sensor simulation models for several autonomous driving platforms.

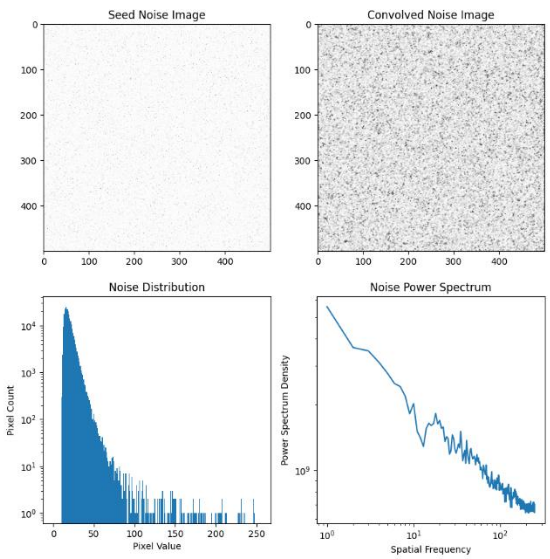

Figure 3. *Results generated from the noise generation algorithm. Top left: seed image with a simple Gaussian distribution. Top right: resulting noise image after the convolution process. These display range of these two images are scaled to 0.5% and 99.5% percentile of the image values. Lower left and right: distribution and power spectrum of the simulation noise image, respectively.*

Conclusion

We have developed a simple dark noise model that attempts to match both the statistical distribution and power spectrum of measured CMOS sensor noise characteristics. It is being integrated into OMNIVISION's real-time sensor simulation library for major driving simulation platforms used in the automotive industry. We expect this approach will provide significantly more accurate noise modelling than the commonly used Gaussian model, thus leading to more effective algorithm development with simulated data and reduced product development time and cost.

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Author Biography

Dr. Steve Wang received his Ph. D in physics from State University of New York at Stony Brook. He is currently Director of Sensor Technology in the Office of the CTO at OMNIVISION Technologies, Inc. focusing on camera systems simulations.