Implementing a CMOS Image Sensor Noise Performance Model

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An accurate model of CMOS image sensor noise performance is useful in optimising sensor design and setting targets, ultimately leading to improvements in image quality. Many attempts at modelling CMOS image sensor noise are based on over-simplistic assumptions and may not incorporate a sufficient variety of noise sources to yield a realistic simulator [1]–[3]. These issues inspire the creation of a unified and accurate sensor noise model capable of displaying noisy end-images. In [4], we describe a noise model that incorporates plausible distributions to create realistic images. This paper presents further details of the implementation of such a tool.

Our model has been implemented in MATLAB. The use of this high level programming tool has aided the speed of model development, as many routines are already available for image manipulation and statistical analysis. Figure 1 shows the well known CMOS image sensor noise chain that has been modelled [5]. Optical effects other than diffusion crosstalk in the silicon have not been considered. Realistic modelling of non-Gaussian effects is required to model shot noise, dark current noise, pixel 1/f and RTS noise, and other readout related noises.

Generation of such distributions for megapixel images and for video sequences can be computationally expensive and acceleration methods are needed for acceptable performance and usability from the simulator. For example, the generation of Poisson statistics to model photon and dark current shot noise involves the generation of a Poisson random variable for each pixel with the variance equal to the mean arrival rate. It was found that repeatedly generating such variables was very slow. Fig 2 shows the method used to reduce the computation time, in which pixels of the same value are grouped together and the same Poisson variable used for those pixels. In typical images, the number of unique values is much less than the total number of pixels, so this results in a considerable reduction in computation time. This technique can equally be applied to photon shot and dark current shot noise.

Fixed pattern noise (FPN) such as photo-response non-uniformity (PRNU) also impacts image quality. Our method of modelling this is shown in Fig 3. In this case, a normal distribution is used to model the PRNU. A single frame of PRNU gain values is generated, and this is used over multiple frames to simulate video sequences, resulting in a fixed pattern noise. This method of generating a single frame of noise values is used to model all the fixed pattern effects. Of course the distribution used must be adjusted depending on the type of FPN [6].

Fixed pattern dark current noise is a key example of this. It is important to account for the non-Gaussian nature of this noise, especially the extreme outliers that appear as white pixels [7]. The exponential temperature dependence of this noise is also very important. Figure 4 shows how the dark current is simulated in our model. Using measured characterisation data, three different distributions have been fitted, one for each temperature. These distributions are then scaled by the gain and exposure time values to produce an FPN frame. Following this the shot noise of the dark current is added. As can be seen in Fig 5, realistic dark current effects are produced using this method.

Furthermore, we have accounted for non-Gaussian random noise, such as in the pixel source follower [8] and other readout electronics. As with the dark current modelling, we did not succeed in finding a single distribution which could account for the majority of the population while also reflecting the extreme outliers. Therefore we combined the Fischer-Tippet-Gumbel [9] distribution with a uniform distribution as is shown in Fig 6. Fig 7 shows in detail how we have modelled the RTS and 1/f noise of the pixel source follower using the combination of these two distributions.

Many noise sources in our model required the use of non-Gaussian distributions. However we were able to model the thermal noise of the readout chain, the vertical fixed pattern noise, and the time varying line noise, using Gaussian random variables with appropriate variance. Figure 8 shows the method of modelling time varying line noise while Figure 9 shows an example of measured values versus the model; they are in good agreement.

Figure 10 shows the complete noise model chain, and a simulated image with all noise sources enabled is given in Figure 11. Exaggerated noise parameters have been used for illustration purposes.

The model has proved useful for evaluating trade-offs between various noise parameters. An example of this is given in Figure 12. For two different values of vertical FPN, the simulated light level is swept. It can be seen that at low light, even a low value of vertical FPN (in this case 5 electrons input referred) is still visible. Many other similar investigations are possible using this model and the results provide a means of setting and justifying design and process targets for image sensors development.

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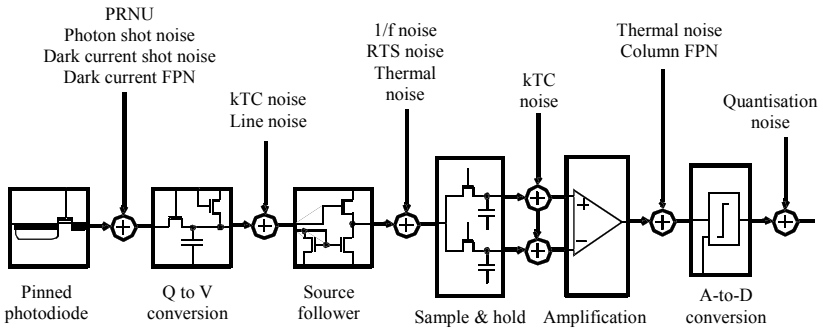

Fig. 1. Main noise sources in the CMOS imager pipeline (adapted from [5]).

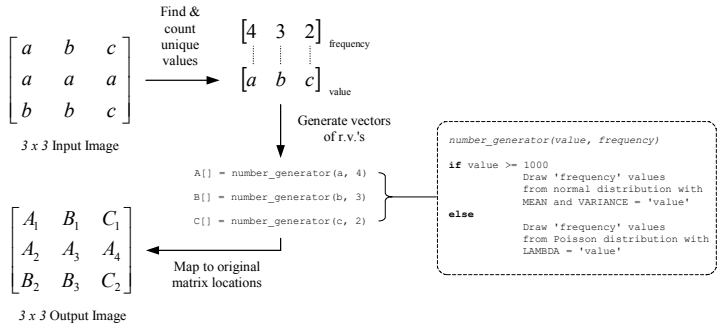

Fig. 2. Simple example of how to exploit recurring pixel values.

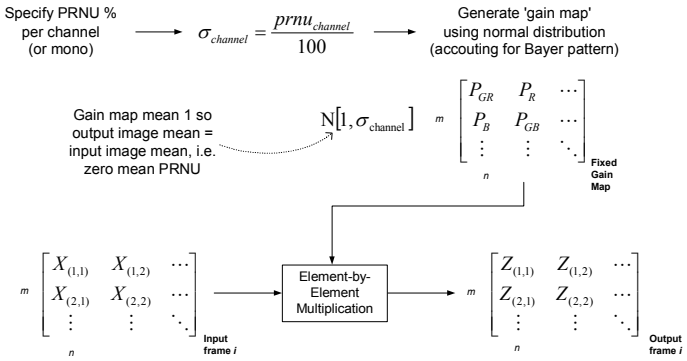

Fig. 3. Technique of modeling PRNU.

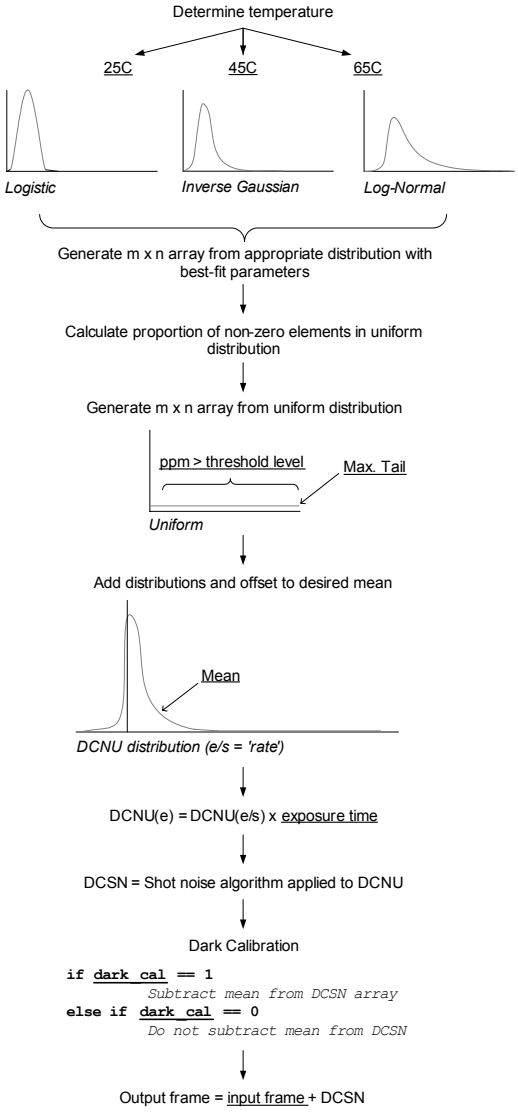

Fig. 4. Process of modeling dark current. Underlined text indicates input parameters specified by the user.

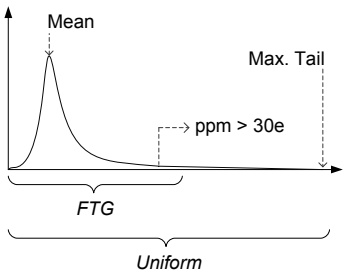

Fig. 6. Sketch of a synthetic flicker noise distribution, indicating the two underlying pdf's used and which parameters are controllable by the user.

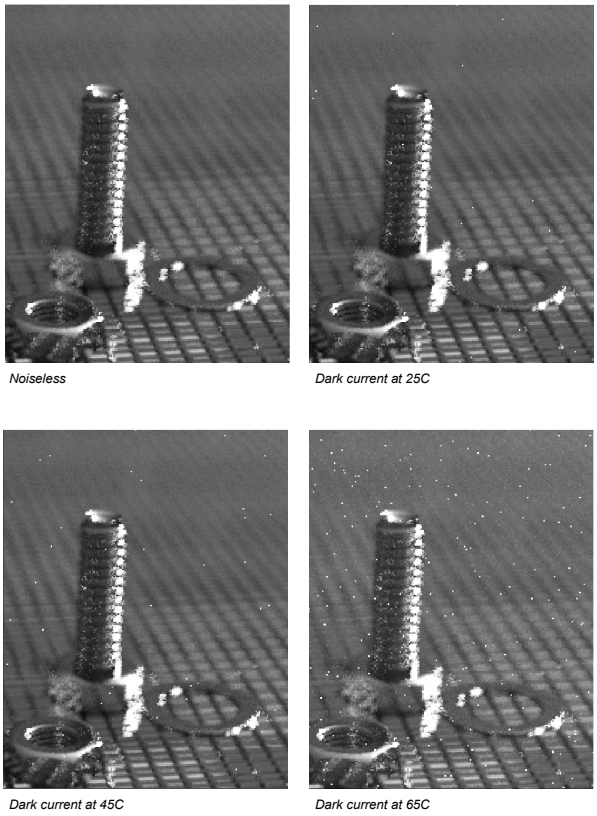

Fig. 5. Impact of dark current at 25˚C, 45˚C and 65˚C on a noiseless image at 0.25s exposure, using exaggerated dark current parameters for illustration.

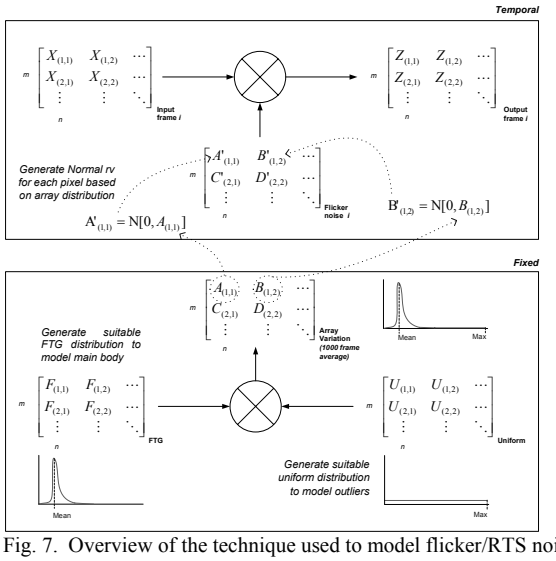

Fig. 7. Overview of the technique used to model flicker/RTS noise.

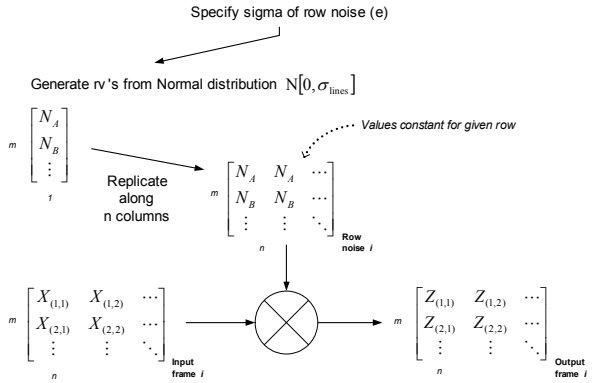

Fig. 8. Technique used to model temporal row noise.

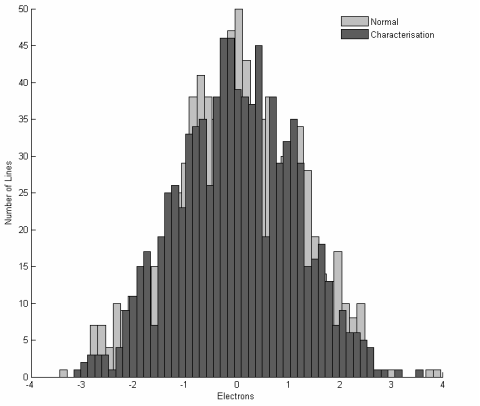

Fig. 9. Comparison of an actual temporal row noise histogram and a normal distribution with the same mean and standard deviation.

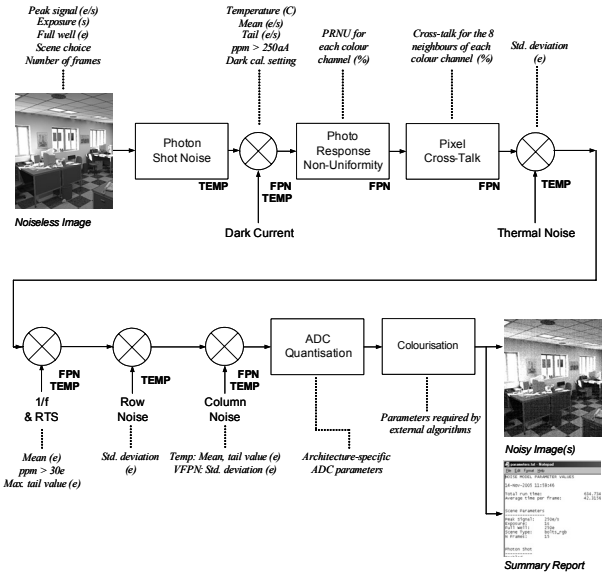

Fig. 10. Block diagram of the overall sensor noise model.

Fig. 11. Simulation of the entire sensor noise chain, based on exaggerated noise values for illustration purposes.

Fig. 12. Images showing the impact of various VFPN levels at low and medium light.