Shot-noise adaptive bilateral filter

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SHOT NOISE ADAPTIVE BILATERAL FILTERING

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ABSTRACT

The bilateral filter [1, 2] has an important place in image denoising. It smooths images while preserving edges using means of nonlinear combination of local pixels values. The method formulation and implementation are simple. However the set of the bilateral filter parameters has an important influence on its filtering behavior. They have to be chosen considering the user application. In the case of noise removing, the parameters have to be adapted to the noise level, the bilateral filter adapting then itself to the image details content. In this paper we propose a method to estimate the best bilateral filter parameters set for shot noise removing, the dominant noise in digital imaging.

***Index Terms*—** Digital imaging; image sensors; Poisson noise model; noise filtering; noise reduction; noise estimation.

1. INTRODUCTION

The bilateral filter is a non linear filter used among others for denoising applications. In this paper we propose a method to estimate automatically this standard deviation using the variance and the mean of smooth image region.

2. BILATERAL FILTER CHARACTERISTICS

The bilateral filter consists to replace a pixel by a weighted mean of its neighbors considering both their geometric closeness and their photometric similarities. In this paper, we focus on the Gaussian bilateral filter because all the practical applications use this version. The Gaussian bilateral filter is defined as follows:

$$v(x) = \frac{1}{C(x)} \int_{\beta} e^{\frac{-|x-y|^2}{\rho^2}} e^{-\frac{|u(y)-u(x)|^2}{h^2}} .u(y).dy \qquad (1)$$

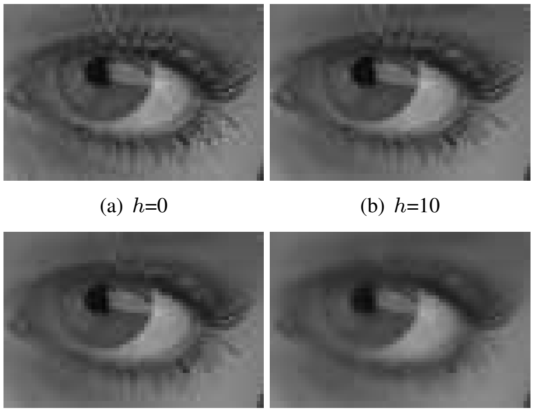
Where β represents the sliding window, y represents a set of 2-D pixel positions in the sliding window, x represents the centered pixel in the sliding window, $u(x)$ is the intensity of the pixel at the x position in the original image, $v(x)$ is the estimated pixel at the x position, ρ and h are respectively the standard deviation of the Gaussian distribution used for the geometrical weight calculation and the intensity weight calculation.

The parameters ρ and h define the bilateral filtering behavior. The geometrical parameter is chosen considering the size of the convolution kernel. The intensity parameter h has to be chosen considering the level of filtering needed for the application. Indeed, the more the standard deviation is high the more the filter is low-pass in the intensity space. An illustration of the h influence is shown on Fig.1. In the case of noise removing the parameter h has to be chosen considering the noise level. The best h could be selected among a set of h by chosing the one that has the lowest mean squarre error measure between the denoised image and the original version. Repeating this task for each image filtering is not acceptable in term of time consumption and computational complexity. In order to avoid this task, a solution consists to calibrate the best h for each noise level. Using this calibration, estimating the best h amouts to estimate the noise level in the image. In the following section we present a new method to estimate shot noise level in a poisson processus acquired image.

3. BEST H PARAMETER ESTIMATION BASED ON IMAGE CONTENT

3.1. Sensor noise assumption

Many sources are cause of noise generation in CCD and CMOS sensors. These can be categorized in four main factors [3]: (1) The photon shot noise – associated with a random Poisson process governing the number of incident photons reaching a photosite; (2) the Photon Response Non Uniformity – caused by small sensitivity differences between photosites; (3) the dark current noise – produced by minority carriers thermically generated in the sensors wells, also associated with a random Poisson process; and (4) the readout noise – resulting from thermal noise cause by MOSFET amplifiers.



(a) h=0 (b) h=10

(c) h=20 (d) h=40

Fig. 1. Bilateral filtering using a 5x5 square window as β and a variable h

A sensor noise model complete with respect to these factors is proposed in [3]. According to this model, photon shot noise has, in standard illumination conditions, the most important influence on the output image.

3.2. Automatic gain control

In a digital imaging system, an automatic gain control (AGC) allows to capture images in varying light conditions by adjusting the average intensity of the output signal (see Fig.2). By having access to the gain factor and knowing the sensor resolution, it is possible to deduce the number of photons that have reached the sensor and estimating then the noise level. In the following section we propose a method to estimate the applied gain by using images statistics and the proporties of a poisson distribution process.

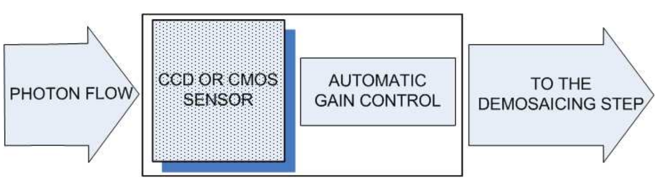


Fig. 2. Digital conversion of a photon flow by a camera sensor, the AGC adjusts the average image output intensity

3.3. Photon density from image statitics

In the presence of gain manipulation only, we expect the noise variance to be proportional to average pixel values in near-constant regions, due to its Poisson characteristics. Let consider I the image before AGC, and I_G the adjusted image after the AGC. Assuming G to be the gain factor, we can write:

$$I_G = G \times I; \tag{2}$$

Considering a Poisson distribution process, we can assume the following relation where $T^-(I)$ represents regions of near constant values in the image I.

$$E(T^-(I)) = Var(T^-(I)) \tag{3}$$

From image I_G we can write:

$$Var(T^-(I)) = E(T^-(I_G)^2) - E(T^-(I_G))^2 \tag{4}$$

Using 2 we can write:

$$T^-(I_G) = G \times T^-(I) \tag{5}$$

$$E(T^-(I)) = G \times E(T^-(I_G)) \tag{6}$$

Replacing the expressions 5 and 6 in 4 we obtain an estimation of the gain:

$$G = \frac{E(T^-(I))}{Var(T^-(I))} \tag{7}$$

The image mean $E(I)$ and variance $Var(I)$ can be simultaneously calculated at each point in I by using an efficient sliding-window algorithm [4]. We seek to establish a correlation between all $E(I)$ and $Var(I)$ at each point where T^- is non-zero. Using all the millions of pixels generally available in modern camera sensors is not necessary, so a random sampling of perhaps approximately 10^4 pixels was found sufficient. Since the mean and the variance are expected to be proportional, a robust linear, intercept-free, least-square correlation should be performed, the slope coefficient can then be interpreted as the gain factor transforming photon numbers to recorded pixel values.

3.4. Regions of near-constant values

In order to estimate the gain, we need to select areas $T^-(I)$ in the noisy image I that correspond to approximately constant values. These can be readily estimated from the image gradient

$$T^-(I) = \varepsilon_w(\nabla(G_\sigma \star I) > \vartheta), \tag{8}$$

where I is the image, G is a Gaussian convolution of variance σ, ε_w the morphological erosion on a window of size $w \times w$. ϑ is an intensity parameter.

3.5. Best h from photon density

The filtering properties of the Gaussian bilateral filter varies with the set of its two parameters. Using a fixed sliding window, the filtering properties vary with the h parameter. Intuitively we can assume that a low h should be required in low noise level, wheras a high h is necessary in high-noise conditions. A calibration of the best h for each noise level is necessary to establish a correspondance between the gain factor estimation and the adapted h. In the following we use a photon shot noise model to do this calibration.

4. EXPERIMENTS AND RESULTS

In this section seek to validate the previous assumptions.

4.1. Photon shot noise simulation

To do so we simulate sensor aquisition via a regionalized cumulative spatial Poisson point process [5] using scene images as probability distribution functions. This simulates individual photons being recorded at each pixel location, as in a Monte-Carlo process. As scene images we used the Kodak PhotoCD database, extracted at the 512x768 resolution. These virtually noise-free images were scanned at the 3 full color samples per pixel from film original following the Kodak professional PhotoCD procedure. Fig.3 illustrate this simulation.

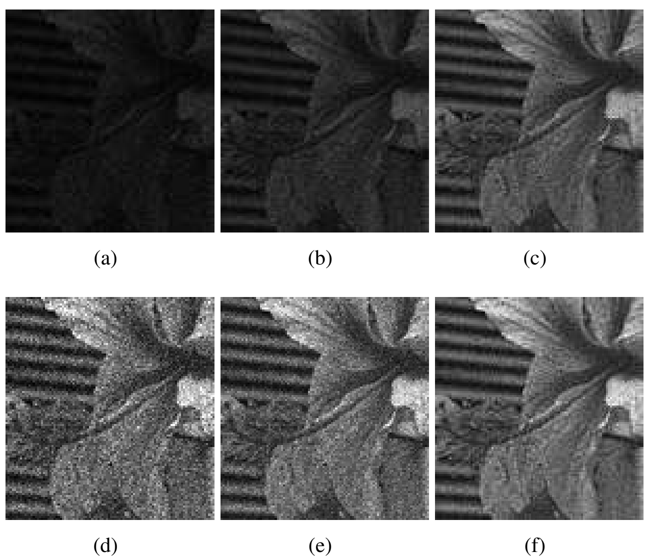


Fig. 3. Shot noise simulation using a sample representative image as a source and a per-pixel Poisson process. From (a) to (c) the mean number of photons per pixel over the whole image are 20, 80, 160. From (d) to (f) the corresponding images with a gain control.

4.2. Photon number estimation

We ran trials with a photon density per pixel between 20 and 320, from an extremely noisy to a clean image. We estimated the number of photons $\bar{\Phi}$ with the following formula:

$$\bar{\Phi}(I) = \frac{\text{nbpix}(I)\overline{E(I)}}{G} = \frac{\sum_{(x,y)\in I} I(x,y)}{G}, \qquad (9)$$

where nbpix(I) is the total number of pixels in I. The excellent correlation between simulated and estimated photons is shown on the log-log plot of Fig. 5 ($R^2 = 0.996$).

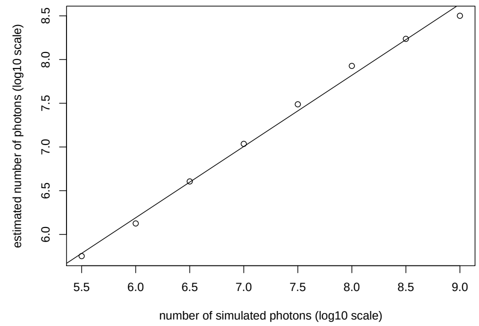


Fig. 4. Correlation between simulated and estimated photon numbers.

4.3. Best h estimation

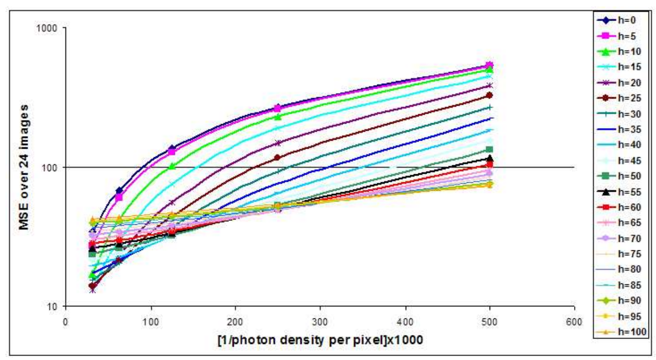


Fig. 5. Correlation between simulated and estimated photon numbers.

5. CONCLUSION

In this paper, we have proposed a methodology for digital image filtering in the presence of photon shot noise and a color filter array. For this, we have studied a subset of known filters that can be efficiently implemented in low-power CPUs and DSPs found in consumer digital cameras. We have shown that modeling noise in this context by a Gaussian distribution over an RGB image is not accurate, especially at high noise levels. We have also shown that when the noise standard deviation is sufficiently low, then it is better not to filter at all, even with the best filters, using fixed parameters. It is therefore important to adapt the level of filtering to the level of noise. Among the tested filters, the bilateral filter was shown to be the one with best performance. In addition, we showed how this filter can be optimised if the noise level is known. We have proposed a simple and efficient noise level detection algorithm. This algorithm was shown to exhibit good correlation between estimated and real noise level. By applying this noise level detection method to set the bilateral filter h parameter, we obtain a novel adaptive bilateral filter, which exhibits best-of-class performance at all noise levels.

6. REFERENCES

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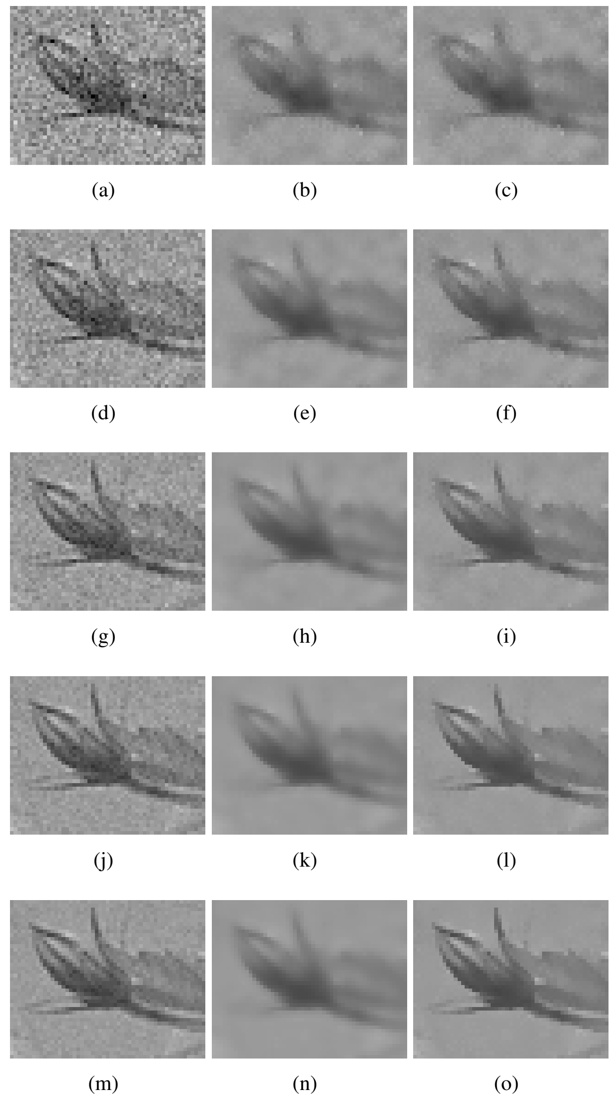

Fig. 6. Shot noise simulation using a sample representative image as a source and a per-pixel Poisson process. From (a) to (c) the mean number of photons per pixel over the whole image are 20, 80, 160. From (d) to (f) the corresponding images with a gain control.