

Signal Activity Estimation with Built-in Noise Management in Raw Digital Images

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Abstract: Discriminating smooth image regions from areas in which significant signal activity occurs is a widely studied subject and is important in low level image processing as well as computer vision applications. In this paper we present a novel method for estimating signal activity in an image directly in the CFA (Color Filter Array) Bayer raw domain. The solution is robust against noise in that it utilizes low level noise characterization of the image sensor to automatically compensate for high noise levels that contaminate the image signal.

1 INTRODUCTION

Digital images are usually acquired by means of image sensors covered by a *CFA* (*Color Filter Array*) which enables sensitivity to only one color component per pixel, either *Red*, *Green*, or *Blue*; demosaicing is eventually required to obtain a color image. Because of the subsampling in the *CFA* pattern, thin edges or texture may occupy just a few pixels in the subsampled lattice, making edges hard to detect (Chen, 2006). Discrimination between areas with signal activity from homogeneous areas can be difficult especially when the signal to noise ratio is low; noise may overpower the image signal or it may have a spatial structure that is similar to texture; this makes it difficult to discern useful signal from noise.

In this paper we propose a method that works directly in the raw CFA domain and exploits the image sensor noise characterization in order to robustly compensate for signal degradation caused by noise. This technique enables early detection of signal activity in the imaging pipeline, allowing subsequent algorithms (e.g. demosaicing, noise filtering) to optimally adapt to the image content.

2 NOISE MODEL

Signal amplification at image sensor level is a blind

process that amplifies both image signal and noise by means of an analog gain usually expressed in terms of the *ISO* setting. The acquired image is contaminated by various sources of noise that are usually modeled as zero mean additive white Gaussian noise; a Poissonian noise component is also present (Foi 2007, 2008; Bosco 2010). In general, the standard deviation of the underlying Gaussian noise distribution is assumed as a measure of the noise level. The signal dependent noise model can be expressed as (1):

$$\sigma_{noise}(i, g) = \sqrt{a(g) \cdot i + b(g)} \quad (1)$$

where $i \in [0, \dots, 2^{bpp} - 1]$ is the recorded signal intensity; bpp is the image bitdepth and $a, b \in \mathcal{R}^+$. The coefficients a and b depend on the sensor gain g (i.e. *ISO*). As the *ISO* increases, the a and b coefficients generate noise curves with increasing σ_{noise} values.

The a and b coefficients can be determined in an offline sensor characterization phase repeated by varying the amplification gain.

3 PROPOSED METHOD

The proposed solution, rather than partitioning image pixels into flat and non-flat classes, estimates a measure of flatness. A block diagram of the proposed solution is illustrated in Figure 1.

The processing kernel is split into 4 layers L_1, \dots, L_4 ; for each layer, a flatness degree measure fD_{L_i} is estimated, for $i=1, \dots, 4$. Finally, the *Signal Activity Estimator* block computes the *Signal Activity Degree* by combining the layers flatness degrees.

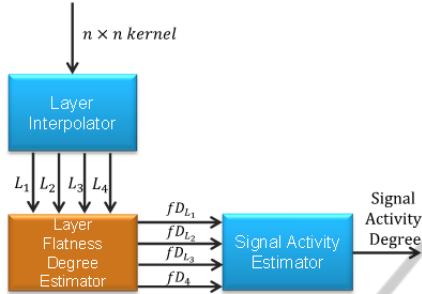


Figure 1: A $n \times n$ kernel moves across the CFA data. Four layers are extracted; for each layer, a flatness Degree (fD_{L_i}) is estimated. The Signal Activity Estimator Block combines the four estimations according to equation 10.

Measuring flatness can be seen as the dual problem of estimating signal activity; by normalizing the flatness degree fD_{L_i} between 0 (no flatness) and 1 (max flatness), the layer signal activity measure sA_{L_i} can be simply expressed as (2):

$$sA_{L_i} = 1 - fD_{L_i} \quad (2)$$

In the rest of the paper we will calculate the flatness degree and obtain the corresponding signal activity by simply applying equation (2).

3.1 Layer Interpolator

The input to the proposed estimator consists of a CFA raw Bayer image that is pixel-wise processed by a moving kernel; a flatness or, dually, signal activity degree is hence assigned to each pixel. The processing kernel is shown in Figure 2.

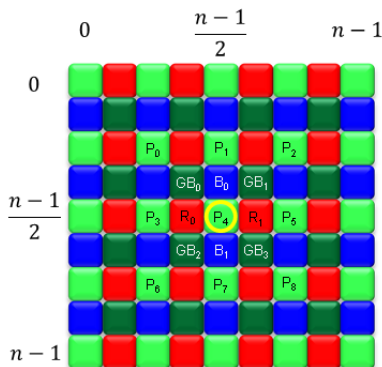


Figure 2: Processing Kernel contains pixels from all CFA channels.

According to Figure 2 we define a $n \times n$ kernel ($Kern_n$), such that $n \bmod 2 \neq 0$, $n \geq 9$. From this kernel, four subkernels are generated; each subkernel has size $s \times s$, $2s - 1 \leq n$ and is centered in $(\frac{n-1}{2}, \frac{n-1}{2})$. The first subkernel, $Kern_s$, is obtained by simply subsampling $Kern_n$ as indicated in Figure 2 and Eq. 3:

$$Kern_s(m_1, m_2) |_{m_1, m_2=0, \dots, s-1} = Kern_n(2i, 2j) |_{i, j=\frac{n-1}{4}, \frac{s-1}{2}, \dots, \frac{n-1}{4} + \frac{s-1}{2}} \quad (3)$$

The elements P_i , ($i = 0, \dots, 8$) of $Kern_s$ with $s = 3$ are shown in Figure 2. The other three subkernels are generated by interpolating the complementary CFA channels in the same spatial positions of $Kern_s$. The three interpolated subkernels are all centered in $P_4 \equiv (\frac{n-1}{2}, \frac{n-1}{2})$ and, taken together, they constitute 9 virtual pixels for which all the CFA information is available. Basically, a trivial demosaicing is performed in the same spatial locations of $Kern_s$; for example the complementary CFA information in P_4 is interpolated by averaging the nearest pixels of the same color to be interpolated: (GB_0, GB_1, GB_2, GB_3) , (R_0, R_1) , (B_0, B_1) for the *green-blue*, *blue*, and *red* CFA channels respectively. The procedure is similar for the other non-central pixels. Though other more sophisticated interpolation choices are possible, simple averaging provides enough precision for our purposes. The four subkernels share the same spatial locations, hence they can be considered as superimposed “layers”. The usage of the interpolated layers is necessary because tiny lines may occupy just a few pixels in the Bayer grid, hence the use of adjacent pixels to $Kern_s$ does not provide satisfactory results.

3.2 Layer Flatness Degree Estimator

The *Layer Flatness Degree Estimator* block is illustrated in Figure 3.

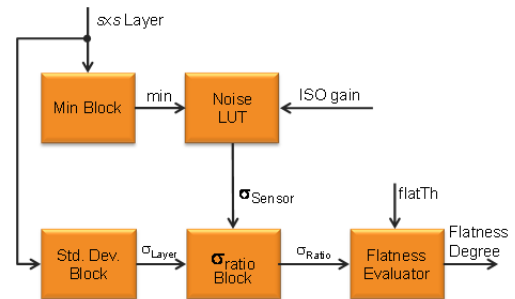


Figure 3: The Layer Flatness Degree Estimator Block processes a $s \times s$ layer and produces the flatness degree estimation for the input layer according to equation 8.

As the kernel moves pixelwise across the raw image, four $s \times s$ layers L_i ($i = 1, \dots, 4$) are obtained at each new position of the kernel; the standard deviation of each layer is computed, i.e. for $P_r \in L_i, r = 0, \dots, s \times s - 1, i = 1, \dots, 4$:

$$\sigma_{L_i} = std(P_r) \quad (4)$$

The minimum value of each layer L_i is computed:

$$\min_{L_i} = \min(P_r), \quad r = 0, \dots, s \times s - 1 \quad (5)$$

Then, the noise level associated to the layer minimum pixel value is retrieved taking into account the acquisition gain g :

$$\sigma_{Sensor}(L_i, g) = \sigma_{noise}(\min_{L_i}, g) = \sqrt{a(g) \cdot \min_{L_i} + b(g)} \quad (6)$$

The values of equation (6) can be stored in a *LUT* instead of computing them. The reference noise level σ_{Sensor} is the one associated to a flat area whose value is equal to the minimum pixel value in the layer, with the given *ISO* gain g ; the minimum value of the layer is chosen to avoid flatness overestimation.

The value σ_{Ratio} is computed as:

$$\sigma_{Ratio}(L_i, g) = \frac{\sigma_{L_i}}{\sigma_{Sensor}(L_i, g)} \quad (7)$$

The value σ_{Ratio} is *ISO* dependent by means of the g factor, hence σ_{Ratio} is implicitly compensated as the noise in the image increases or decreases. The basic idea underlying the equation (7) is that if the area is homogeneous, then the ratio between the standard deviation of the pixels in the layer (σ_{L_i}) and the minimum noise standard deviation (σ_{Sensor}) of the layer, should be close to 1. Ideally, when σ_{Ratio} exceeds 1, the central pixel of the layer should be classified as belonging to a non-flat area because the standard deviation of the pixels in the layer overpowers the standard deviation of the noise in a flat area whose value corresponds to the minimum value in the layer; however, as detailed in paragraph 4, this is an ideal condition because some biasing effects need to be considered.

In particular, a threshold $flatTh_{L_i}$ must be defined for each layer to compensate the biasing factors:

$$fD_{L_i} = \begin{cases} 1 & \text{if } \sigma_{Ratio} \leq flatTh_{L_i} \\ \frac{flatTh_{L_i} - \sigma_{Ratio}}{\Delta} + 1 & \text{if } flatTh_{L_i} < \sigma_{Ratio} \leq flatTh_{L_i} + \Delta \\ 0 & \text{if } \sigma_{Ratio} > flatTh_{L_i} + \Delta \end{cases} \quad (8)$$

The term Δ is used to avoid a strong binary classification; its value can be chosen to define a linearly fading zone that extends beyond $flatTh_{L_i}$.

3.3 Signal Activity Estimator

The final flatness degree fD_P associated to the central pixel $P\left(\frac{n-1}{2}, \frac{n-1}{2}\right)$ of the kernel, is obtained by summation of the flatness degrees fD_{L_i} of all layers:

$$fD_P = \sum_{i=1}^4 k_i \cdot fD_{L_i} \quad (9)$$

Where k_i is a weighting coefficient, currently set to "1" for $i=1,2,3,4$.

Finally, we obtain the *signal activity degree* sA_P associated to the central pixel of the kernel $P\left(\frac{n-1}{2}, \frac{n-1}{2}\right)$ as:

$$sA_P = 4 - \sum_{i=1}^4 k_i \cdot fD_{L_i} \quad (10)$$

4 COMPENSATING THE BIASING EFFECTS

As described in (Kim, 2005), two areas can have the same standard deviation but different pixel arrangements, such that one area contains some detectable pattern whereas the other area does not; we mitigate this problem by using the four data layers. Additionally, the assumption that σ_{Ratio} is close to 1 for flat areas is only ideal; σ_{Ratio} must be compared with $flatTh_{L_i} < 1$, compensating the two other important biasing factors: the small kernel size and the layers interpolation process. After compensating for these biases, the thresholds are mathematically defined and they do not need to be changed when noise levels change. In case a different image sensor is used, only the sensor noise profile *LUT* generated during the sensor characterization process needs to be updated.

5 EXPERIMENTAL RESULTS

Experiments have been performed using a noise profiled image sensor for mobile devices.

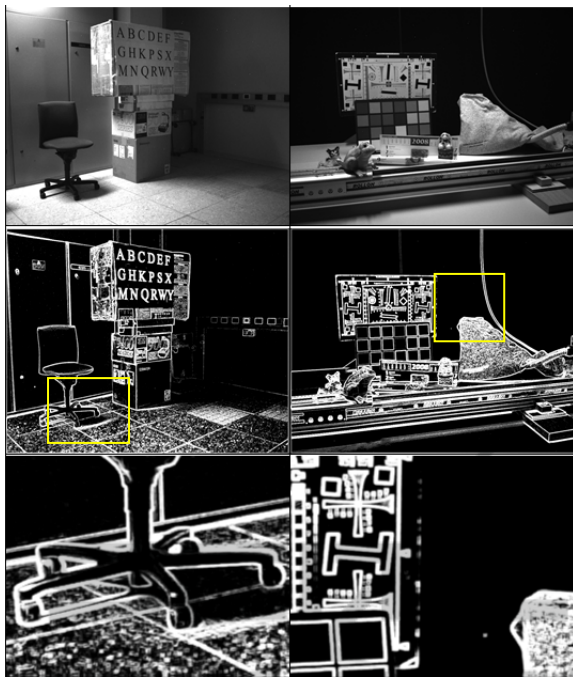


Figure 4: Scaled output examples. Top: original CFA ISO 100 (left) and ISO 1600 (right). Center: estimated signal activity maps. Bottom: Two magnified crops of the signal activity maps.

Figure 4 shows the results of the signal activity estimator for two *CFA* images taken at ISO 100 and ISO 1600. Images are scaled to fit them in the figure.

Areas with signal activity are shown using increasing values of grey, whereas *flat* classified pixels are shown using low values of grey. It can be observed how the method works very well in the detection of the signal activity related to the texture of the floor tiles, without misclassifying it as noise (Figure 4 (bottom left)).

6 CONCLUSIONS

A method for estimating the signal activity in the *CFA* raw domain has been presented. The solution works prior any pre-processing algorithm. The image sensor noise profiling is embedded in the estimation process; hence the solution is robust in the presence of noise and does not require tuning thresholds at different noise levels. Experimental results show the high robustness of the estimator also in presence of high levels of noise. Future work includes further refinements of the solution and incorporating the method in noise filters and demosaicing algorithms.

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