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Signal-dependent and independent Optical Image System in CCD Cameras

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Abstract

This article deals with a pristine method to estimate the noise introduced by optical imaging systems, such as CCD cameras. The puissance of the signal-dependent photon noise is decoupled from the puissance of the signal-independent electronic noise. The method relies on the multivariate regression of sample mean and variance. Statistically kindred image pixels, not obligatorily connected, engender scatter points that are clustered along a straight line, whose slope and intercept measure the signal-dependent and signal-independent components of the noise puissance, respectively. Experimental results carried out on a simulated strepitous image and on true data from a commercial CCD camera highlight the precision of the proposed method and its applicability to dissever R–G–B components that have been redressed for the nonlinear effects of the camera replication function, but not yet interpolated to the full size of the mosaiced R–G–B image.

Keyword: Optical Image System; CCD Cameras; signal-dependent and signal-independent

1. Introduction

Whenever the postulation of additive white Gaussian noise (AWGN) no longer holds, noise modeling, and estimation becomes a preliminary step of the most advanced image analysis and interpretation systems. Preprocessing of data acquired with certain modalities, like optoelectronic and coherent, either ultrasound or microwave, may benefit from felicitous parametric modeling of the dependence of the signal on the noise and from precise quantifications of the noise model parameters. The cognizance of the noise model parameters is crucial for the task of de noising. Maximum a posteriori probability estimators exhibit a scarce tolerance to mismatches in the parametric noise model [1]. Recent advances in the technology of optoelectronic imaging contrivances have lead to the availability of image data, in which the photon noise contribution may no longer be neglected with reverence to the electronic component, which is becoming less and less germane. As a consequence, preprocessing and analysis methods must be revised or even designed anew to take into account that the noise is signal dependent.

To date, the most puissant noise estimation models are predicated on the multivariate regressions of local statistics [2-5]. However, the solution is intricate by the presence of two parametric noise components, one signal dependent and another signal-independent. The pristine contribution of this article is twofold: on one side a robust multivariate procedure is proposed to estimate the parameters of the commixed photon + electronic noise from a single image. On the other side, the circumscriptions in the validity of the optoelectronic noise model are discussed, a topic that has never been elucidated by any of the most prominent articles, e.g., [5,6]. On raw data such a model does not stringently hold, or better it holds only for a inhibited range of values above zero.

Genuinely, raw data are available after a nonlinear mapping performed through the camera replication function (CRF) of the contrivance in order to evade saturation effects. The optoelectronic noise model is correctly estimated on true raw data by other authors, e.g., [5], only if the range of nonlinearity is punctiliously eschewed by the estimation procedure. Conversely, on CRF-rectified data, which are much more available and widespread (they might be in principle obtained by felicitously decimating the demosaiced R–G–B image) the optoelectronic noise model holds on the whole dynamic range and can be more facilely estimated. Other authors develop their analysis in a local mean versus standard deviation space, which makes hard to devise a concrete parametric noise model [6]. Instead, we develop our model in the local mean versus variance space, in which a proximately linear cognation can facilely be apperceived and exploited to obtain the noise parameters.

1.1 Signal-dependent noise modeling:

A generalized signal-dependent (GSD) noise model has been proposed to deal with several different acquisition systems. Many types of noise can be described by utilizing the following parametric model [7]

$$g(m, n) = f(m, n) + f(m, n)^{\gamma} \cdot u(m, n) + w(m, n)$$
$$= f(m, n) + v(m, n) + w(m, n) \quad (1)$$

where (m, n) is the pixel location, $g(m, n)$ the observed noisy image, $f(m, n)$ the noise-free image, modeled as a non-stationary correlated random process, $u(m, n)$ a stationary, zero-mean uncorrelated random process independent of $f(m, n)$ with variance σ^2_u, and $w(m, n)$ is electronics noise (zero-mean white and Gaussian, with variance σ^2_w). For a great variety of images, this model has been proven to hold for values of the parameter γ such that $|\gamma| \leq 1$. The additive term$v = f^{\gamma} \cdot u$ is the GSD noise. Since f is generally non-stationary, the noise v will be nonstationary as well. The term w is the signal-independentnoise component and is generally assumed to be Gaussiandistributed.

A purely multiplicative noise ($\gamma = 1$) is typical of coherent imaging systems; the majority of despeckling filters rely on the multiplicative *fully developed* speckle model [8]. In SAR imagery, the thermal noise contribution w is negligible, compared to the speckle term, $f \cdot u$ [9]. A more complex scenario is related to ultrasound image generation. Due to the great variability of scatterers size in each tissue, the electronics noise w cannot be neglected. Although a simplified noise model without electronic term with value of γ in $(0, 1)$, e.g., $\gamma = 1/2$, is accepted as characteristic of this kind of images, the presence of the additional term w alleviates for the need of exactly knowing the γ . In fact, if γ is taken to be unity, as for *coherent* noise, an *equivalent signal-dependent* γ may be defined, such that.

$$f\ (m,\ n)\cdot u(m,\ n)+w(m,\ n)\ \approx\ f\ (m,\ n)^{\gamma eq\ (f\ (m,n))}\cdot u_{eq}{}^{(m,\ n)}. \quad (2)$$

The signal-dependent noise in Equation (2) is the combination of a purely multiplicative term and of a signal independent term. The outcome exhibits a dependence on the signal that vanishes as $f \rightarrow 0_+$. Whenever $f \cdot u$ _ w, as it happens for SAR speckle, it stems that $\gamma_{eq}(f) \rightarrow 1_-$. In practice, the left-hand side of (2), i.e., (1) with $\gamma = 1$, is taken as a noise model suitable for ultrasonic images [10].

The model (1) is also suitable for *film-grain* noise [11], typical of images obtained by scanning a film (transparent support) or a photographic halftone print (reflecting support). In the former case, $\gamma > 0$ and values $1/3 \leq \gamma \leq 1/2$ are typically encountered; in the latter case, negative values of γ are found [11]. For images obtained from monochrome or color scanners, the electronics noise w may not be neglected. Its variance is easily measured on a dark acquisition, i.e., when $f = 0$. The unknown exponent γ may be found by drawing the scatterplot of the logarithm of measured local variance diminished by the dark signal variance (estimate of σ^2_w) against the logarithm of local mean [12]. Homogeneous pixels are clustered along a straight line in the log-scatterplot plane. The unknown γ is estimated as the slope of the regression line, σ^2_uas the intercept.

Eventually, the model (1) applies also to images produced by optoelectronic devices, such as CCD cameras, multispectral scanners, and imaging spectrometers. In that case, the exponent γ is equal to 0.5. The term $\sqrt{f}\, u$ stems from the Poisson-distributed number of photons captured by each pixel and is therefore denoted as *photon* noise [13]. This case will be investigated in the remainder of this article.

2. Related Work& Implementation

2.1 Optoelectronic noise:

In this section, the optoelectronic noise model will be reviewed in a deeper detail. The main contributions of photon noise and electronic noise will be derived and physically related to the instrument. Signal-to-noise ratio (SNR) will be defined and its relationships to the noise model parameters will be addressed. Let us rewrite the model (1) with $\gamma = 0.5$:

$g(m, n) = f(m, n) + \sqrt{f(m, n)} \cdot u(m, n) + w(m, n)$. (3)

Equation (3) represents the electrical signal resulting from the photon conversion and from the dark current. The mean dark current has preliminarily been subtracted to yield $g(m, n)$. However, its statistical fluctuations around the mean constitute most of the zero-mean electronic noise $w(m, n)$. The term $\sqrt{f(m, n)} \cdot u(m, n)$ is the photon noise, whose mean is zero and whose variance is proportional to $E[f(m, n)]$. It represents a statistical fluctuation of the photon signal around its noise-free, $f(m, n)$, due to the granularity of photons originating electric charge.

2.2 SNR

If the variance of (3) is calculated on homogeneous pixels, in which $\sigma^2_f(m, n) = 0$, by definition, thanks to the independence of f, u and w and the fact that both u and $w$have null mean and are stationary, we can write

$\sigma^2_g(m, n) = \sigma^{2u} \cdot \mu_f(m, n) + \sigma^2_w$ (4)

in which $\mu_f(m, n)$ _ $E[f(m, n)]$ is the non-stationary mean of f. The term $\mu_f(m, n)$ equals $\mu_g(m, n)$, from (3). Let us define the local SNR at pixel position (m, n) as

$SNR_{dB}(m, n) = 10 \log_{10}(\frac{E[f2(m,n)]}{\mu f(m,n)\sigma 2u + \sigma 2w})$(5)

Which on homogeneous pixels (i.e., $\sigma^2 f(m, n) = 0$) becomes

$SNR_{dB}(m, n) = 10 \log_{10}(\frac{\mu f(m,n)2}{\mu f(m,n)\sigma 2u + \sigma 2w})$. (6)

In (6), if $\mu_f(m, n)\sigma^2_u \gg \sigma^2_w$, then

$SNR_{dB}(m, n) \approx 10 \log_{10}(\frac{\mu f(m,n)}{\sigma 2u})$. (7)

That is SNR depends on the mean photon signal.

Instead, if $\mu_f(m, n)\sigma^2_u \ll \sigma^2_w$, then

$SNR_{dB}(m, n) \approx 10 \log_{10}(\frac{\mu f(m,n)2}{\sigma 2w})$ (8)

Which states that the SNR depends on the square of the Mean photon signal?

In practical applications, the *average* SNR is used:

$SNR_{dB} = 10 \log_{10}(\frac{\bar{f}2}{f\sigma 2u + \sigma 2w})$. (9)

Where $\bar{f}$ is obtained by averaging the observed noisy image, the noise being zero-mean and the average local variance of f is assumed to be negligible, i.e., $(\bar{f}2) \approx (\bar{f})2$.

3. Experimental Results

The proposed method has preliminarily been validated on simulated strepitous images. Results on the synthetic noise free test image utilized in [5] are presented here. The pristine test image is shown in Figure 2a. A strepitous versions with average SNR (9) equipollent to 17 dB and 77% signal-dependent photon noise

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(γ = 0.5) and 23% signal-independent electronic noise has been engendered and is shown in Figure 2b. The variance-to-mean scatter plots, shown in Figure 2c,d, highlight the noise model. In Figure 2c no noise has been superimposed and nine points can be

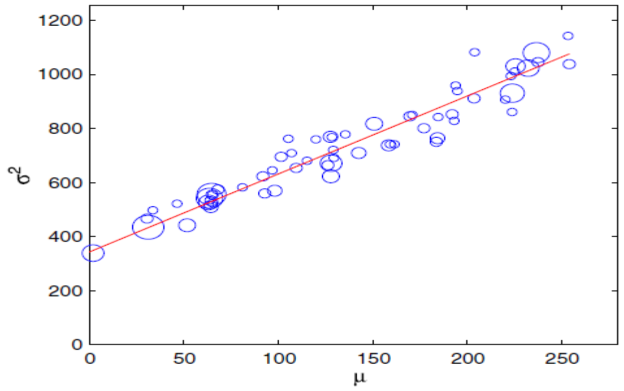

Fig 1: Calculation of slope and intercept of mixedphoton/electronic noise from centroids of scatterplotscalculated from blocks/ROIs of test image: scatterplot ofhomogeneous areas with regression line superimposed (dotssize proportional to mass of clusters).

Detected, approximately lying aligned over the x-axis. The slope of the joining line is identically tantamount to zero and the intercept is identically tantamount to the variance of integer roundoff error, i.e., to 1/12. Conversely, Figure 2d evidences the presence of nine clusters that are aligned along a straight line having slope and intercept equipollent to the parameters of the superimposed noise.

Strepitous versions of the test image with 50% photon and 50% electronic noise have been engendered with SNR ranging between 15 and 30 dB. The proposed method and the method described in [5],b which conversely exploits a wavelet decomposition in order to find homogeneous regions, have been used to estimate the noise model parameters. In the latter case, the strepitous image is clipped below zero, as it transpires with an authentic CCD camera. For the proposed method, the results without clipping are virtually identical to those with clipping, provided that the gravity centers of clusters originated by dark image blocks are preliminarily discarded by thresholding their mean. Figure 3a,c,e shows estimated slope and intercept of the noise model in the (μ, σ2) plane, as well as estimated SNR, varying with the true SNR, for the proposed method; Figure 3b,d,f for the method in [5].

The precision of both is very high, especially on SNR. The proposed method, however, exhibits a remotely better ability in splitting the noise contribution into its two signal-dependent and signal-independent components.

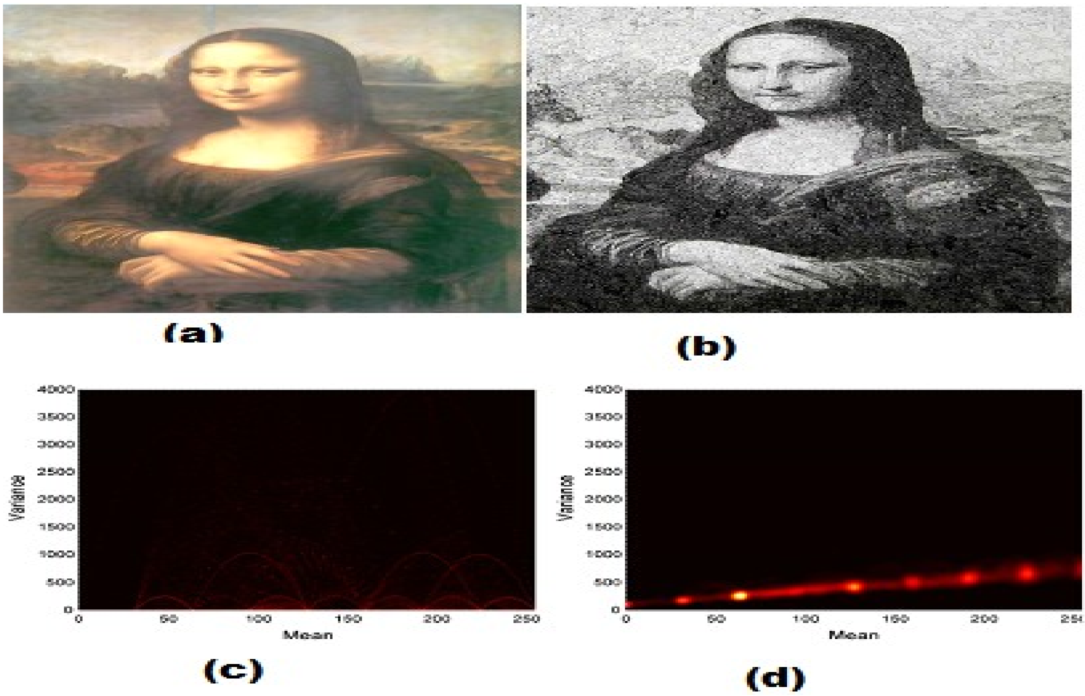

Fig 2: Original piecewise-smooth test image taken from [5]: **(a)** noise-free original; **(b)** corrupted with simulated optoelectronic noise (77% photon, 23% electronic, SNR=17 dB); **(c)** variance-to-mean scatterplot of original; **(d**) variance-to-mean scatterplot of noisy version.

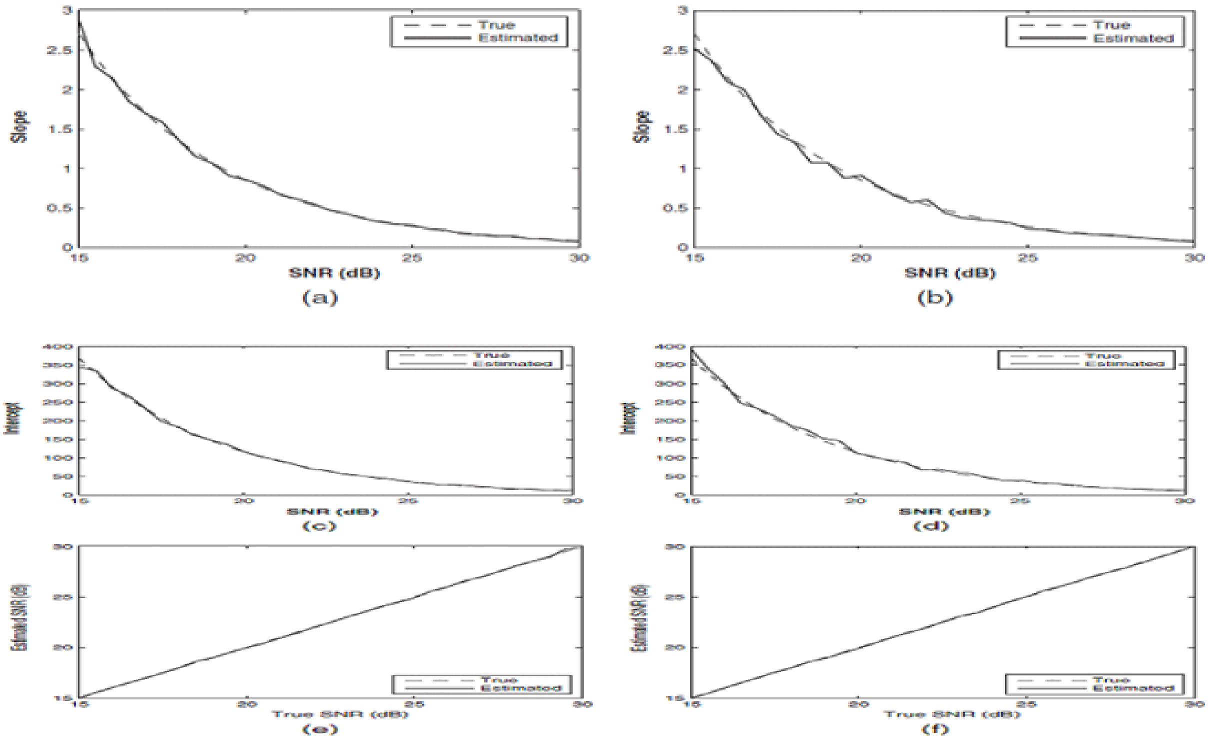

Fig 3: Tests with simulated signal-dependent noise on a piecewise-smooth test image.Estimated (solid) and true (dashed) parameters of the photon (slope of regression line) and electronic (intercept) noise model as a function of true SNR. **(a)** Slope of the proposed method; **(b)** slope of the method in

[5]; **(c)** intercept of the proposed method; **(d)** intercept of the method in [5]; **(e)** SNR of the proposed method; **(f)** SNR of the method in [5].

4. Conclusion

Modern CCD color cameras engender rectified R–G–B images dominated by opto-electronic noise, an amalgamation of signal-dependent photon noise and signal-independent electronic noise. The parameters of the noise model can be quantified on a single image by denotes of a pristine unsupervised procedure relying on a bivariate linear regression of local mean and variance. It is eminent that such a noise model does not rigorously hold for raw data, but only once the CRF has been redressed and the pristine LS has been recuperated from nonlinearities introduced by the electronic chain.

The full cognizance of the parametric noise model can be subsidiary not only in applications requiring preliminary denoising, but withal in application of surveillance, in which no denoising is performed, but automatic detection is ruled by thresholds that are presumably cognate with the noise model. Withal recuperation will benefit from the cognizance of a parametric noise model, including its autocorrelation function. Its estimation, however, whenever performed on R–G–B data, is perplexed by the demosaicing and interpolation steps, especially because interpolation algorithms, aimed at reducing impairments originated by Bayer's mosaicing pattern, are generally adaptive, may be nonlinear and especially they are not disclosed by manufacturers. Therefore, the most congruous domain for this kind of processing is indubitably the one where color components have been split, but have not yet been interpolated.

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