Image sensor-noise estimating using Bayesian modeling

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Sensor noise performance is responsible for some kind of uncertainty in digital images. An accurate and meaningful procedure to model the image sensor noise is useful for optimizing sensor design as well as for knowing how much sensor uncertainty in its different sources is present in an image.

Theoretical image-sensing noise-parameters model: Image sensing and its different noise components, from the absorption of light photons by the sensing material, to the conversion into a voltage, the amplification and conversion into a digital signal, are well-documented in the literature, where the manifestations and relationships among all these components are well-understood and defined [De-Jiang and Tao 2001, Reibel et al. 2003].

$$y(i,t,r,s) = \mu_K \cdot \mu_e(r,s) + \underbrace{dK(i)}_{\text{Photo-response non-uniformity (PRNU)}} \cdot \mu_e(r,s) + \mu_K \cdot \overbrace{D(i)}^{\text{Fixed pattern noise (FPN)}} + \mu_K \cdot \underbrace{C(t,r,s)}_{\text{Current noise}} + K(i) \cdot \overbrace{de(i,t,r,s)}^{\text{Photon noise}} + \mu_K \cdot \underbrace{R(i,t)}_{\text{Reset noise}} + \overbrace{A(i,t)}^{\text{Amplification noise}}$$

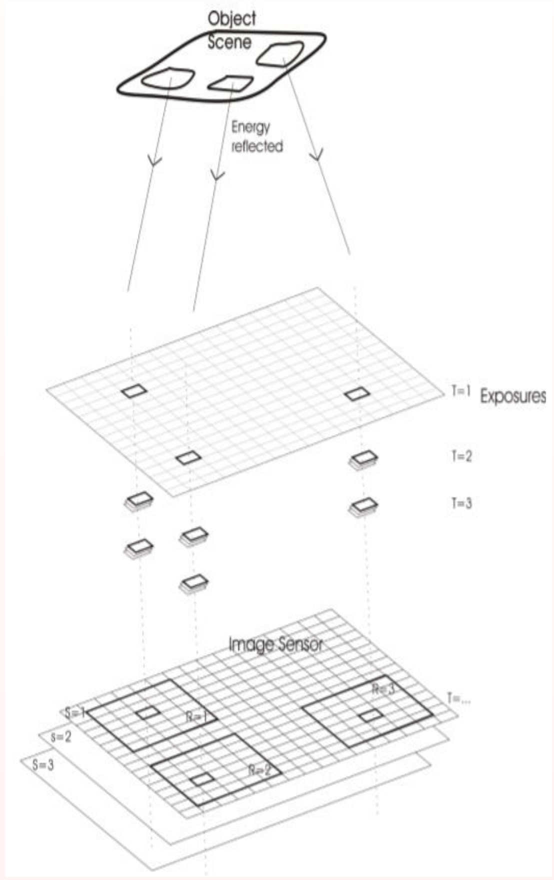


Figure 1

The focus of this study is on calibrating the effects of those sensor noise sources by means of modelling and estimating the variability they cause on imaging-sensing observational data. The observational data consist of image data collected from different reflectance sources using a colourchecker (Figure 2) and from different exposures in the time-longitudinal dimension (Figure 1).


Figure 2

The proposed modeling is based on formulating a Bayesian hierarchical model composed of the addition of independent random effects which is trying to approximate, as much as possible (according to the collected data), the theoretical model of image sensing. Zero-mean recentering constraints have been taken account for avoiding indentifiability problems among parameters.

i: pixel-spatial dimension
t: time−longitudinal dimension
r: reflectance factor
s: wavelength factor

$$y(i,t,r,s) \sim Normal\left(\mu(i,t,r,s),\ \sigma_y^2\right)$$

Reset + Amplification noises

$$\mu(i,t,r,s) = \mu_0(r,s) + S(i,r,s) + F(i) + T(t,r,s) + P(i,t,r,s)$$

$$S(i,r,s) \sim Normal\left(0,\sigma_S^2(r,s)\right)$$

PRNU

$$F(i) \sim Normal(0,\sigma_F^2)$$

FPN

$$T(t,r,s) \sim Normal\left(0,\sigma_T^2(r,s)\right)$$

Current noise

$$P(i,t,r,s) \sim Normal\left(0,\sigma_P^2(r,s)\right)$$

Interaction **PRNU-Photon noise**

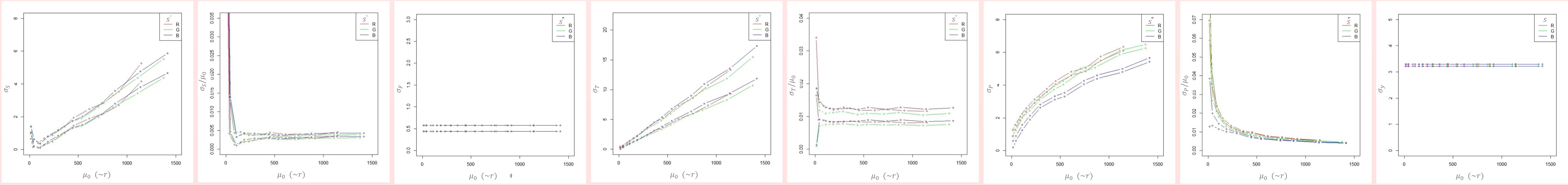
Theoretical model:

$$y(i,t,r,s) = \mu_K \cdot \mu_e(r,s) + dK(i) \cdot \mu_e(r,s) + \mu_K \cdot D(i) + \mu_K \cdot C(t,r,s) + K(i) \cdot de(i,t,r,s) + \mu_K \cdot R(i,t) + A(i,t)$$

Correspondence between components of variability in both models, theoretical and proposed

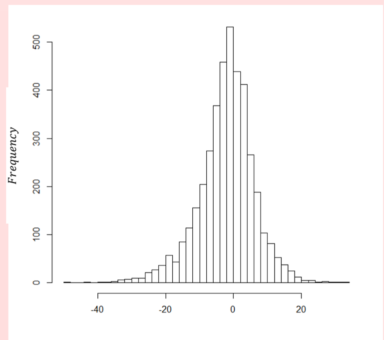
Estimates of the parameters:

$\sigma_S(r,s)$ | $\sigma_S(r,s)/\mu_0(r,s)$ | σ_F | $\sigma_T(r,s)$ | $\sigma_T(r,s)/\mu_0(r,s)$ | $\sigma_P(r,s)$ | $\sigma_P(r,s)/\mu_0(r,s)$ | σ_y

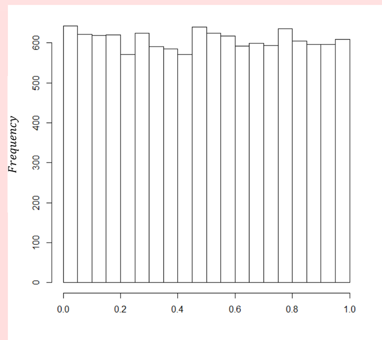


Model diagnosis: Checking for normality of the residuals and checking similarity of the Bayesian posterior predictive p-values distribution to a standard uniform distribution [Bayarri and Berger 2000, Marshall and Spiegelhalter 2003]. Provenance of the p-values from a U(0,1) distribution indicates good performance of the model, good prediction and good fit to the data.

residuals



p − values



Conclusions: Bayesian hierarchical modeling and MCMC estimating methods are known to be well suited to deal with complicated situations. That is the case of the image sensing, where many parameters, different coefficients and relationships are involved, with particular distributions in each parameter. Therefore, Bayesian modeling has revealed itself as a very powerful methodology allowing for a reliable definition, estimation and monitoring of the noise parameters as random variables.

This work may be the first Bayesian approach to characterizing the sensor-noise parameters. It is for this reason that we have simplified the model as much as possible where components of variability involving each one of the noise parameters has been identified and proper interpretation for these components has been achieved.

References:

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Acknowledgements: Ministerio Español de Economía y Competitividad, proyecto I+D+I RETOS 2014: *Análisis espectrofotométrico de calibración de cámaras aplicados al estudio de arte rupestre*, HAR2014-59873-R