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► **To cite this version:**

Anna Jezierska, Hugues Talbot, Caroline Chauv, Jean-Christophe Pesquet, Gilbert Engler. POISSON-GAUSSIAN NOISE PARAMETER ESTIMATION IN FLUORESCENCE MICROSCOPY IMAGING. to be updated, Nov 2011, France. hal-00646382v1

HAL Id: hal-00646382

<https://hal.science/hal-00646382v1>

Submitted on 29 Nov 2011 (v1), last revised 20 Apr 2012 (v2)

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POISSON-GAUSSIAN NOISE PARAMETER ESTIMATION IN FLUORESCENCE MICROSCOPY IMAGING

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ABSTRACT

In this paper, we present a new fully automatic approach for noise parameter estimation in the context of fluorescence imaging systems. In particular, we address the problem of Poisson-Gaussian noise modeling in the nonstationary case. In microscopy practice, the nonstationarity is due to the photobleaching effect. The proposed method consists of an adequate moment based initialization followed by Expectation-Maximization iterations. This approach is shown to provide reliable estimates of the mean and the variance of the Gaussian noise and of the scale parameter of Poisson noise, as well as of the photobleaching rates. The algorithm performance is demonstrated on both synthetic and real fluorescence microscopy image sequences.

Index Terms— Noise identification, confocal imaging systems calibration, fluorescence photobleaching, Expectation-Maximization algorithm, image calibration

1. INTRODUCTION

The purpose of this work is to provide an estimation method for the noise parameters arising in fluorescence imaging systems. In many image restoration methods, these parameters are required to be known [1, 2]. Moreover, noise parameters provide feedback concerning imaging conditions, and thereby they can be used in the microscope calibration process [3]. The noise sources were described from a physical viewpoint in [4], where also the corresponding statistical characteristics were studied. In practice, one usually considers simplified models e.g. either Gaussian [5] or Poisson [6]. Recently some works have begun investigating a more realistic Poisson-Gaussian model with non-zero mean [7, 8]. In the literature addressing the noise parameter identification problem, one can also find methods handling more sophisticated models that include multiplicative components in addition to Poisson and Gaussian ones [9, 10]. However, to the best of our knowledge, we are not aware of any restoration methods actually taking such sophisticated formulations into account. Consequently, we focus on the non-zero mean Poisson-Gaussian model in this paper. Indeed, despite its practical usefulness, especially when a low level signal is expected, this model is nonetheless little-studied in the literature. Among the few existing contributions, the author in [11] proposes a cumulant-based approach. A regression based approach is proposed for estimating General Anscombe transform parameters in [7, 8]. Finally, a method estimating only the Gaussian component was proposed in [12].

This work was supported by the Agence Nationale de la Recherche under grant ANR-09-EMER-004-03.

In this paper, we propose a novel approach based on an Expectation-Maximization (EM) algorithm, following our previous work in [13]. We focus on fluorescence imaging systems, especially in the field of confocal microscopy and so-called MACROscopy systems [14]. As input data we use time-lapse fluorescence images, which consist of repeated images of motionless specimens at given times. The considered problem is more challenging than the one investigated in [13] due to the nonstationarity of the acquired signal caused by photobleaching. This effect is a process of intensity decay in time usually modeled with an exponentially decreasing function [15, 3]. Although other photobleaching forms were also investigated [16], our analysis in this paper is based on the latter model, also known as three-parameter exponential model [17]. More specifically, in order to characterize the dependency between Poisson noise and photobleaching, we adopt the same model as the one presented in [6]. However, we relax the assumption of constant bleaching decay for the whole image, which is not realistic according to our experiments in the last section of this paper. Since the EM optimization framework is not guaranteed to converge to a global minimizer of the negative log-likelihood, its behavior can be improved by carefully setting its initialization. Usually the choice of a good starting value is discussed in the context of specific applications [18, 19, 20, 13]. We address this key problem for Poisson-Gaussian parameter estimation in the presence of photobleaching by proposing an adequate moment based initialization. Moreover, we provide an extension of the EM approach developed in [13] in order to allow us to jointly estimate Poisson-Gaussian noise parameters, to reconstruct the original signal and to estimate its photobleaching rates.

The paper is organized as follows. We provide a description of the noise identification problem from a time-series standpoint in Section 2. We then present the proposed iterative method in Section 3. Section 4 illustrates the algorithm performance on synthetic data and real confocal MACROscope image sequences. Section 5 concludes the paper.

2. NOISE MODEL

2.1. Adopted scheme

We consider data $(u_s)_{1 \leq s \leq S}$ where s corresponds to a location index (e.g. locating pixel (x, y) in 2D or voxel (x, y, z) in 3D), which are corrupted with a Poisson-Gaussian noise, and for which we observe T realizations. Each realization will be indexed by the time index $t \in \{1, \dots, T\}$. Such a framework leads us to the following model:

$$(\forall s \in \{1, \dots, S\})(\forall t \in \{1, \dots, T\}) R_{s,t} = \alpha Q_{s,t} + N_{s,t} \quad (1)$$

where $\alpha \in \mathbb{R}$ is a scaling parameter and $R_{s,t}$ is the observed random variable at time t and location s . In the above model, the following auxiliary random variables intervenes

$$Q_{s,t} \sim \mathcal{P}(u_s e^{-k_s t}) \quad (2)$$

$$N_{s,t} \sim \mathcal{N}(c, \sigma^2) \quad (3)$$

where $(u_s)_{1 \leq s \leq S} \in [0, +\infty)^S$ is the ‘‘clean’’ image (possibly resulting from a blur of the original image and some offset), $(k_s)_{1 \leq s \leq S} \in (0, +\infty)^S$ denote the photobleaching rates, and $c \in \mathbb{R}$ (resp. $\sigma > 0$) is the mean value (resp. standard-deviation) of the Gaussian noise.

2.2. Considered problem

The problem is to estimate $u = (u_s)_{1 \leq s \leq S}$, $k = (k_s)_{1 \leq s \leq S}$, α , c and σ^2 from the available observation vector $r = (r_{s,t})_{1 \leq s \leq S, 1 \leq t \leq T}$, which is a realization of the random field $R = (R_{s,t})_{1 \leq s \leq S, 1 \leq t \leq T}$. We have thus $2S + 3$ parameters to estimate. We define the vector of unknown parameters as $\theta = (u, k, \alpha, c, \sigma^2)$.

In the following, it is assumed that u is deterministic and that $Q = (Q_{s,t})_{1 \leq s \leq S, 1 \leq t \leq T}$ and $N = (N_{s,t})_{1 \leq s \leq S, 1 \leq t \leq T}$ are mutually independent random fields. In addition, the components of N (resp. Q) are assumed to be independent. These assumptions let us define the cumulant of order n as $\kappa_n[R_{s,t}] = \alpha^n \kappa_n[Q_{s,t}] + \kappa_n[N_{s,t}]$. This leads to following results:

- mean value: $\kappa_1[R_{s,t}] = \mathbb{E}[R_{s,t}] = \alpha e^{-k_s t} u_s + c \quad (4)$
- variance: $\kappa_2[R_{s,t}] = \text{Var}[R_{s,t}] = \alpha^2 e^{-2k_s t} u_s + \sigma^2 \quad (5)$
- higher-order cumulants: $n \geq 3$, $\kappa_n[R_{s,t}] = \alpha^n u_s e^{-k_s t} \quad (6)$

3. NOISE ESTIMATION METHOD

3.1. Moment based method

Several procedures may be derived from (4), (5), and (6) in order to estimate θ , but they are not equally reliable. For example, according to our observations, $\frac{\kappa_4[R_{s,t}]}{\kappa_3[R_{s,t}]}$ does not provide a very accurate estimate of α . Thus, we propose to define preliminary estimates of $(k_s)_{1 \leq s \leq S}$, c and $(a_s = \alpha u_s)_{1 \leq s \leq S}$ by noticing that (4) can be reexpressed as

$$R_{s,t} = a_s e^{-k_s t} + c + E_{s,t} \quad (7)$$

where $(E_{s,t})_{1 \leq s \leq S, 1 \leq t \leq T}$ are independent zero-mean random variables. This suggests to employ a nonlinear least squares approach to compute estimates $\hat{a} = (\hat{a}_s)_{1 \leq s \leq S}$, $\hat{k} = (k_s)_{1 \leq s \leq S}$, \hat{c} of the parameters:

$$(\hat{a}, \hat{k}, \hat{c}) = \underset{a, k, c}{\operatorname{argmin}} \sum_{s=1}^S \sum_{t=1}^T \omega_{s,t} \left(r_{s,t} - c - a_s e^{-k_s t} \right)^2 \quad (8)$$

where $(\omega_{s,t})_{1 \leq s \leq S, 1 \leq t \leq T}$ are positive weights. In order to efficiently solve the associated minimization problem, we propose to use an alternating optimization method (see Algorithm 1). For every $s \in \{1, \dots, S\}$, the minimization subproblem to be solved at each iteration reduces to a linear least squares one for a given value of k_s . The minimization procedure thus reduces to a one-variable search (over k_s) which can be performed by standard numerical methods, e.g. the Nelder-Mead simplex method [21].

The estimates provided by this method are sufficiently stable, as only first order statistics are used. These results allow us to provide

Algorithm 1

$$\begin{aligned} & c^{(0)} = \min \left\{ \frac{1}{T} \sum_{t=1}^T r_{s,t}, 1 \leq s \leq S \right\} \\ & \text{For } n = 1 \dots N \\ & \quad \text{For } s = 1 \dots S \\ & \quad \quad (a_s^{(n)}, k_s^{(n)}) = \underset{a_s, k_s \geq 0}{\operatorname{argmin}} \sum_{t=1}^T \omega_{s,t} \left(r_{s,t} - c^{(n-1)} - a_s e^{-k_s t} \right)^2 \\ & \quad \quad c^{(n)} = \sum_{s=1}^S \sum_{t=1}^T \omega_{s,t} (r_{s,t} - a_s^{(n)} e^{-k_s^{(n)} t}) / \sum_{s=1}^S \sum_{t=1}^T \omega_{s,t} \\ & \quad \quad \hat{a} = a^{(N)}, \hat{k} = k^{(N)}, \hat{c} = c^{(N)} \end{aligned}$$

simple estimates of the remaining parameters. Indeed, by rewriting (5) as

$$\mathbb{E}[(R_{s,t} - \mathbb{E}[R_{s,t}])^2] = \alpha a_s e^{-2k_s t} + \sigma^2, \quad (9)$$

the following least squares estimate for α can be derived:

$$\hat{\alpha} = \frac{W \sum_{s=1}^S \nu_s m_s v_s - \sum_{s=1}^S \nu_s m_s \sum_{s=1}^S \nu_s v_s}{W \sum_{s=1}^S \nu_s m_s^2 - (\sum_{s=1}^S \nu_s m_s)^2}, \quad (10)$$

where $(\nu_s)_{1 \leq s \leq S}$ are positive weights, $W = T \sum_{s=1}^S \nu_s$ and

$$(\forall s \in \{1, \dots, S\}) \quad m_s = \hat{a}_s e^{-\hat{k}_s} \frac{1 - e^{-\hat{k}_s T}}{1 - e^{-\hat{k}_s}} \quad (11)$$

$$v_s = \sum_{t=1}^T v_{s,t} \quad (12)$$

with, for every $t \in \{1, \dots, T\}$, $v_{s,t} = (r_{s,t} - \hat{a}_s e^{-\hat{k}_s t} - \hat{c})^2$. Then, the estimate of u is given by:

$$(\forall s \in \{1, \dots, S\}) \quad \hat{u}_s = \frac{\hat{a}_s}{\hat{\alpha}}. \quad (13)$$

Finally, the estimation process is completed by computing:

$$\hat{\sigma}^2 = \frac{\sum_{(s,t) \in \mathbb{I}} \nu_s (v_{s,t} - \hat{\alpha} \hat{a}_s e^{-\hat{k}_s t})}{\sum_{(s,t) \in \mathbb{I}} \nu_s} \quad (14)$$

where

$$\mathbb{I} = \{(s, t) \in \{1, \dots, S\} \times \{1, \dots, T\} \mid v_{s,t} - \hat{\alpha} \hat{a}_s e^{-\hat{k}_s t} \geq 0\}.$$

3.2. Refined estimation

The main limitation of the previous moment based method is that the unknown parameters are not jointly estimated. Due to this fact, we may face large error propagation with respect to the estimation of some parameters. Thus, similarly to the work in [13], we propose to improve the moment based method results by resorting to an EM approach. The proposed noise identification procedure is summarized in Fig. 1.

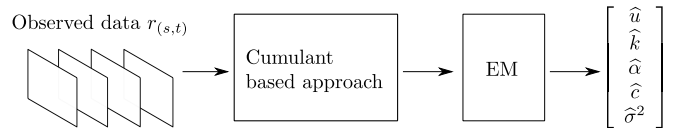


Fig. 1. Flowchart of the proposed noise identification method.

It must be emphasized that photobleaching was not discussed in [13], so that significant modifications of the EM algorithm were

necessary to include this effect into this framework. More precisely, in the $(n + 1)$ -th maximization step, it can be shown that, for every $s \in \{1, \dots, S\}$, the photobleaching rate $k_s^{(n+1)} = -\ln x^{(n+1)}$ where $x^{(n+1)}$ is the solution in $(0, 1)$ of the polynomial equation of order T :

$$\begin{aligned} & (1 + Tx^{T+1} - (T + 1)x^T) \sum_{t=1}^T \mathbb{E}_{Q|R=r, \theta^{(n)}} [Q_{s,t}] \\ &= (1 - x - x^T + x^{T+1}) \sum_{t=1}^T t \mathbb{E}_{Q|R=r, \theta^{(n)}} [Q_{s,t}]. \end{aligned} \quad (15)$$

We propose to compute $x^{(n+1)}$ from (15) using Halley's algorithm [22]. Then, u can be derived as follows

$$(\forall s \in \{1, \dots, S\}) \quad u_s^{(n+1)} = \frac{1 - x^{(n+1)}}{x^{(n+1)}(1 - |x^{(n+1)}|^T)} \sum_{t=1}^T \mathbb{E}_{Q|R=r, \theta^{(n)}} [Q_{s,t}]. \quad (16)$$

Finally, the maximization step is completed by update formulas for $\alpha^{(n+1)}$, $c^{(n+1)}$ and $(\sigma^2)^{(n+1)}$, which are unchanged with respect to the stationary case described in [13]. In the n -th expectation step, taking into account the photobleaching effect yields the following expressions:

$$\mathbb{E}_{Q|R=r, \theta^{(n)}} [Q_{s,t}] = \frac{\zeta_{s,t}^{(n)}}{\eta_{s,t}^{(n)}} \quad (17)$$

$$\zeta_{s,t}^{(n)} = \sum_{q_{s,t}=1}^{+\infty} e^{-\frac{(r_{s,t} - \alpha^{(n)})_{q_{s,t}} - c^{(n)}}{2(\sigma^2)^{(n)}}} \frac{(u_s^{(n)})_{q_{s,t}}}{(q_{s,t} - 1)!} e^{-tk_s^{(n)} q_{s,t}} \quad (18)$$

$$\eta_{s,t}^{(n)} = \sum_{q_{s,t}=0}^{+\infty} e^{-\frac{(r_{s,t} - \alpha^{(n)})_{q_{s,t}} - c^{(n)}}{2(\sigma^2)^{(n)}}} \frac{(u_s^{(n)})_{q_{s,t}}}{q_{s,t}!} e^{-tk_s^{(n)} q_{s,t}}. \quad (19)$$

4. SIMULATION EXAMPLES

In this section, we present experiments on both synthetic and real data in order to demonstrate the performance of the proposed approach. In particular, the simulations on synthetic data allow us to evaluate the reliability of our algorithm (Section 4.1) and the real data case study illustrates its potentials in microscopy applications (Section 4.2).

4.1. Synthetic data validation

We evaluate the proposed algorithms using $S = 200$ randomly generated u_s values uniformly distributed over $[0, 150]$ and k_s values uniformly distributed over $[10^{-4}, 10^{-3}]$. Signal $r_{s,t}$ is generated according to (1) for $c = 10$, $\alpha = 30$ and $\sigma^2 = 100$ and $T = 180$. The algorithm performance is measured by the SNR defined as the average of $10 \log_{10}(P)$ with $P = (ST)^{-1} \sum_{(t,s)} (a_s e^{-k_s t})^2 / \sum_{(t,s)} (a_s e^{-k_s t} - \hat{a}_s e^{-\hat{k}_s t})^2$ computed over 50 noise realization, where the estimated value are designated with a hat. Moreover, we examine the estimator properties by presenting the bias and standard deviation of the resulting noise parameters $\hat{\alpha}$, \hat{c} and $\hat{\sigma}$.

The results presented in Table 1 indicate that in the first step of the algorithm (Fig. 1) a majority of the unknown parameters are identified accurately. As expected, the estimates are further improved in the second step by EM, achieving high accuracy, indicated

Method.	$\hat{\sigma}$		\hat{c}		$\hat{\alpha}$		$\overline{\text{SNR}}$
	bias	std	bias	std	bias	std	
Init.	357.5	3.1	1.9	1.0	-0.3	0.4	39.5
EM	2.9	0.9	1.4	0.8	-0.3	0.4	39.7

Table 1. Synthetic data results.

by high $\overline{\text{SNR}}$ values, and low standard deviation of the estimated noise parameters.

4.2. True data results

In the real case, the noise parameters identification and the true image intensities reconstruction follows registration of time lapse series of images. The measurements were acquired using fluorescence confocal MACROscope. The following settings were applied: pinhole 1.06 airy, 800 Hz scan speed, PMT Offset -4.3% and PMT Gain 848. The reported signal intensities at each location within a sample is produced by fluorescence induced by tissue itself, namely in the mixed autofluorescence process caused by the presence of lignin molecules. As discussed in the literature [23], one can expect in this case the photobleaching profiles to depend on the concentration of the dye and its interaction with the medium.

The processed time lapse sequence consists of 180 images with 12-bit resolution of size 128×128 , which translates into $T = 180$ and $S = 16384$. The first and last images of the sequence are illustrated in Fig. 2 (a) and Fig. 2 (b), respectively. One can observe that, due to the photobleaching effect, some parts of the image $r_{s,1}$ (Fig. 2 (a)) are not visible in the last image $r_{s,180}$ (Fig. 2 (b)), e.g. quadrant 4. Thus these parts of the image are essentially lost when calculating the mean over all realizations (Fig. 2 (c)). In contrast, these areas are well preserved in our result (Fig. 2 (d)). It is also worth noticing that our image provides significantly more visual details. Our algorithm also allows us to establish the parameters of the noise model (1), which are given as $25.8 \mathcal{P}(\hat{u}_s e^{-\hat{k}_s t}) + \mathcal{N}(8, 119)$. The plots in Fig. 3 illustrate the change of the measured and reconstructed signal along t , while s is fixed. They show the variety of acquired signals. For instance, the signal presented in Fig. 3(b) corresponds to a weak photobleaching effect, while in Fig. 3(c), a strong photobleaching effect is identified. One can observe a good match between the predicted bleaching curves and the experimental ones. The identified bleaching rates \hat{k}_s belong to the set $(0, 3.9 \times 10^{-6}]$ Hz, and \hat{u}_s lie in $[0, 147]$. This example shows that the proposed method is well suited for fluorescence imaging systems.

5. CONCLUSIONS

The present study has addressed the problem of Poisson-Gaussian noise parameter identification from time-lapse data, taking into account the photobleaching effect. We have proposed a new, fully automatic, two step statistical approach to deal with this problem. It has been demonstrated through both simulations and experiments that it can lead to quite accurate results. The proposed algorithm has direct applications in the calibration of fluorescence microscopy imaging systems and as a preliminary step of image restoration tasks.

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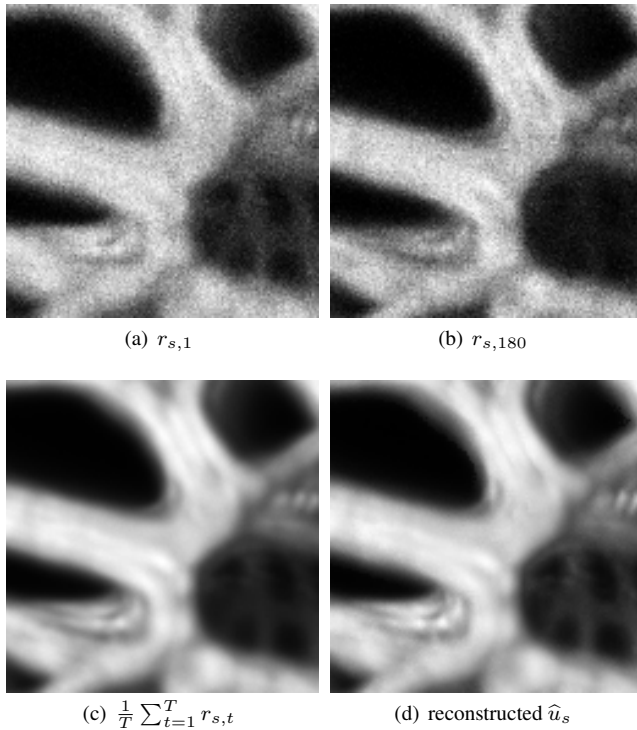


Fig. 2. (a,b) illustrate first and last observations of time series images $r_{s,t}$, (c) mean over all realizations and (d) reconstructed image.

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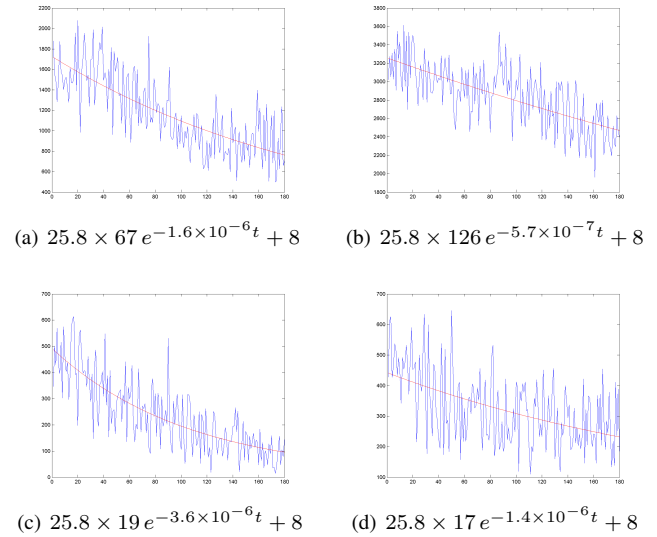


Fig. 3. (a,b,c,d) illustrate time variations for fixed s . The true data are plotted in blue and the reconstructed one (using formula $\hat{\alpha} \hat{u}_s e^{-\hat{k}_s t} + \hat{c}$) in red.

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