Radiation Measurements 87 (2016) 13–23

Contents lists available at ScienceDirect

Radiation Measurements

journal homepage: www.elsevier.com/locate/radmeas

Implementation of a nonlinear filter for online nuclear counting

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HIGHLIGHTS

- An efficient approach based on nonlinear filtering has been implemented.
- The hypothesis test provides a local maximum likelihood estimation of the count rate.
- The filter ensures an optimal compromise between precision and response time.

ARTICLE INFO

Article history:
Received 5 April 2014
Received in revised form
2 February 2016
Accepted 4 February 2016
Available online 6 February 2016

Keywords:
Nuclear
Measurement
Filter
Signal processing

ABSTRACT

Nuclear counting is a challenging task for nuclear instrumentation because of the stochastic nature of radioactivity. Event counting has to be processed and filtered to determine a stable count rate value and perform variation monitoring of the measured event. An innovative approach for nuclear counting is presented in this study, improving response time and maintaining count rate stability. Some nonlinear filters providing a local maximum likelihood estimation of the signal have been recently developed, which have been tested and compared with conventional linear filters. A nonlinear filter thus developed shows significant performance in terms of response time and measurement precision. The filter also presents the specificity of easy embedment into digital signal processor (DSP) electronics based on field-programmable gate arrays (FPGA) or microcontrollers, compatible with real-time requirements. © 2001 Elsevier Science. All rights reserved.

1. Introduction

Disintegration of a radioactive source is a purely stochastic phenomenon because of the indeterministic nature and respective independence of unstable nuclei. Such a source is characterized by its half-life $T_{1/2}$ and radioactive constant $\lambda' = ln(2)/T_{1/2}$. Nuclear measurement in pulse mode consists in estimating the output count rate λ expressed in counts per second $\lambda = \eta\lambda'$, where η is the transfer function taking into account the radiation emission probability and the intrinsic and geometric efficiencies of the sensor. This study deals with filters allowing smoothing of the nuclear counting signal. The aim of this study is to accurately estimate the evolution of λ as a function of time t. Fig. 1 illustrates the processing of a row-counting signal by two different filters. The first filter smooths the signal more efficiently than the second one, but involves a longer response time. A filter optimized according to this trade-off is thus introduced.

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http://dx.doi.org/10.1016/j.radmeas.2016.02.007

As pulses are considered well separated and uncorrelated (no pile-up), the probability to count $N = n$ events during an elementary integration time interval Δt follows the Poisson law (Eq. (1)), where λ is the expected count rate (Knoll, 1989):

$$\mathrm{P(N = n) = e^{-(\lambda\Delta t)}\frac{(\lambda\Delta t)}{n!}}. \quad (1)$$

Specificity of the Poisson distribution is the equality of the expected count value $\mathbb{E}[N]$ and its variance $\sigma^2(N)$:

$$\mathbb{E}[N] = \sigma^2(N) = \lambda\Delta t. \quad (2)$$

At low and constant λ, the maximum likelihood estimate $\hat{\lambda}^i_{LM}$ of the count rate over a sample of i measured count values $N_{j,1\le j\le i}$ is given by the empirical mean calculated during the total integration time $i\Delta t$ (Eq. (3)) (Rodriguez, 2007) a function of count expectation as presented in ref. (Devroye, 1986)

$$\hat{\lambda}^i_{LM} = \frac{1}{i\Delta t}\sum_{j=1}^{i} N_j. \quad (3)$$

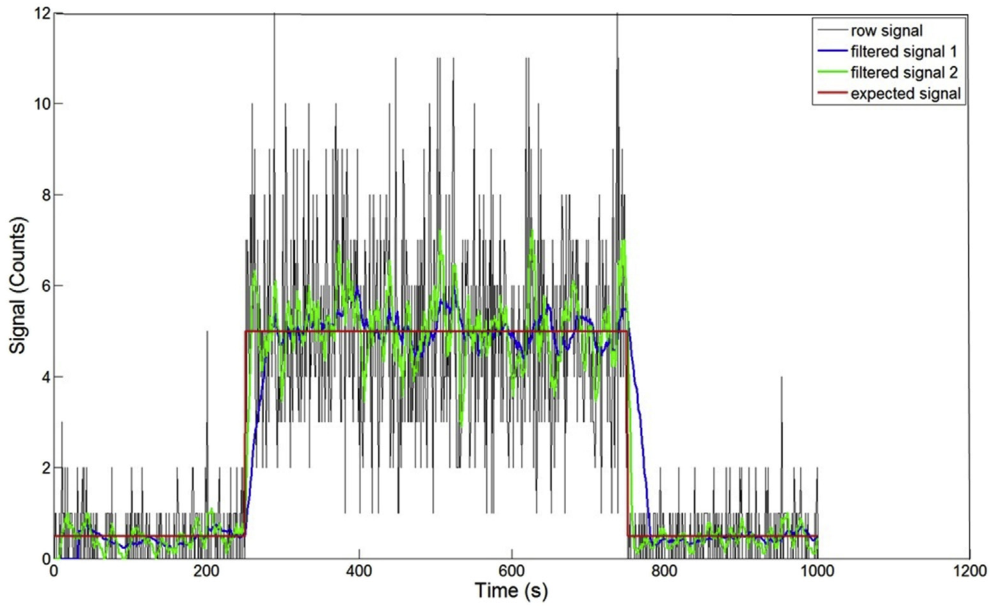

Fig. 1. Illustration of nuclear counting filtering.

According to Eqs. (2) and (3) and considering a null variance associated with Δt, the statistical variance of $\widehat{\lambda}_{LM}^{i}$ is evaluated as follows:

$$\sigma^2\left(\widehat{\lambda}_{LM}^{i}\right) = \left(\frac{\partial\widehat{\lambda}_{LM}^{i}}{\partial N_i}\right)^2 \sigma^2(N_i) = \left(\frac{1}{i\Delta t}\right)^2 \sum_{j=1}^{i} N_j. \tag{4}$$

The relative standard deviation associated with the estimation of λ with a given i is therefore expressed as

$$\frac{\sigma^2\left(\widehat{\lambda}_{LM}^{i}\right)}{\widehat{\lambda}_{LM}^{i}} = \frac{1}{\sqrt{\widehat{\lambda}_{LM}^{i}\, i\Delta t}}. \tag{5}$$

The choice of the sample size i retained for the measurement therefore results in a trade-off between the response time $i\Delta t$ and the precision proportional to $1/\sqrt{i\Delta t}$, both to be minimized. As an example of Fig. 1, the first and second filtered signals correspond to integration lengths $i = 8$ and 32, respectively.

The organization of this paper is as follows. First, a state of the art regarding smoothing filters applied to nuclear instrumentation is introduced. Then, implementation of the proposed CST filter is described and the method used for benchmarking the different filters is detailed. Finally, the results are presented to highlight the performance of the CST filter compared with its counterparts.

2. Related work

The main filter used in industrial implementations is labeled "Moving Average" (MA) and exploits the empirical mean estimator. This filter provides a different estimation for every value of i. This linear low-pass filter is suitable for estimating a nonvarying λ, but becomes nonspecific when an abrupt change in radioactivity occurs. Then, a trade-off regarding the experimental conditions and the purpose of the measurement has to be found. Indeed, if the requirement of the system lies only within the response time performance to a variation of λ, a fixed value of i is set ("preset time ratemeter"). On the contrary, if the requirements are only to display a precise value (low fluctuation), the signal is integrated until a prefixed required statistical precision is achieved ("preset count ratemeter") (Vincent, 1963; Vankov et al., 1983; Arandjelovic et al., 2002). A way of reconciling both requirements may be to introduce a weighted function with factors $\mu_{j,1\le j\le i}$ as described in Eq. (6) (these factors are also called *forgetting factors*):

$$\widehat{\lambda}_{\mu}^{i} = \frac{1}{i\Delta t}\frac{\sum_{j=1}^{i} N_j\mu_j}{\sum_{j=1}^{i} \mu_j}. \tag{6}$$

The most frequent implementation of this alternative to preset ratemeters is the exponential moving average (EMA), with exponential weight factors $\mu_j = exp(-\theta j)$, where θ is the parameter of the filter (Dumesnil and Greco, 1985; Savic, 1991; Jeonget al, 2008). In general, finite impulse response filters have been studied earlier (Rudnick et al., 1969; Byrd, 1974; White, 1975; Longden-Thurgood and Pople, 1981). Linear filters have shown limits with regard to the trade-off between precision and response time. More recently, edge-preserving filters have been developed in nonlinear algorithms to deal with this issue.

A nonlinear strategy has been developed (SPRT and GLR filters) by several authors (Coop, 1985; Fehlau, 1993; Willsky and Jones, 1976; Colluraet al, 1987; Apostolopoulos, 2008), which consists in adapting the sample size i retained for a local maximum likelihood estimation according to the detection of any abrupt change in the Poisson statistics (Charnes et al., 1976; Basseville and Nikiforov, 1993). The detection method is based on a hypothesis testing model, and allows for making a quick decision. A nonlinear filter implementing a hypothesis test labeled CST is described in this study.

3. Implementation of the nonlinear filter

The algorithm of the CST filter is divided into schematic steps for the ease of representation. These steps are as follows: reading the new sample, calculating the estimate vector, decision made after the hypothesis test, and action performed based on the test result (Fig. 2).