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# An Adaptive Smoother for Counting Measurements

Vladimir Kondrasovs, Romain Coulon and Stephane Normand

**Abstract**—Counting measurements associated with nuclear instruments are tricky to carry out due to the stochastic process of the radioactivity. Indeed events counting have to be processed and filtered in order to display a stable count rate value and to allow variations monitoring in the measured activity. Smoothers (as the moving average) are adjusted by a time constant defined as a compromise between stability and response time.

A new approach has been developed and consists in improving the response time while maintaining count rate stability. It uses the combination of a smoother together with a detection filter. A memory of counting data is processed to calculate several count rate estimates using several integration times. These estimates are then sorted into the memory from short to long integration times. A measurement position, in terms of integration time, is then chosen into this memory after a detection test.

An inhomogeneity into the Poisson counting process is detected by comparison between current position estimate and the other estimates contained into the memory in respect with the associated statistical variance calculated with homogeneous assumption. The measurement position (historical time) and the ability to forget an obsolete data or to keep in memory a useful data are managed using the detection test result.

The proposed smoother is then an adaptive and a learning algorithm allowing an optimization of the response time while maintaining measurement counting stability and converging efficiently to the best counting estimate after an effective change in activity. This algorithm has also the specificity to be low recursive and thus easily embedded into DSP electronics based on FPGA or micro-controllers meeting “real life” time requirements.

**Index Terms**— Adaptive - Algorithm - Contamination meter - Counting - Filter - Instrument - Learning - Measurement - Nuclear - Radioactive - Ratemeter - Signal processing - Smoother

## I. INTRODUCTION

NUCLEAR measurements operating in pulse mode consists in estimating radioactive materials disintegration rate intensity to obtain, after calibration, an exposure dose rate or an activity measurement evaluation. As nuclear disintegrations are considered independents and uncorrelated from one to another this discrete signal can be considered as a Poisson process [1] [2]. The probability to count  $N = k$  counts during a given time  $t$  is described in Eq. 1.

$$P(N = k) = e^{-N} \frac{(N)^k}{k!} \quad (1)$$

The count rate  $S$  is the ratio of measured counts by integration time  $t$ .

$$S = \frac{N}{t} \quad (2)$$

A specificity of the Poisson distribution is the equality of the  $N$  expected value and its variance.

$$E(N) = var(N) \quad (3)$$

This specificity induces an intrinsic impossibility for gross counting measurement to achieve both temporal and statistical accuracy as shown in Eq. 4.

$$\sigma(S)t = \sqrt{N} \quad (4)$$

A compromise is then found taking into account experimental conditions of the measurement. If the requirement of the system is only the response time, a fixed integration time could be set. At the opposite if requirements considered only the counting stability, counts are integrated until they achieve a prefixed required statistical accuracy. In practice, both requirements have to be considered. Two kinds of filters are then applied according to the context (displaying or detecting).

First filter type consists in smoothers most useful when measurements stability is the priority. It ensures a stable measurement value displayed. The moving average filter is currently used to achieve the best  $S$  estimate for a constant activity but is not still adapted if any change in the activity occurs. Some other filters as the exponential moving average smooth the signal out with a better response time and could then offer a better compromise [3].

Second types are detection filters, used in priority to detect as fast as possible a significant change in the activity and trigger an alarm. These tests could be a simple threshold estimate using the prior knowledge of the background or variability analysis based on variance tests, the  $X^2$  test or Kolmogorov-Smirnov tests [4].

A smothering filter could be coupled with a detection filter to improve the radioactive signal monitoring. This kind of

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methods has been developed by G. Apostolous [5]. The detection of abrupt changes is notably done in its paper by the generalized likelihood ratio GLR test given well optimized results.

This kind of approach is proposed in this paper and addressed by on-line measurement systems where the algorithm has to be embedded on programmable electronic compound maintaining real life time requirements. This smother carried on a moving average filter for the smother part and a variance test for the detection part. A learning action is also added using the detection test result. The memory time is then managed to erase, obsolete data and keep in memory data remaining useful. The convergence after a change in activity is then optimized in this smoother.

## II. METHODS

During a given time period,  $\Delta t$ , events are counted into the first location  $l$  of the data memory stack. Data are moved following “First In First Out” FIFO memory rules filling all the stack locations  $N_j$ . During this counting time period, data are processed to determine the best count rate estimate. A vector containing several intensity estimates  $\lambda_i$  is built as shown in Eq. 5.

$$\lambda_i = \frac{\sum_{j=l}^i N_j}{a_i \Delta t} \quad (5)$$

The vector  $\lambda$  contains count rate estimates with several temporal versus statistical accuracy compromise. The stack is scanned to compare each value  $\lambda_i$  to the current estimated position  $\lambda_p$ . The variation in intensity  $\Delta\lambda_i$  (see Eq. 6) is calculated and compared to a statistical variance calculated considering an homogeneous Poisson assumption. The test is presented in the Eq. 7 where  $Q$  is the filter detection threshold. If the threshold is too low the system is unstable and if  $Q$  is too high the system is too rigid (no more flexible). To obtain a fast response and stability the threshold has to be set between 0.5 and 3 (1.5 or 2 seems to be optimum).

$$\Delta\lambda_i = |\lambda_p - \lambda_i| \quad (6)$$

$$u^2(\Delta\lambda_i) = Q^2 \sigma^2(\Delta\lambda_i) = Q^2 \left( \frac{\lambda_p}{p\Delta t} + \frac{\lambda_i}{i\Delta t} \right) \quad (7)$$

The difference is considered to be significant when the test  $\Delta\lambda_i^2 > u^2(\Delta\lambda_i)$  becomes true. The measurement position  $p$  is then shifted to a “faster” position ( $p = p - 1$ ). After a change in activity the older counting data could disturb the convergence of the estimate. An extra-FIFO action is then done deleting the oldest data ( $l = l + 1$ ). If no change is detected the measurement position is moved to a smother position ( $p = p + 1$ ) and the memory time is extended ( $l = l - 1$ ).

## III. RESULTS

The adaptive smoother (AS) performance is compared to the performance of other smoothers for several  $Q$  threshold values.

The Moving Average (MA) is the most commonly used smoother into ratemeters. The Exponential Moving Average (EMA) is sometimes implemented for activity changing applications and is tested for several time constant values (constant contained into the exponential term).

The Polyà Tree mixtures (PT) gives an optimal smother for Poisson signal and is notably used for photons-limited imaging reconstruction and gamma spectrum unfolding [7] [2].

The fluctuation given by the smoothers is measured by the variation coefficient  $V$  (ratio of the standard deviation and the average) calculated during a constant activity.

$$V = \frac{\sigma(x)}{\bar{x}} \quad (8)$$

The time response (time to reach 90 % of the final value) is calculated during a decade step of activity (increase and decrease).

A large number of measurement simulations are performed to obtain accurate distributions of fluctuations and time responses. Fig. 1 to 3 illustrate distributions obtained for an input count rate of 1 cps (count per second). The response time is calculated ensuring that 95 % of response times remain below it.

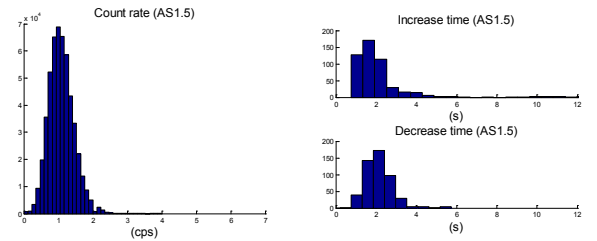


Fig. 1. Distribution of the count rate estimates and response times obtained with the adapted smoother for a signal of 1 cps.

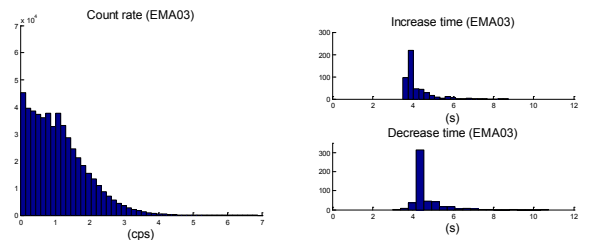


Fig. 2. Distribution of the count rate estimates and response times obtained with the exponential moving average for a signal of 1 cps.

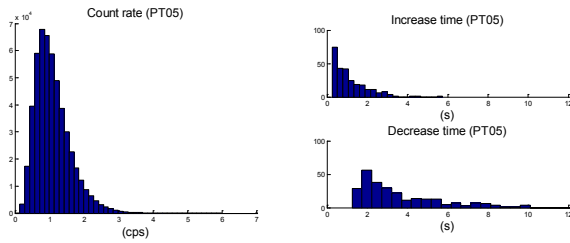


Fig. 3. Distribution of the count rate estimates and response times obtained with Polyà Tree mixtures for a signal of 1 cps.

Performances in terms of fluctuations and response times are then evaluated for each filter. A fixed memory size of 32 slots of 0.25 s each has been set and filters have been tested with several parameters. Fig. 4 shows fluctuations as a function of the time response for a signal of 1 cps and Fig. 5 for a count rate of 10 cps. The horizontal axis is the maximum response time between an increase and a decrease.

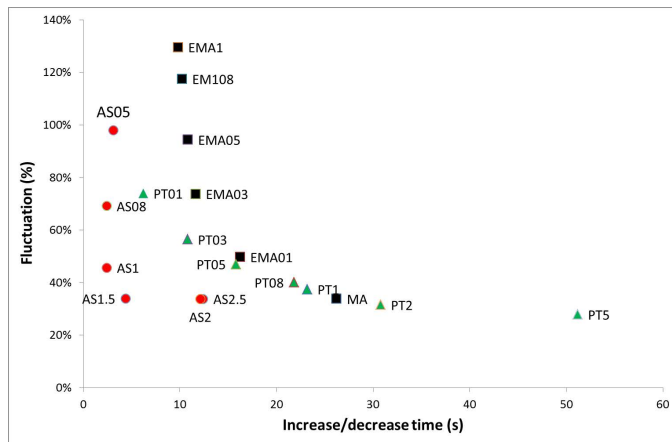


Fig. 4. Comparison of smoother performances for an input count rate of 1cps.

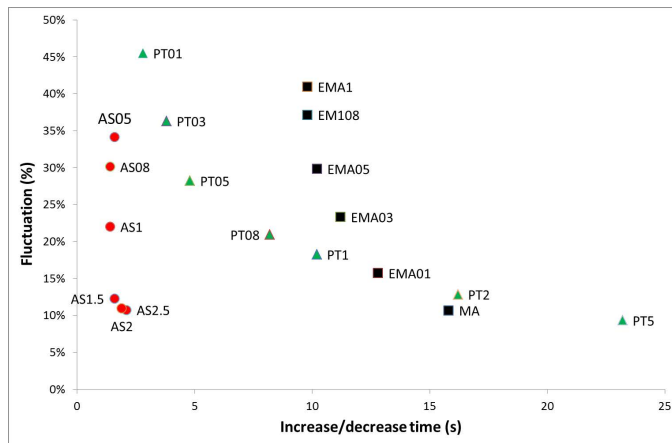


Fig. 5. Comparison of smoother performances for an input count rate of 10 cps.

The adaptive smoother gives a better compromise between fluctuation and response time in comparison with other smoothers. Indeed, the smoother is six times faster to the moving average for a given fluctuation smothering ability. The adaptive smoother shows then significant improvements compared to the moving average method for radiation monitors.

#### IV. CONCLUSION

The proposed smoother is an adaptive and a learning algorithm allowing response time optimization maintaining measurement stability and focusing quickly to the best counting estimate after a change in the activity. It is a low recursive algorithm and could be easily embedded into DSP electronics based on FPGA or micro-controllers maintaining real life time requirements.

It could then address a large industrial application field as process monitoring, area monitoring, portable monitoring, and embedded detection [6] [7] [8].

Regarding the conventional moving average smoother, the adaptive smoother shows significant improvements for radioprotection monitors applications (six times faster than moving average filter for equivalent stability).

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