Nuclear Instruments and Methods in Physics Research A 795 (2015) 335–342

Contents lists available at ScienceDirect

Nuclear Instruments and Methods in Physics Research A

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

A robust hypothesis test for the sensitive detection of constant speed radiation moving sources

Jonathan Dumazert [a,*], Romain Coulon [a], Vladimir Kondrasovs [a], Karim Boudergui [a], Yoann Moline [a], Guillaume Sannié [a], Jordan Gameiro [a], Stéphane Normand [a], Laurence Méchin [b]

[a] CEA, LIST, Laboratoire Capteurs Architectures Electroniques, 91191 Gif-sur-Yvette, France
[b] CNRS, UCBN, Groupe de Recherche en Informatique, Image, Automatique et Instrumentation de Caen, 14050 Caen, France

ARTICLE INFO

Article history:
Received 9 March 2015
Received in revised form
29 May 2015
Accepted 8 June 2015
Available online 16 June 2015

Keywords:
Moving source detection
Temporal series analysis
CBRN-E applicatio
Hypothesis test

ABSTRACT

Radiation Portal Monitors are deployed in linear networks to detect radiological material in motion. As a complement to single and multichannel detection algorithms, inefficient under too low signal-to-noise ratios, temporal correlation algorithms have been introduced. Test hypothesis methods based on empirically estimated mean and variance of the signals delivered by the different channels have shown significant gain in terms of a tradeoff between detection sensitivity and false alarm probability. This paper discloses the concept of a new hypothesis test for temporal correlation detection methods, taking advantage of the Poisson nature of the registered counting signals, and establishes a benchmark between this test and its empirical counterpart. The simulation study validates that in the four relevant configurations of a pedestrian source carrier under respectively high and low count rate radioactive backgrounds, and a vehicle source carrier under the same respectively high and low count rate radioactive backgrounds, the newly introduced hypothesis test ensures a significantly improved compromise between sensitivity and false alarm. It also guarantees that the optimal coverage factor for this compromise remains stable regardless of signal-to-noise ratio variations between 2 and 0.8, therefore allowing the final user to parametrize the test with the sole prior knowledge of background amplitude.

1. Introduction and related work

The detection of radiological material in motion forms a burning issue in addressing CBRN threats [1]. Whether the potential carrier may be a pedestrian, a train or a vehicle, Radiation Portal Monitors (RPM) are deployed so that the radiation sensor inserted into the device is placed as close as possible to the radioactive source path. Classical industrial detection systems for moving sources perform the detection by mere signal amplitude triggering on a recording channel interfaced with the sensor. The alarm of the detector is triggered as soon as the relevant signal rises over a given threshold, which is set with regards to the amplitude of the background activity as well as to some assumptions formulated based on the laws followed by the different signals. For the detection to be efficient when the carrier is in motion, a large volume sensor is supplied, typically a gas or plastic scintillator for scalability and cost-effectiveness reasons [2,3]. To obtain significant gains in the richness of the information provided by such a single RPM, *ad hoc* strategies have been developed. Guillot et al. have, for instance, described and patented [4] a method for the detection and identification of moving sources using a spectrometry device, which lies outside the scope of the present paper, focused on pure detection applications. To increase the sensitivity of the detection, especially critical under low signal-to-noise ratios (*SNR*, for which we hereby use the classical definition of the source signal count divided by the square root of the background fundamental count), energy windowing strategies have been introduced. Robinson et al. [5] compare at each given time the observed spectrum to adequately chosen energy windows over a background previously acquired at the RPM level. To maximize the gain in sensitivity, Vilim et al. [6] select the energy ranges providing the highest *SNR* values. It then follows that such methods are highly dependent on the energy resolution of the provided spectrometric information. Hence the quest for alternative methods continues for utilizing large-scale plastic scintillators exhibiting high detection efficiencies but mediocre energy resolutions.

A powerful strategy to address sensitivity issues when dealing with challenging *SNR* moving sources lies within the deployment of not only one RPM, but a network of such sensors. While independent multichannel triggering remains available for such a network,

* Corresponding author. Tel.: +33 1 69 08 53 24.
E-mail address: jonathan.dumazert@cea.fr (J. Dumazert).

http://dx.doi.org/10.1016/j.nima.2015.06.016
0168-9002/

the measurement then being computed by the logical summation of all channel detection answers, some valuable information may be extracted by analyzing the delayed temporal evolution of the signals recorded in front of the respective RPM. Such networks, of variable geometries and dimensions, are particularly praised for source localization applications, in which they typically appear two-dimensional (2-D) and large-scale. Dedicated algorithms have then been elaborated to track the source trajectory without prior knowledge, as carried out with Markov Chains calculations and Bayesian methods by Brennan et al. [7] or triangulation by Chin et al. [8]. Such highly iterative and finely optimized methods are poorly suited for typical CBRN issues dealing with straight trajectories of pedestrian or vehicle source carriers under real time, immediate response constraint. Alternatively, faster algorithms have been proposed: Nemzek et al. [9] describe a method based on the combination of different channels and final comparison to the signal of a single chosen RPM. Stephens et al. [10] additionally justify a preliminary probabilistic triggering on the acquisition channels. Both these methods nevertheless require that the speed of the source carrier be known with a certain degree of precision, which in real life situations is difficult to achieve and may thus constitute an excessive constraint for the detection system conceiver. Sundaresan et al. [11] have, on the other hand, set up a measurement based on *a priori* independent multichannel detections which are all correlated *a posteriori* to lower the false alarm probability. Such an approach, as firstly based on a single channel variation monitoring, does not allow for any sensitivity improvement of the system, so that the false alarm reduction does not reveal itself sufficient to operate the detector under challengingly low *SNR*. Rao et al. have additionally established in a recent paper [12] that a network of NaI sensors associated with a particle filter method allows the detection of a cesium-137 moving source with shorter delays and over a wider spatial range when combining the data acquired by several networked detectors.

Coulon et al. have described and patented [13,14] an alternative exploitation of the compared temporal information contained in the different recording channel memories. As the source carrier, supposedly following a linear or quasi-linear trajectory, successively passes in front of each of the RPM, displayed in a network, it induces for a short time an increase in the signal level. Such an increase, in the cases of challenging *SNR*, may be impossible to detect in front of the first RPM among the inherent level of fluctuations induced by the Poisson statistical nature of the measured radiation background. Nevertheless, supposing that the carrier moves at constant speed or quasi-constant speed along the network (which forms a more versatile assumption than the one of a *precisely determined constant* speed and a reasonable one for a pedestrian, a car or a train before its final deceleration), an echo of the undetected additional signal may be found on every other channel and, as the speed is constant, these successive appearances are periodic. It is therefore possible to search for a temporal delay, on the form of a multiple value of the fundamental sampling time step, which will, to the maximum possible extent, superimpose the successive echoes of the undetected signal increases and exploit the multiplied values of these echoes as the significant variation to be detected, by a specified amplitude triggering, among the inherent fluctuations of a computed temporal multiplication vector. Coulon et al. have calibrated a hypothesis test for moving source detection without any assumption made on the expected nature and intensity of such a product vector, making use of the empirical estimates for the mean and standard deviation of the vector. Their approach has proven itself efficient for a relatively high speed ($7\,\mathrm{m.s^{-1}}$) low count rate (12 cps) source among a challenging count rate background (20 cps). A preliminary set of simulations has additionally corroborated the choice of Coulon et al. to search for the echo of the source passage in the product rather than in the summation of the different channel recordings, the higher amplification of the background then being advantageously balanced by a vast gain in the amplitude of the useful signal. The authors of the present paper propose to investigate an improved version of the detection test introduced by Coulon et al. first describing the underlying statistics governing the temporal product vector used for the test, and then parametrizing the said test by a novel expectation and widening as computed under the assumption of a product of Poisson laws.

2. Mathematical formalism

Let us consider the signals registered on the two RPM of a given linear network to be generated by two real and independent underlying random variables S_1 and S_2 with Poisson density laws respectively parametrized by λ_1 and λ_2. Providing λ_1 and λ_2 are high enough, both distributions may be approached by the normal distributions $\mathcal{N}(\lambda_1, \lambda_1)$ and $\mathcal{N}(\lambda_2, \lambda_2)$. We consider the aleatory variable $Y = S_1 \cdot S_2$ formed by the product of both previous ones.

2.1. Calculation of the expected value and variance of Y

The expected value $E[Y]$ of the random variable formed by the product of two real and independent variables is given by the product of both expected values $E[S_1]$ and $E[S_2]$ of the considered variables

$$E[Y] = E[S_1 \cdot S_2] = E[S_1] \cdot E[S_2] = \lambda_1 \cdot \lambda_2 \tag{1}$$

The variance $V(Y)$ of Y is a function of both variances $V(S_1)$ and $V(S_2)$ of the multiplied variables, as well as of their expected values $E[S_1]$ and $E[S_2]$

$$\begin{aligned} V(Y) &= V(S_1) \cdot V(S_2) + V(S_1) \cdot (E[S_2])^2 + V(S_2) \cdot (E[S_1])^2 \\ V(Y) &= \lambda_1 \cdot \lambda_2 \cdot (1 + \lambda_1 + \lambda_2) \end{aligned} \tag{2}$$

2.2. Generalization to the product of n variables

The previous formalism may be generalized to the case of a linear network displaying any number n of RPM. Let us then consider n real and independent random variables $S_1, S_2 \ldots S_n$ with Poisson density laws respectively parametrized by $\lambda_1, \lambda_2 \ldots \lambda_n$, which are respectively approached by the normal law distributions $\mathcal{N}(\lambda_1, \lambda_1)$, $\mathcal{N}(\lambda_2, \lambda_2) \ldots \mathcal{N}(\lambda_n, \lambda_n)$. We consider the random variable $Y = S_1 \cdot S_2 \ldots S_n$ formed by the product of the n previous ones.

The expected value $E[Y]$ of the variable defined as the product of n real and independent variables is given by the product of the expected values $E[S_1], E[S_2] \ldots E[S_n]$ of the considered variables

$$E[Y] = E[S_1] \cdot E[S_2] \ldots E[S_n] = \lambda_1 \cdot \lambda_2 \ldots \lambda_n = \prod_{i=1}^{n} \lambda_i \tag{3}$$

The calculation of the variance $V(Y)$ of Y is carried out by applying recursively the result of Section 2.1

$$\begin{aligned} V(Y) &= V(S_1 \cdot S_2 \ldots S_{n-1}) \cdot V(S_n) + V(S_1 \cdot S_2 \ldots S_{n-1}) \cdot (E[S_n])^2 \\ &\quad + V(S_n) \cdot (E[S_1 \cdot S_2 \ldots S_{n-1}])^2 \\ V(Y) &= V(S_1 \cdot S_2 \ldots S_{n-1}) \cdot (\lambda_n + \lambda_n^2) + \lambda_n \cdot \left(\prod_{i=1}^{n-1} \lambda_i \right)^2 \end{aligned} \tag{4}$$

The same treatment is then applied to the variables $S_1 \cdot S_2 \ldots S_{n-1}$, then $S_1 \cdot S_2 \ldots S_{n-2} \ldots$, lowering the number of factors after every iteration until only 2 remain and we are therefore brought back to the case dealt with in Section 2.1.

3. Method

This section divulges the steps followed by the simulation code (simulation of the recorded radiation signal, data storage, calculation