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# Moving Sources Detection System

Romain Coulon, Vladimir Kondrasovs, Karim Boudergui, and Stephane Normand

**Abstract** - To monitor radioactivity passing through a pipe or in a given container such as a train or a truck, radiation detection systems are commonly employed. These detectors could be used in a network set along the source track to increase the overall detection efficiency. However detection methods are based on counting statistics analysis. The method usually implemented consists in triggering an alarm when an individual signal rises over a threshold initially estimated in regards to the natural background signal. The detection efficiency is then proportional to the number of detectors in use, due to the fact that each sensor is taken as a standalone sensor.

A new approach is presented in this paper taking into account the temporal periodicity of the signals taken by all distributed sensors as a whole. This detection method is not based only on counting statistics but also on the temporal series analysis aspect. Therefore, a specific algorithm is then developed in our lab for this kind of applications and shows a significant improvement, especially in terms of detection efficiency and false alarms reduction. We also plan on extracting information from the source vector.

This paper presents the theoretical approach and some preliminary results obtain in our laboratory.

**Index Terms**— Algorithm – Detection – Filter - Instrument – Measurement – Monitor – Moving – Nuclear – Radiation – Radioactive – Safeguard – Signal processing – Source - Time series analysis

## I. INTRODUCTION

MONITORING a moving source is currently required for numerous nuclear safeguards applications. Nuclear materials could be contained into a car, a truck, or a train and could also be disseminated into a water pipe or an air vent. The detection is tricky due to the source motion and its speed implying a fast motion when passing by the probe. To increase the detection sensitivity, sensors have to be set along the source track.

Detection is commonly done by a threshold calculated according to the background fluctuation level estimated with the Poisson counting assumption. The detection probability increases then proportionally with the number of sensors in use.

The sensors network gives other information about the signal thanks to the temporal correlation between sensors. Studies have been carried out for the source track using matrix sensors networks. MCNC calculations and Bayesian approach

allowing sources tracking without any knowledge of the source trajectory has been developed [1]. Algorithm based on triangulation has also been studied for source localization purposes [2]. These methods using interactive algorithms are optimized for 2-D problems and are not useful when the source trajectory is well known (1-D).

Faster algorithm has then been developed but requires the accurate knowledge of the source velocity which is not usually the case for safeguard problematic [3] [4].

This paper presents a detection method based on temporal series analysis associated with linear sensor network. It allows a continuous and fast detection without accurate knowledge of the source velocity. The method is described and a comparison study with counting statistics detection is presented.

## II. METHODS

The radioactive source passes from channel 1 to channel N. Count rates are recorded in memories corresponding to each channel (see Fig. 1).

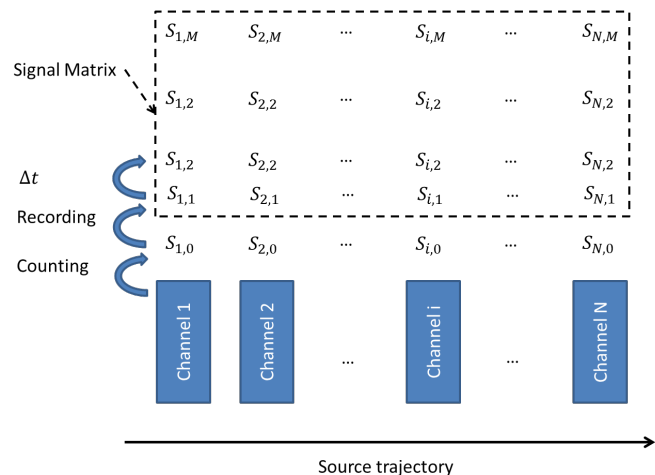


Fig. 1. Principle of the signal recording.

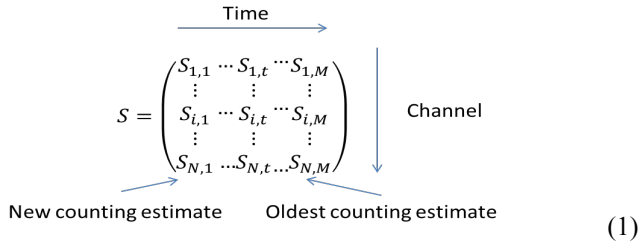
The detection filter and measurement are processed with the following steps:

### A. Memory Management

At the end of the counting process  $\Delta t$ , a “First In First Out” FIFO memory action is done in each channel memories. After, the last counting is recorded into the first value of the memories. Counting values are noted  $S_{i,t}$  where  $i$  is the channel number and  $t$  the time into the memories.

Authors are with the French Alternative Energies and Atomic Energy Commission, Laboratoire Capteurs et Architectures Electroniques (CEA/LIST) F-91191 Gif-sur-Yvette, France.

(e-mail: [romain.coulon@cea.fr](mailto:romain.coulon@cea.fr), [vladimir.kondrasovs@cea.fr](mailto:vladimir.kondrasovs@cea.fr), [karim.boudergui@cea.fr](mailto:karim.boudergui@cea.fr), [stephane.normand@cea.fr](mailto:stephane.normand@cea.fr))



### B. Correlation Vector Building

A temporal correlation vector  $R_t$  is calculated as a function of delayed times  $t$  between sensors. The calculation is presented in Eq.2.

$$R_t = \prod_{i=1}^N S_{i,(N-i)t+1} \quad (2)$$

### C. Decision Threshold Determination

A decision threshold is built using the mean of the static product  $\bar{R}$  (Eq.3) and its associated standard deviation  $\sigma(\bar{R})$  (Eq.4).

$$\bar{R} = \frac{1}{M} \sum_{t=1}^M \prod_{i=1}^N S_{i,t} \quad (3)$$

$$\sigma(\bar{R}) = \sqrt{\frac{1}{M} \sum_{t=1}^M (\bar{R} - S_{i,t})^2} \quad (4)$$

### D. Detection Test

A detection test consists then in determining if a correlation between the channels is considered significant. The test is done for all delayed times  $t$ . The parameter  $K_2$  is the filter threshold.

$$R_t > \bar{R} + K_2 \sigma(\bar{R}) \quad (5)$$

### E. Speed Estimation

If detection occurred, the time period  $T$  corresponding to the maximum of vector  $R_t$  could give, using the distance between sensors value  $d$ , an approximation of the source speed  $V$ . The accuracy in velocity estimation is then linked to the time sampling  $\Delta t$  of the detection system.

$$T = \{t; \max(R_t)\} \quad (6)$$

$$V = \frac{d}{T \Delta t} \quad (7)$$

### F. Intensity Estimation

A non-biased intensity estimation  $I$  (equivalent to the count rate obtained when the source is in front of a detector) is finally estimated to obtain a measurement quantification after an appropriate calibration.

$$I = \frac{1}{N} \sum_{i=1}^N S_{i,(N-i)T+1} - \frac{1}{N \times M} \sum_{t=1}^M \left[ \sum_{i=1}^N S_{i,t} \right] \quad (8)$$

## III. RESULTS

The signal is simulated considering constant background intensity  $\lambda_b$  and source intensity  $\lambda_s$  (count rate in front of a detector). A geometrical model permits to simulate the global intensity  $\lambda_i(t)$  of a channel  $i$  as a function of time (see Fig.2).

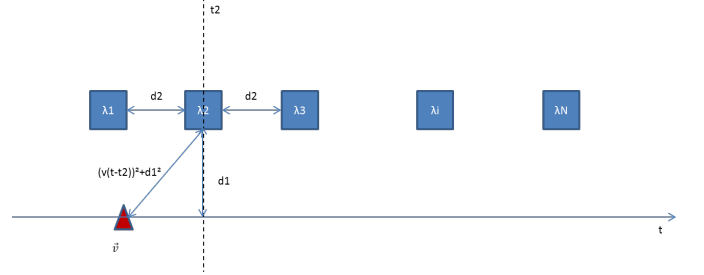


Fig. 2. Geometrical model.

The intensity is then a function of the distance between probes  $d_2$ , the distance to the source track line  $d_1$  and the source velocity  $v$ .

$$\lambda_{i,t} = \frac{\lambda_s d_1^2}{d_1^2 + v^2 (t - t_i)^2} + \lambda_b \quad (9)$$

$$t_i = t_{i-1} + d_2 v \quad (10)$$

The inhomogeneous Poisson process is then generated for each channel as illustrated in Fig. 3.

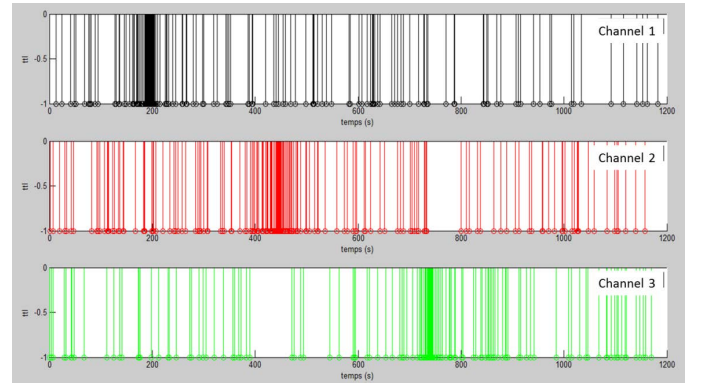


Fig. 3. Example of pulses arrivals from 3 sensors while a source is passing.

Statistical and time analysis detection methods are presented in Fig. 3 where a network of five sensors and a source passing at 17 m.s-1 is considered. The top part of the figure is the injected intensity from the geometrical model  $\lambda_i(t)$  ( $\lambda_b = 40$  ;  $\lambda_s = 10$  ). The middle part of the figure is the row counting signal obtained from each channel. The yellow line represents the threshold of the statistical method calculated as described in Eq.9 where  $K_1$  is the statistical filter

parameter.

$$Sl_i > K_1 \sqrt{2(\lambda_b \Delta T + 1) + \lambda_b \Delta T} \quad (11)$$

The bottom part of the figure is the correlation product  $R_t$  see Eq.2 where the corresponding speed appears on the x-axis ( $R_v = R_{d_2/t}$ ). The red line is the detection threshold calculated from Eq. 5 ( $K_2 \sigma(\bar{R}) + \bar{R}$ ).

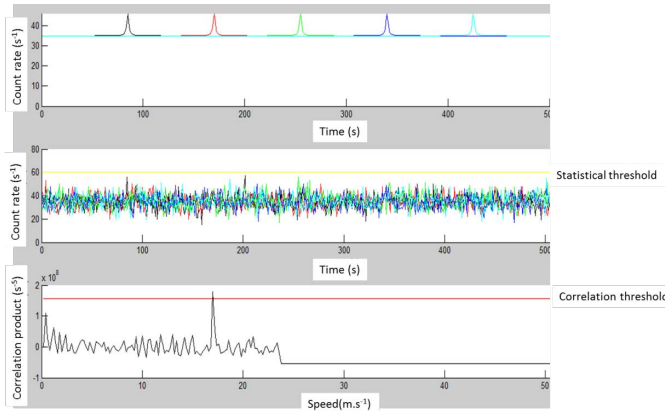


Fig. 4. Demonstration of the correlation detection method using five channels showing injected signals (top) row the signals (middle) and the correlation product (bottom).

To compare the metrological performance of these two methods parameters  $K_1$  and  $K_2$  are first set to give an approximated equivalent false alarm rate. A constant signal ( $\lambda_s = 0$ ) is injected several times to estimate a false detection rate with good accuracy. Fig. 5 shows the false alarm rate evolution as a function of the number of sensors in use. The correlation method allows false alarms reduction more efficiently while increasing sensors in use in the network.

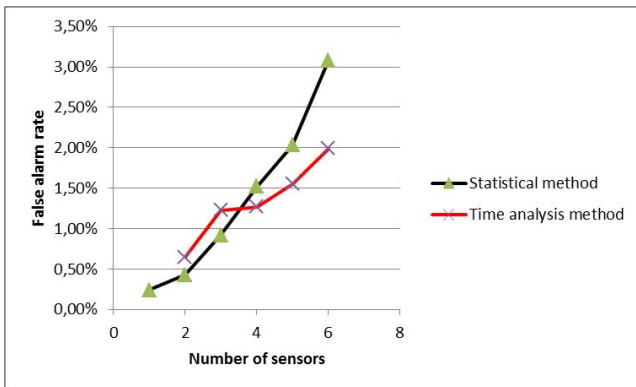


Fig. 5. False alarm rate as a function of sensors in use for the statistical method (black) and the correlation method (red).

A signal ( $\lambda_s = 12$  cps) is then injected a large number of time to estimate detection rates with good accuracy. Fig. 6 shows the detection rate as a function of the number of sensors in use for both methods using the same  $K_1$  and  $K_2$  thresholds as determined before.

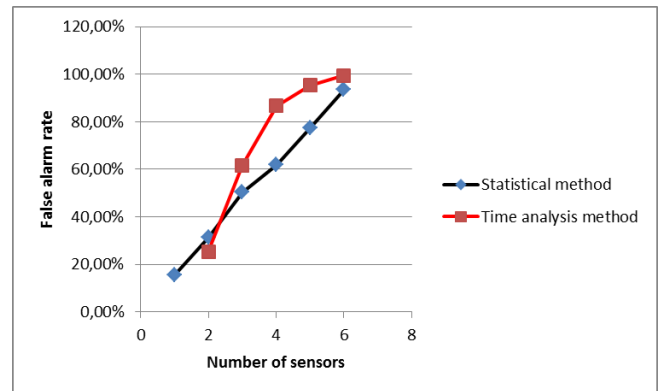


Fig. 6. Detection rate as a function of sensors in use for the statistical method (black) and the correlation method (red).

The time analysis method, especially when the number of sensors exceeds three, shows better detection efficiency. Using a sensor network containing five sensors, the time analysis methods gives an improvement of 24 % for false alarms reduction and 23 % for detection ability. To illustrate the improvement given by the time analysis approach and more precisely the correlation method, Fig. 5 presents the evolution of the detection rate as a function of the source signal intensity.

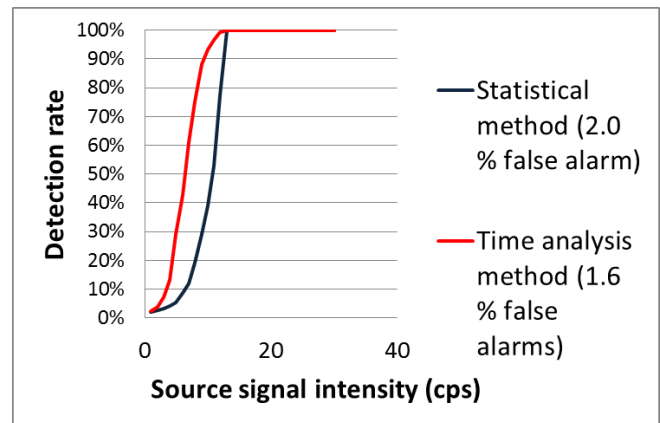


Fig. 7. Detection rate as a function of the signal source in a background of 20 cps for 5 probes using statistical method (black) and time analysis method (red).

The source intensity is calculated by the mean of the measurement when the detection has already occurred, the quantitative estimation could be then biased at low intensity. Using the velocity estimated by the correlation algorithm a non-biased estimation could be reconstructed (see Eq.6).

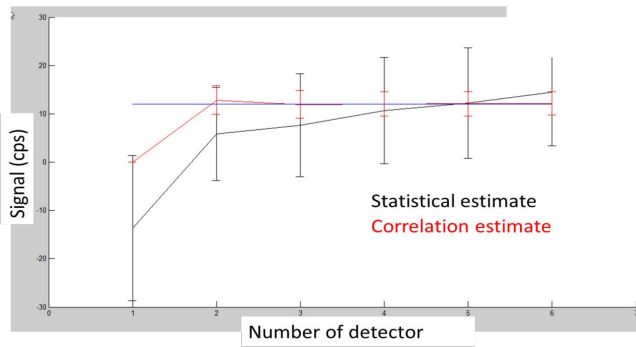


Fig. 8. Estimated source intensity by conventional method (black) and by velocity corrected method (red) and injected intensity (blue line).

#### IV. DISCUSSION

The time analysis is encouraging promising approach for moving sources detection applications. Other methods considering time analysis approach have to be developed to improve the detection ability for moving sources applications.

Row counting data has been used in this paper but the overall system could be also improved coupling time analysis detection with an upstream adaptive smoother as proposed by V. Kondrasovs [5].

#### V. CONCLUSION

The detection of moving radioactive sources is a challenge for nuclear safeguards applications. Processing the signal given by a sensor network allows the detection ability improvement for a given nuclear measurement system.

Statistical approaches are currently implemented for detection but time analysis approach could improve the system performance.

The correlation method proposed in this paper shows an improvement of 24 % for false alarms reduction and 23 % for detection ability for a network of five sensors compared to a statistical method. This method presents also promising results in terms of activity quantification and velocity estimation. This system is planned to be tested soon for safeguards applications purposes.

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