NEW INSIGHTS INTO INVERSE DISPERSION MODELLING AND PROBABILISTIC SOURCE TERM ESTIMATE AT LOCAL SCALE IN COMPLEX ENVIRONMENTS

Harmo 20 international conference

V. Watson [1,2], **F. Septier** [1], **P. Armand** [2], **C. Duchenne** [2]

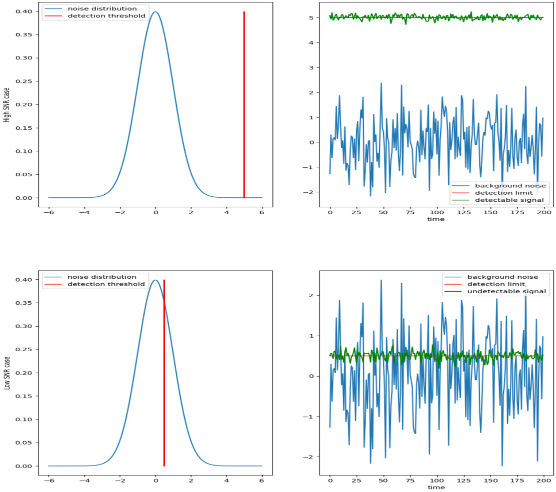
1. Université Bretagne Sud, LMBA UMR CNRS 6205, F-56000 Vannes, France
2. CEA, DAM, DIF, F-91297 Arpajon, France

June 2021

Outlines

- **Detection** technique at **low** Signal to noise ratio (**SNR**)
- Atmospheric pollution control with Adaptive Multiple Importance Sampling (AMIS) [Rajaona et al., 2015]
- Completion to **Source Term Estimate** techniques in **weak signal** cases

Introduction - detection problem



- Use of the knowledge of the signal **statistics** to detect weak signals **over time**

$$\begin{aligned} H_0 &: X_n \sim f_0(x_n; \theta_0) \\ H_1 &: X_n \sim f_1(x_n; \theta_1) \end{aligned} \quad (1)$$

- With change-point ν (before H_0 is true, after H_1 is true) the hypothesis test relies on the following likelihoods:

$$\begin{aligned} H_0 &: p(x_1, \ldots, x_n) = \prod_{k=1}^{n} f_0(x_k|\theta_0) \\ H_1 &: p(x_1, \ldots, x_n; \nu) = \prod_{k=1}^{\nu} f_0(x_k|\theta_0) \prod_{l=\nu+1}^{n} f_1(x_l|\theta_1). \end{aligned} \quad (2)$$

- We can write the likelihood ratio:

$$\Lambda_n^{\nu} = \prod_{k=\nu+1}^{n} \frac{f_1(x_k;\theta_1)}{f_0(x_k;\theta_0)}. \quad (3)$$

- Because ν is unknown $\rightarrow$ *Generalized Likelihood Ratio Test*(*GLRT*)[Tartakovsky et al., 2014]

$$V_n = \max_{0\leq\nu<n} \prod_{i=\nu+1}^{n} L_i, \quad (4)$$

with:

$$L_i = \frac{f_1(x_i;\theta_1)}{f_0(x_i;\theta_0)}. \quad (5)$$

- CUSUM for CUmulative SUM [Page, 1954] is an effective **online solution**

$$g_n = \max(0, g_{n-1} + \log(L_n)) \quad (6)$$

- detection is triggered by comparing g_n to a threshold

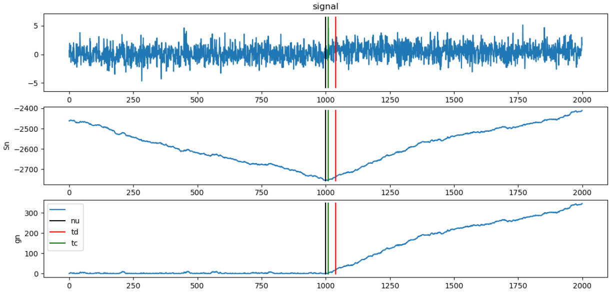


Figure: Example of CUSUM at low SNR (-15dB): 'nu' shows the real value of ν, 'td' is time of detection and 'tc' the estimate of the change-point time.

- Use of a **network of sensors** to detect events
- Common ways to deal with a network of sensors are Max-CUSUM and Sum-CUSUM [Mei, 2010]:

$$T_{MC}(n) = \max_{l}(W_{l,n}) \quad (7)$$

$$T_{SC}(n) = \sum_{l} W_{l,n} \quad (8)$$

- these are the most effective either when only one of the sensors or all sensors are affected by the signal

- Censoring [Mei, 2010]

$$T_{cSC}(n) = \sum_{l}^{L} W_{l,n} > c \tag{9}$$

- Weighting censored

$$T_{wcSC}(n) = \sum_{l}^{L} (n - \nu_l) \times W_{l,n} > \alpha \times \max_{l}(W_{l,n}) \tag{10}$$

- Detection of a **change of mean** value which randomly hits L out of 10 sensors with **gaussian noise** SNR = -20dB while the average length to false alarm (ARL2FA) = 10,000 time samples

L	1	3	5	8	10
SC	1544	649	481	**286**	**213**
MC	**902**	571	491	454	424
cSC	957	554	486	442	331
wcSC	961	**472**	**456**	367	318

Table: Average detection delay in time samples of each method with L sensors monitoring the change of mean

- Data from [Rajaona et al., 2015] release simulated using the SPRAY dispersion model [Tinarelli et al., 2013] on an urban area of $1km^2$ with 20 sensors.

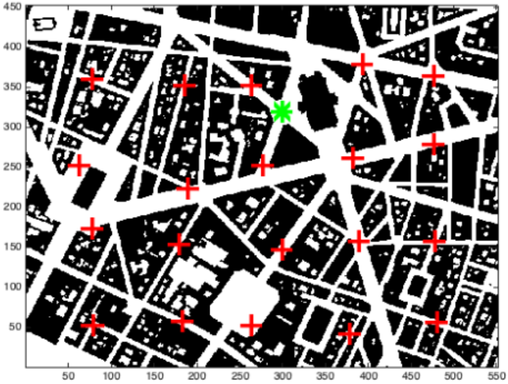


Figure: Sensors positions

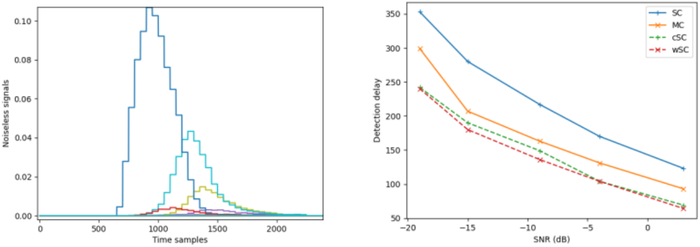
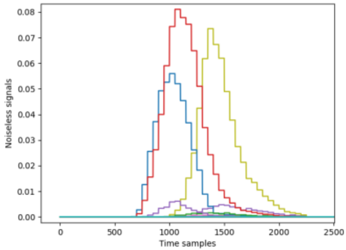


Figure: Case where one of the sensors is a lot more impacted than the others



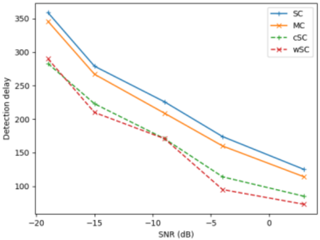


Figure: Case where few of the sensors are impacted

- CUSUM derived methods: **Robust** for detecting **low SNR events** with a network of sensors such as small leakages
- **Weighted and Censored** version seems to be a **good compromise** when the the number of impacted sensors is unknown
- Possibility of monitoring **wider areas and more areas** as it can compensate the weakness of cheap sensors and allocate more efficiently computational resources necessary for the STE method.

- Tackle the issue of the delay between sensors so that events which are not simultaneously monitored by the sensors can be detected.
- Application to other atmospheric propagation problems and association to the AMIS STE method to create a complete detection, location and characterization tool.

Mei, Y. (2010).
Efficient scalable schemes for monitoring a large number of data streams.
Biometrika, 97(2):419–433.

Page, E. S. (1954).
Continuous inspection schemes.
Biometrika, 41(1-2):100–115.

Rajaona, H., Septier, F., Armand, P., Delignon, Y., Olry, C., Albergel, A., and Moussafir, J. (2015).
An adaptive bayesian inference algorithm to estimate the parameters of a hazardous atmospheric release.
Atmospheric Environment, 122:748–762.

Tartakovsky, A., Nikiforov, I., and Basseville, M. (2014).
Sequential Analysis: Hypothesis Testing and Changepoint Detection p. 111.

Tinarelli, G., Mortarini, L., Trini Castelli, S., Carlino, G., Moussafir, J., Olry, C., Armand, P., and Anfossi, D. (2013).
Review and Validation of MicroSpray, a Lagrangian Particle Model of Turbulent Dispersion, volume 200, pages 311–328.