H21-024 Detection of low level concentrations of hazardous materials in the air using sequential multivariate detection methods

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Introduction

Detection of weak signals in noisy data streams is a generic challenge that can be useful to society to prevent dangerous situations or raise the alarm. As an example, the releases of noxious materials into the air can have dramatic effects if an appropriate response comes too late. In this work, we present an efficient method to detect weak signals in noisy time series. Based on the Cumulative Sum (CUSUM) technique (Page, 1954) and its adaptation to multivariate cases (Mei et al. 2010 ; Watson et al. 2022), the method is applied to a twin experiment implying a fictitious atmospheric release in a complex urban area.

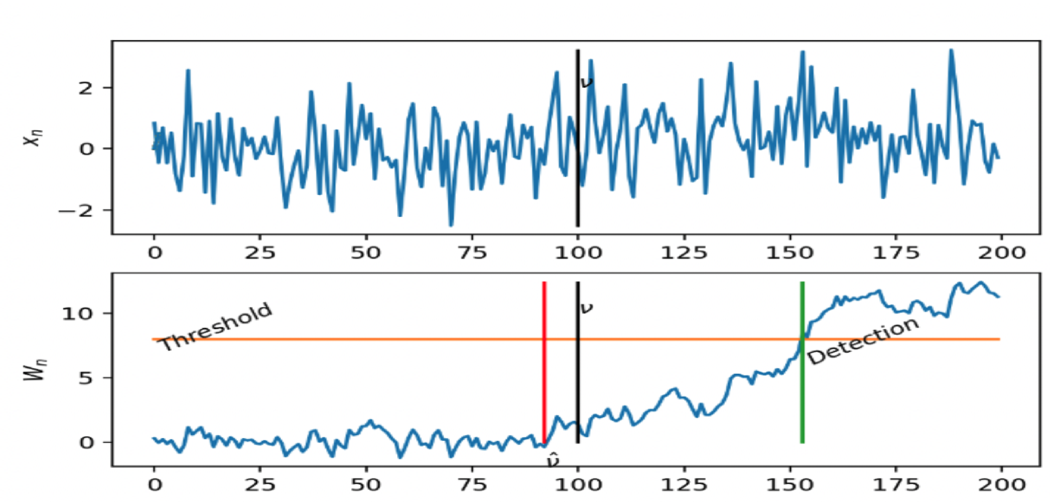
Univariate sequential detection

The CUSUM technique is a efficient way to recursively compute the likelihood ratio and detect a small change in the distribution of the data over time. The CUSUM variable is computed recursively as:

$$W_n = \max(1, W_{n-1}) + \log(L_n), \quad n \geq 1, W_0 = 0$$

This is equivalent to maximizing the likelihood ratio:

$$\max_{\nu}(\Lambda_n^{\nu}) = \max_{\nu}(L_n) \qquad L_n = \prod_{k=\nu+1}^{n} \frac{f_1(x_k|\theta_1)}{f_0(x_k|\theta_0)}$$



Application of CUSUM to univariate data

Extension to multivariate detection

The extension to multivariate cases is carried out with the Sum-CUSUM:

$$T_{SC}(n) = \frac{1}{L}\sum_{l=1}^{L} W_{l,n}.$$

Mei et al. (2010) showed that for space-sparse data, it is possible to select sensors to improve the detection rate:

$$T_{cSC}(n) = \frac{1}{\sum 1_{W_{l,n} \geq c}} \sum_{l}^{L} W_{l,n} \; 1_{W_{l,n} \geq c}.$$

Watson et al. (2022) proposed an adaptive threshold:

$$c_n = \alpha \times \max_{l \in [1,\cdots,L]}(W_{l,n})$$

and an extension to consider time-sparse data, hence maximize the detection rate for asynchronous signals. The local CUSUM variable becomes:

$$G_n = \max(G_{n-1}, W_n) = \max_{0<k\leq n}(W_k)$$

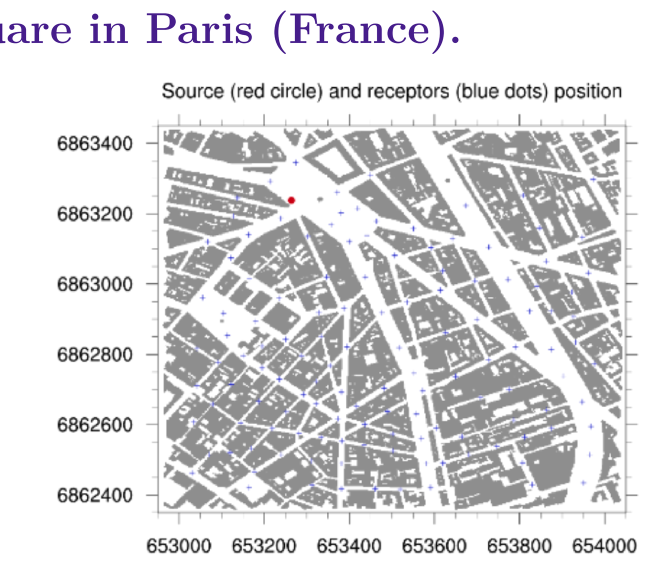
This new local variable changes the Sum-CUSUM so that it reads:

$$T_{STEC}(n) = \frac{1}{L}\sum_{l=1}^{L} \max_{[\nu_l, N_l]} \sum_{k=\nu_l}^{N_l \leq n} \log \frac{f_{1,l}(X_{k,l}|\theta_{1,l})}{f_{0,l}(X_{k,l}|\theta_{0,l})}$$

This new variable developed by Watson et al. (2022) is called the Temporary-Events CUSUM(TE-CUSUM)

Twin experiment of an atmospheric release

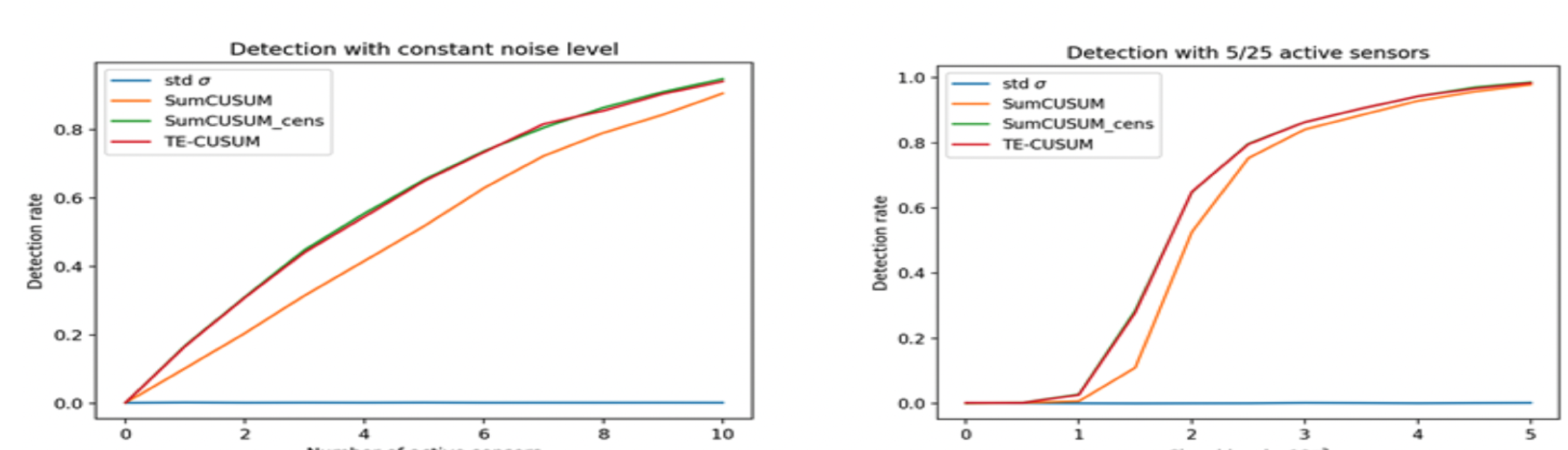
In this work, we generated synthetic signals with Gaussian noise on virtual sensors distributed in an urban environment. These signals are fictively due to a surreptitious atmospheric release. High resolution 3D flow and dispersion simulations were performed with the Parallel-Micro-SWIFT-SPRAY modelling system. PMSS is the parallel version of Micro-SWIFT-SPRAY (Tinarelli et al. 2013) which was developed to provide a simplified but rigorous CFD solution in a limited amount of time. Météo France AROME predictions at a resolution of 0.025° (around 2.5 km at mid-latitude) were used as input meteorological data and downscaled with PMSS in order to zoom in on the district south of Republic Square in Paris (France).



Simulation domain in Paris (France) with the locations of the fictitious source (red dot) and the virtual sensors (blue dots)

Detection results

The detection rate increases with the number of sensors as well as it does with the signal to noise ratio. The consideration of space-sparsity improves the performances with the TE-CUSUM. A second experiment with time-sparse signals would be necessary for the TE-CUSUM to improve the detection rate from the Censored Sum-CUSUM which is another method developed in the frame of this work.



Detection rate depending either on the number of affected sensors (left) or on the signal to noise ratio (right). The lower blue line is obtained by a simple threshold on the signal, the orange represents the standard Sum-CUSUM, the green one takes into account the space-sparsity, and the red one considers both time- and space-sparsity.

Conclusion

In this work, we proved the interest of using a sequential detection method to quickly identify the variation of a signal characterized by a low signal-to-noise ratio. This signal could be the concentration of a hazardous material transported and dispersed into the air. The method not only consider data sparsity in space but also sparsity in time and asynchronicity of the data (not all sensors monitor the signals at the same time). The method was satisfactorily tested on synthetic data sparse in space. It also showed very good results on synthetic data sparse in time (Watson et al., 2022). Besides using these techniques on other complex data set, our future work will demonstrate its efficiency on different noise distributions such as Poisson, which is more realistic for some of the detectors used in our targeted applications. Eventuelly, as our method can detect weak signals, it can be used as a powerful prevention and warning tool in case of adverse atmospheric releases and, also, in the presence of a radiation source.

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