



HAL
open science

Change-point detection method for the prediction of dreaded events during online monitoring of lung transplant patients

Nassim Sahki, Anne Gégout-Petit, Sophie Wantz-Mézières

► **To cite this version:**

Nassim Sahki, Anne Gégout-Petit, Sophie Wantz-Mézières. Change-point detection method for the prediction of dreaded events during online monitoring of lung transplant patients. Annual PhD students conference IAEM Lorraine, APIL 2019, Dec 2019, Nancy, France. hal-02392756

HAL Id: hal-02392756

<https://inria.hal.science/hal-02392756>

Submitted on 4 Dec 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Change-point detection method for the prediction of dreaded events during online monitoring of lung transplant patients

Nassim Sahki¹ - Anne Gégout-Petit¹ - Sophie Wantz-Mézières¹

¹ Université de Lorraine, CNRS, Inria, IECL, F-54000 Nancy, France

Context

- Survival after lung transplantation is about 80% at 1 year and 50% at 6 years.
- The two main complications responsible for deaths in lung transplant patients are infection and/or rejection.

Main objective

- Test the monitoring of lung transplant patients by connected sensors ;
- Propose a methodology for real-time prediction of a serious event (infection and/or rejection) via the change-point detection in the evolution of the multivariate signals collected by these connected sensors.

Clinical test & Health data

• AP-HP (Assistance Publique-Hôpitaux de Paris) launches the EOLE-VAL Test (duration= 2 years, observation= 6 months, patients number≈25) at Bichat Hospital.

• Health data come from the real-time medical surveillance of some **respiratory health parameters** (physiological and spirometry) of lung transplant patients by **connected objects**.

- **Physiological** : • Skin temperature • Pulse oximeter oxygen saturation (SpO₂) • Heart rate • Respiratory rate • Physical activity • Sleep quality
- **Spirometry** : • Forced Expiratory Volume in 1 second (FEV1).

Figure 1: Connected objects

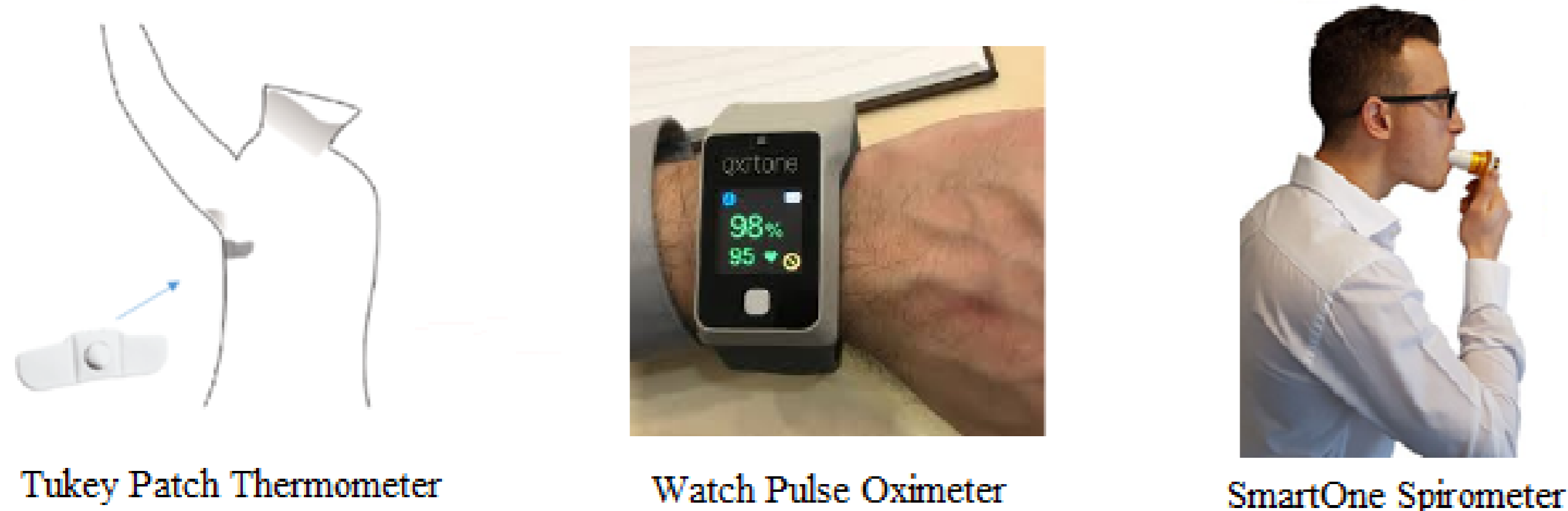
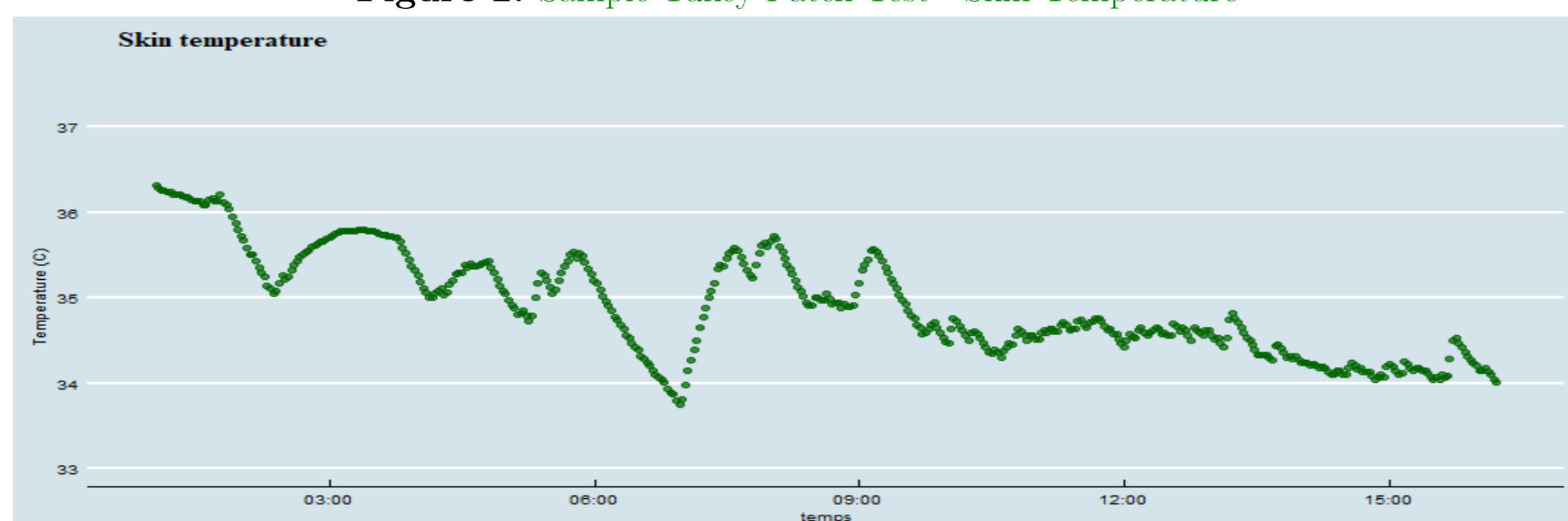


Figure 2: Sample Tukey Patch Test - Skin Temperature



Online change-point detection

- The application context places us in the sequential framework where the series $\{x_t\}_{t=1,\dots,n} = \{x_1, \dots, x_n\}$ is sequentially observed until time n , not fixed.
- The challenge here is to minimize the average detection delay "ADD" while maintaining a given probability of false alarm " α ".
- Statistically, the problem of change-point detection is to sequentially test for each new observation x_n , the hypotheses :

$$\begin{cases} H_{0,n} : v > n, & X_t \sim f_0(\cdot) & \forall t = 1, \dots, n \\ H_{1,n} : \exists v \leq n, & X_t \sim f_0(\cdot) & \forall t = 1, \dots, (v-1) \\ & X_t \sim f_1(\cdot) & \forall t = v, \dots, n \end{cases} \quad (1)$$

- Change-point detection here is based on the choice of a **recursive statistic** and the **threshold** it must reach to signal a detection.

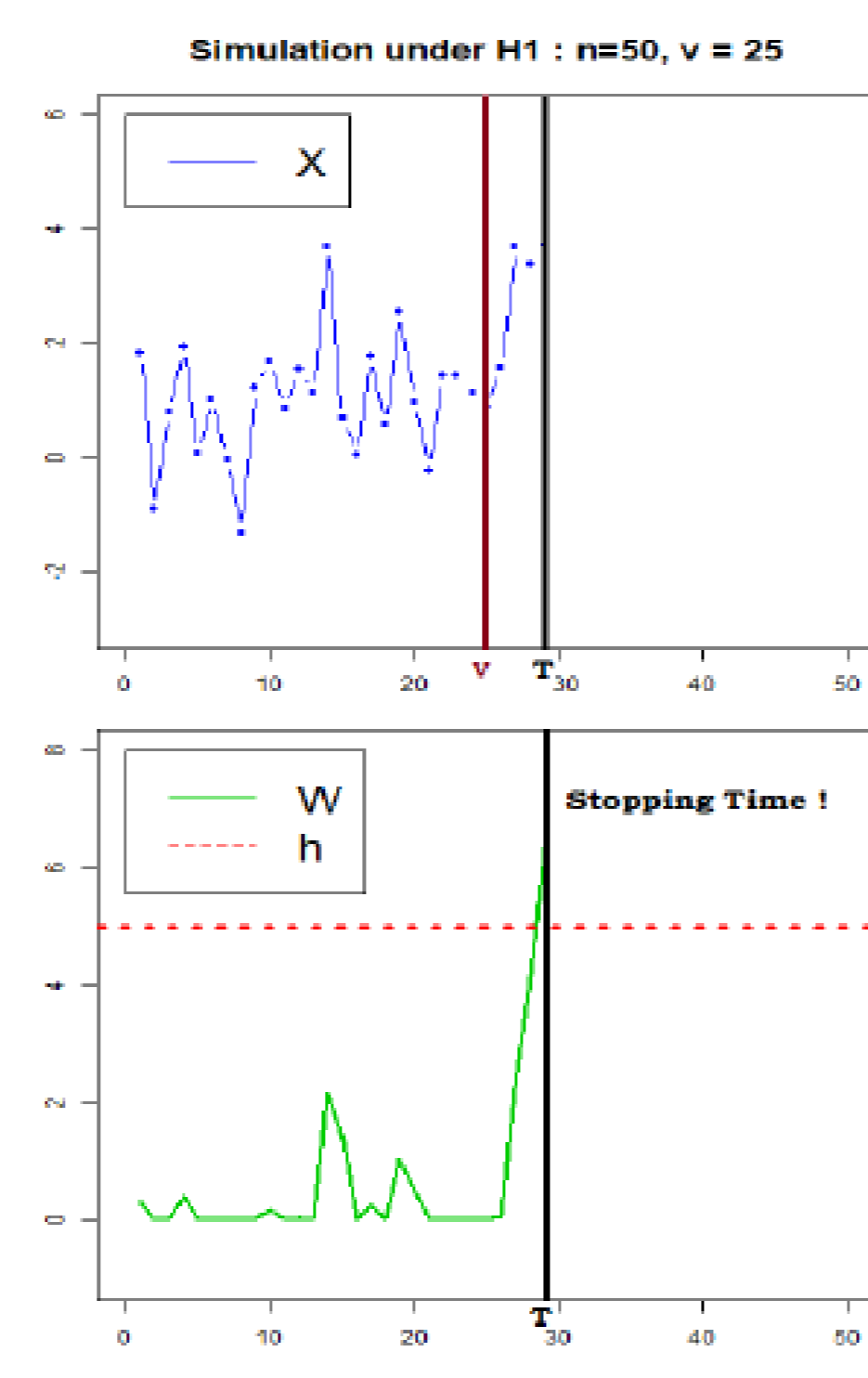
⇒ CUSUM statistics of Page based on the score S_t :

$$W_t(\delta, q) = \max\{0, W_{t-1}(\delta, q) + S_t(\delta, q)\}, \quad t \geq 1, W_0(\delta, q) = 0$$

- The score function $S_t(\delta, q; X_1, \dots, X_t)$ of Tartakovsky & al. (2012) is calculated according to the observations and the detection objective :

$\delta = (\mu_1 - \mu_0)/\sigma_0$, $q = \sigma_0/\sigma_1$ respectively the minimum change on the mean and on the variance that we want to detect. μ_0, σ_0^2 and μ_1, σ_1^2 the mean, the variance of the pre-change and the post-change regimes.

⇒ The traditional method suggested for setting a **constant threshold** is based on Wald inequality, after fixing the tolerated false alarm rate " α ", while respecting : $h_\alpha \leq -\ln(\alpha)$.



⇒ Margavio & al. (1995) suggest a **conditional instantaneous threshold** by controlling the false conditional alarm rate at each instant of the trajectory.

Contribution

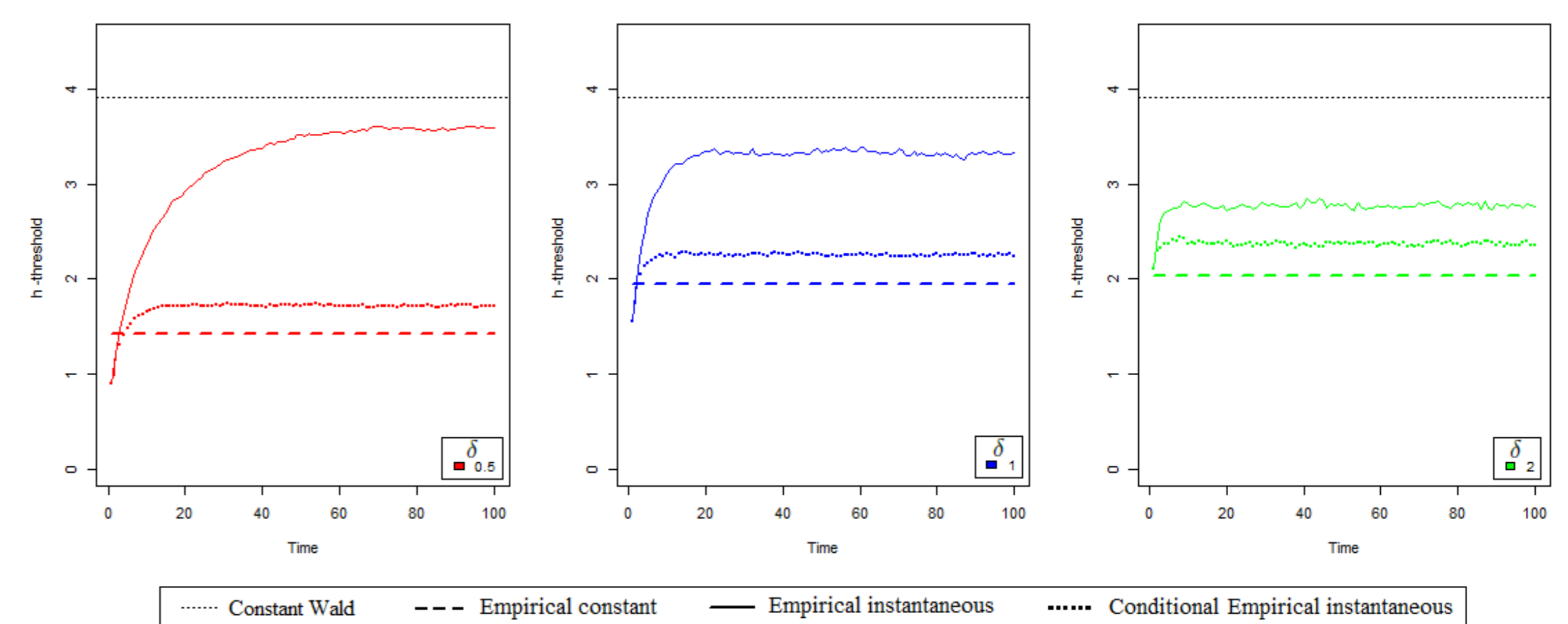
⇒ We propose new detection thresholds : the empirical constant, the empirical instantaneous and the empirical instantaneous dynamic ;

⇒ The thresholds are built by an empirical method which consists in performing simulations of the statistic $W_t(\delta, q)$ under the pre-change regime and constructing the threshold by **the empirical quantile of the law of statistics**, as following :

1. **Empirical constant threshold** is the quantile of the maximum values of the simulated statistics obtained along the trajectory.
2. **Empirical instantaneous threshold** is the quantile of the values of the simulated statistics obtained at each time of trajectory.
3. **Empirical instantaneous dynamic threshold** consists to use the previous instantaneous threshold and adapt it to the behavior of the statistics (data-driven). It moves in time when the statistic returns to its initial value (zero).

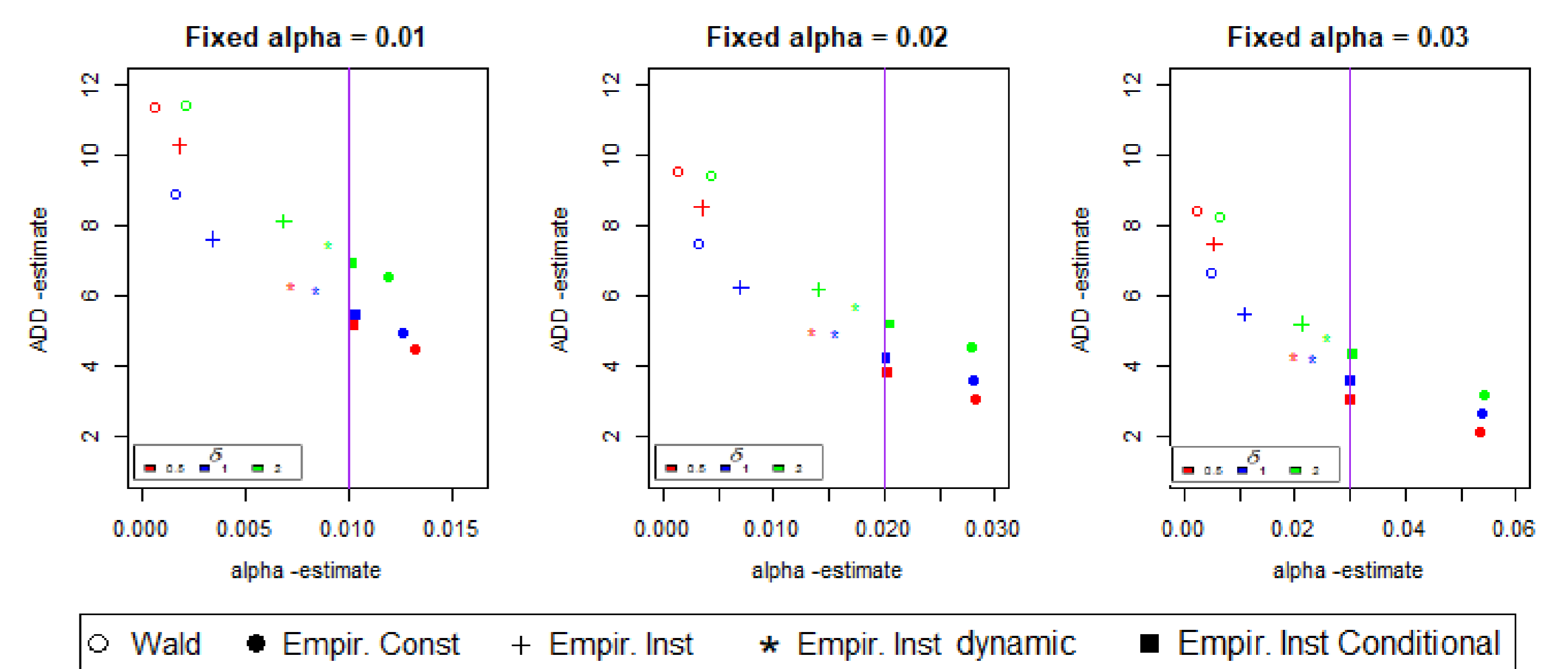
⇒ The thresholds depend on the chosen objective detection.

Figure 3: Comparison of the different empirical thresholds and that of Wald, built for $\alpha = 0.02$ and according to different detection objectives $\delta \in \{0.5, 1, 2\}$, $q = 1$, $\sigma_0 = 1$.



Thresholds performance

Figure 4: Simulation results under the pre-change regime (estimation of α) and under the post-change regime (estimation of ADD) obtained by the different detection thresholds and according to three detection objectives on the mean $\delta \in \{0.5, 1, 2\}$, $q = 1$. We have the results for three different values of the tolerated false alarm rate α . The real change-point is of a level of $\delta^R = 1$.



- The results show that the empirical thresholds are faster than that of Wald.
- The best threshold is the conditional instantaneous because it makes a compromise between the detection delay and the false alarm level. It gives the best average detection delay while respecting the tolerated false alarm rate.

Perspectives

- Estimation of signal parameters (mean and variance) of the pre-change regime.
- Adaptation of the change-point detection methodology to the multivariate case.
- Application of proposed methodology to respiratory health data collected from lung transplant patients.

Références

- [1] Thomas M Margavio, Michael D Conerly, William H Woodall, and Laurel G Drake. Alarm rates for quality control charts. *Statistics & Probability Letters*, 24(3) :219-224, 1995.
- [2] Ewan S Page. Continuous inspection schemes. *Biometrika*, 41(1/2) :100-115, 1954.
- [3] Alexander G Tartakovsky, Aleksey S Polunchenko, and Grigory Sokolov. Efficient computer network anomaly detection by changepoint detection methods. *IEEE Journal of Selected Topics in Signal Processing*, 7(1) :4-11, 2012.
- [4] Abraham Wald. Sequential tests of statistical hypotheses. *The annals of mathematical statistics*, 16(2) :117-186, 1945.