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

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#### 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  $(Sp0_2)$

Figure 1: Connected objects

- Heart rate Respiratory rate Physical activity Sleep quality
- —Spirometry: Forced Expiratory Volume in 1 second (FEV1).

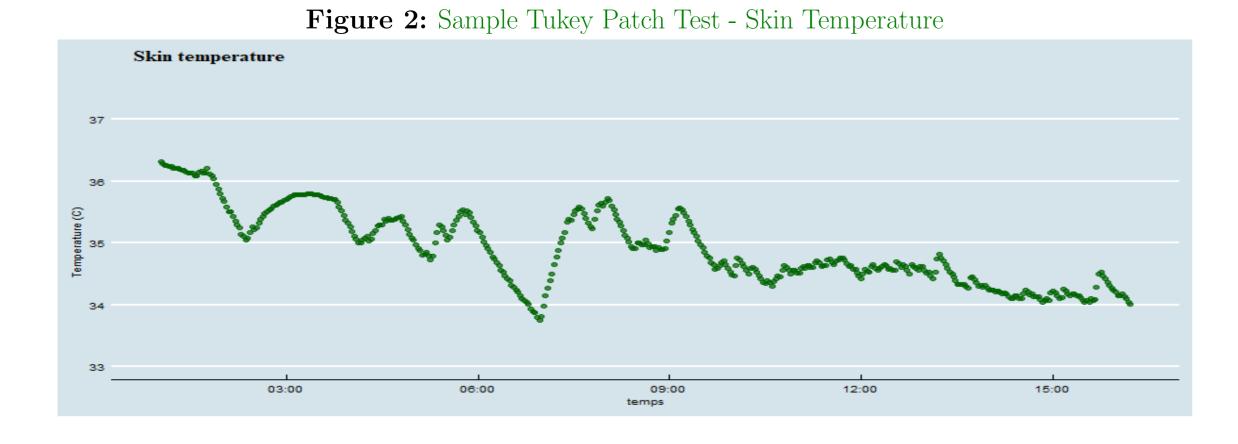




Tukey Patch Thermometer

Watch Pulse Oximeter

SmartOne Spirometer

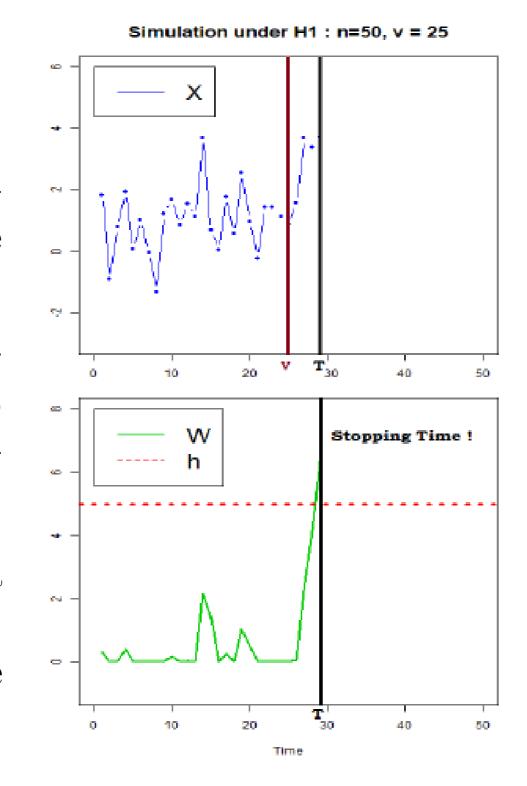


## Online change-point detection

- The application context places us in the sequential framework where the series  $\{x_t\}_{t=1,...,n} = \{x_1,...,x_n\}$  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 " $\alpha$ ".
- Statistically, the problem of change-point detection is to sequentially test for each new observation  $x_n$ , the hypotheses :

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

- Change-point detection here is based on the choice of a **recursive statistic** and the **threshold** it must reach to signal a detection.
- $\Rightarrow$  CUSUM statistics of Page based on the score  $S_t$ :  $W_t(\delta, q) = \max\{0, W_{t-1}(\delta, q) + S_t(\delta, q)\}, \ t \geq 1, W_0(\delta, q) = 0$
- The score function  $S_t(\delta, q; X_1, ..., X_t)$  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.  $\mu_0$ ,  $\sigma_0^2$  and  $\mu_1$ ,  $\sigma_1^2$  the mean, the variance of the pre-change and the post-change regimes.
- $\Rightarrow$  The traditional method suggested for setting a **constant threshold** is based on Wald inequality, after fixing the tolerated false alarm rate " $\alpha$ ", while respecting:  $h_{\alpha} \leq -\ln(\alpha)$ .

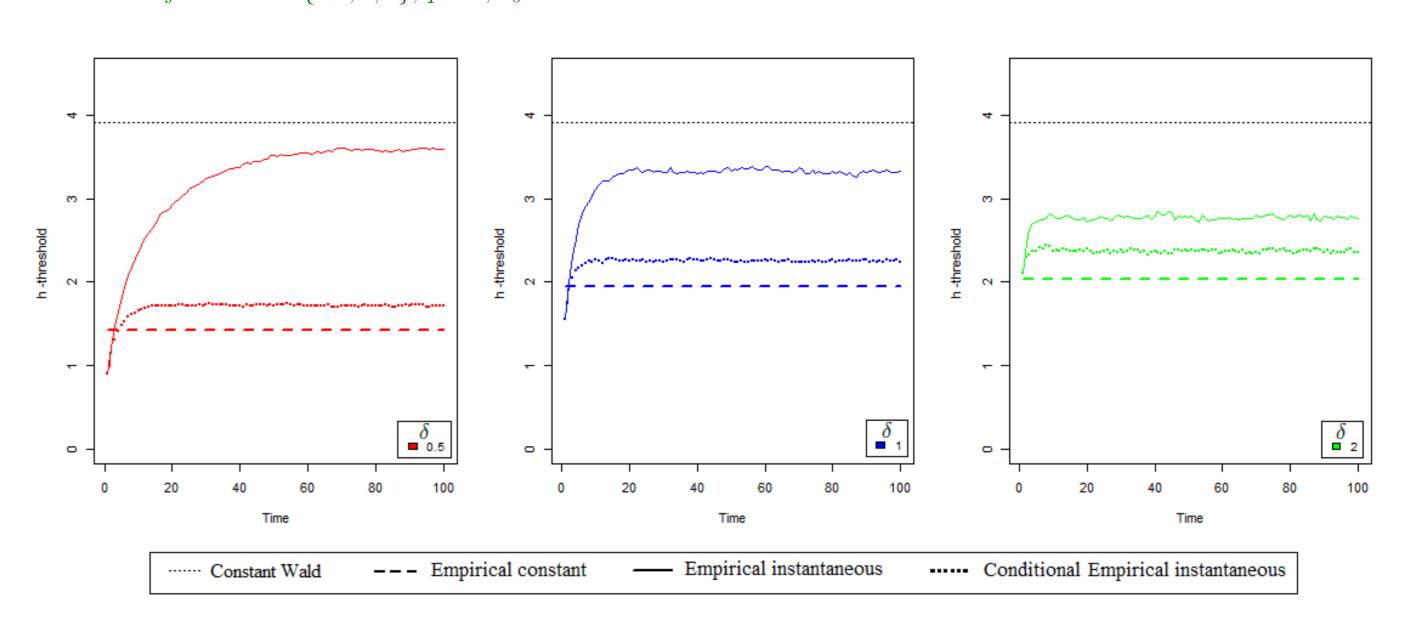


⇒ Margavio & al. (1995) suggest a **conditional instantaneous threshold** by controlling the false conditional alarm rate at each instant of the trajectory.

#### Contribution

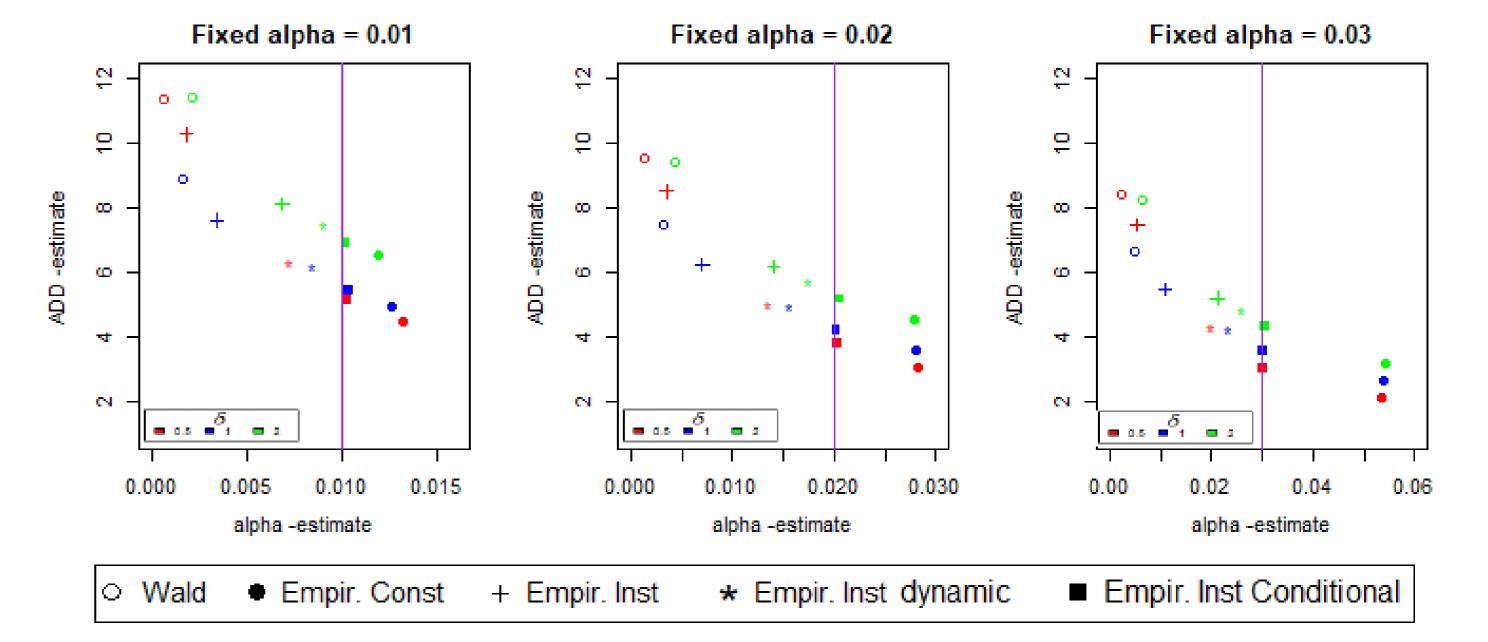
- ⇒ We propose new detection thresholds : the empirical constant, the empirical instantaneous and the empirical instantaneous dynamic;
- $\Rightarrow$  The thresholds are built by an empirical method which consists in performing simulations of the statistic  $W_t(\delta, q)$  under the pre-change regime 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).
- $\Rightarrow$  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  $\alpha$ ) 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  $\alpha$ . 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.