Tuning and comparing fault diagnosis methods for aeronautical systems via Kriging-based optimization

Julien Marzat, Hélène Piet-Lahanier, Frédéric Damongeot, Eric Walter

4th European Conference for Aerospace Sciences
Saint-Petersburg, Russia, July 4-8 2011

ONERA

THE FRENCH AEROSPACE LAB

retour sur innovation

Outline

Problem formulation

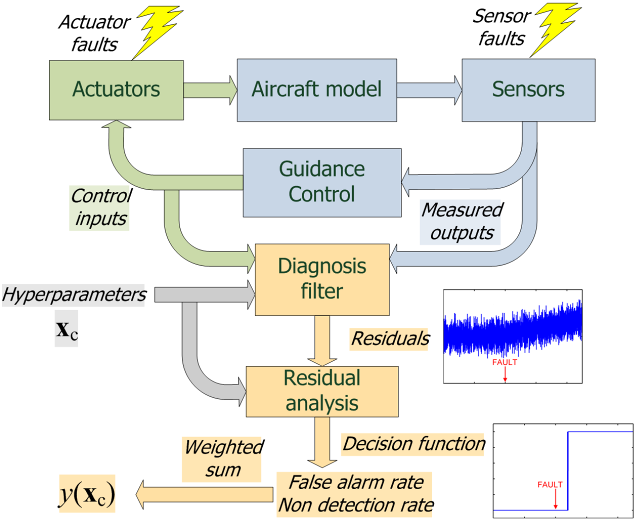
Hyperparameters of fault diagnosis methods

- Observer gains
- Covariance matrices
- Thresholds
- Size of expected change
- Time horizon
- ...

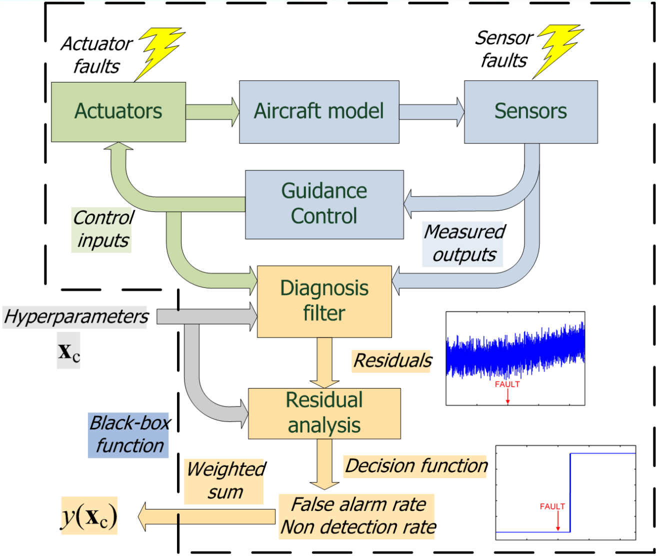
Optimal tuning of Hyperparameters

- Best performance of a method on a complex problem?
- Required to compare fault detection methods
- Involves costly simulations of a test case
- Global minimization of performance indices to find hyperparameters

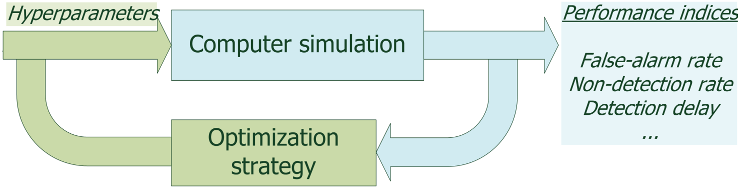
Simulation of a test case : example



Simulation of a test case : example



Problem formulation



Tuning viewed as a *Computer Experiment*

- *Kriging* as a surrogate approximation of the complex simulation
- *Efficient Global Optimization*, iterative search for the global optimizer based on the Kriging prediction

Starting point

Performance index $y(\mathbf{x}_c)$ already computed for an initial sampling of hyperparameter vectors $\mathcal{X}_n = [\mathbf{x}_{c,1}, ..., \mathbf{x}_{c,n}]$, $\mathbf{x}_c \in \mathbb{X}_c$

Kriging

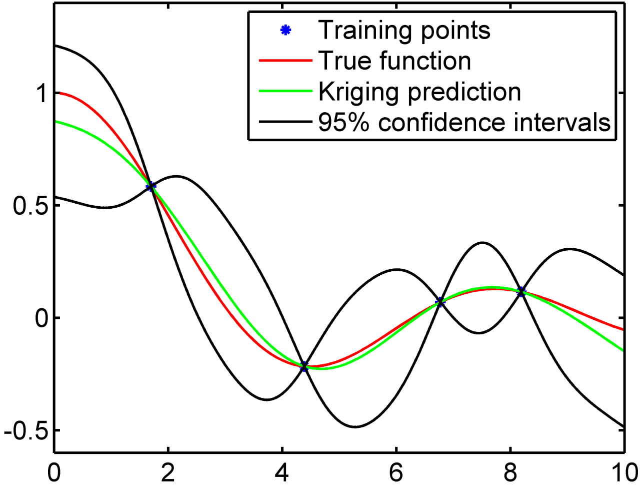
$y(\cdot)$ modeled as a Gaussian process $Y(\mathbf{x}_\mathrm{c}) = \mathbf{f}^\mathrm{T}\mathbf{b} + Z(\mathbf{x}_\mathrm{c})$ where

- $\mathbf{f}$ parametric prior, $\mathbf{b}$ to be estimated from available data
- $Z(\cdot)$ zero-mean Gaussian process with covariance $k\left(Z(\mathbf{x}_\mathrm{c}), Z(\mathbf{x}_\mathrm{c} + \mathbf{h})\right) = \sigma^2 R(\mathbf{h})$
- Chosen correlation function, e.g., $R(\mathbf{h}) = \exp\left\{-\sum_{k=1}^{d}\left|\frac{h_k}{\theta_k}\right|^2\right\}$

What Kriging provides

- $\widehat{Y}(\mathbf{x}_\mathrm{c})$, best linear unbiased prediction of $y(\cdot)$ at any $\mathbf{x}_\mathrm{c} \in \mathbb{X}_\mathrm{c}$
- Variance of the prediction error $\widehat{\sigma}^2(\mathbf{x}_\mathrm{c})$

Kriging illustration



Efficient Global Optimization (EGO) algorithm

Objective: find iteratively the minimum of $y(\cdot)$

1. Choose an initial sampling and compute the value of $y(\cdot)$ at those points
2. Find the empirical minimum in the available data points, y_{min}
3. Fit a Kriging predictor on those data points
4. Find a new point of interest to evaluate $y(\cdot)$ by maximizing Expected Improvement, given by

$$\mathrm{EI}(\mathbf{x}_c) = \widehat{\sigma}(\mathbf{x}_c)\left[u\Phi(u) + \phi(u)\right]$$

   where

$$u = \frac{\left(y_{\text{min}} - \widehat{Y}(\mathbf{x}_c)\right)}{\widehat{\sigma}(\mathbf{x}_c)}$$

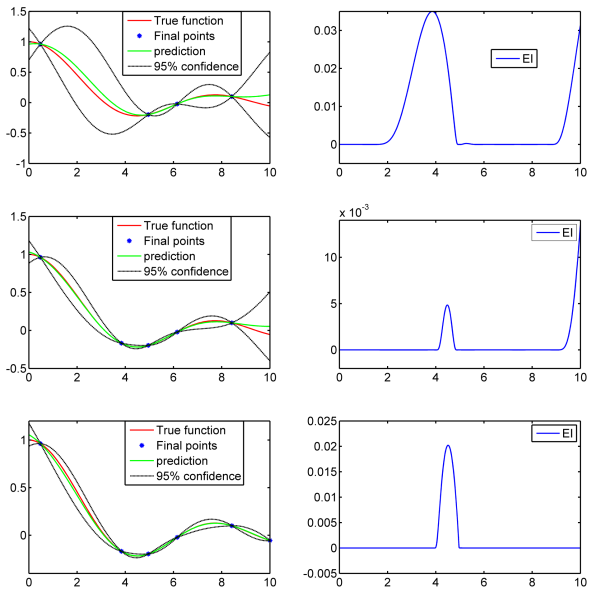
5. Go to step 2 until EI reaches a threshold or sampling budget is exhausted

Illustration of EGO

Iteration 1

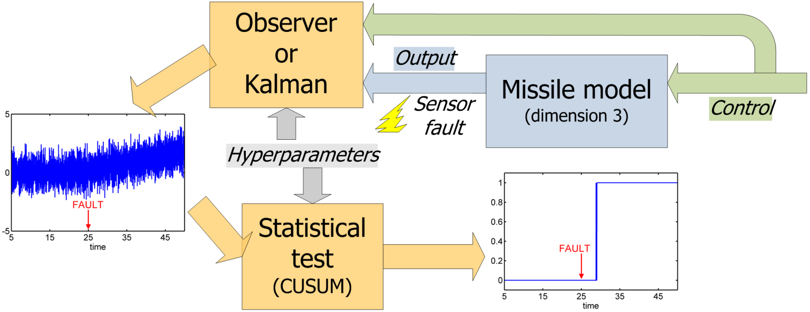
Iteration 2

Iteration 3



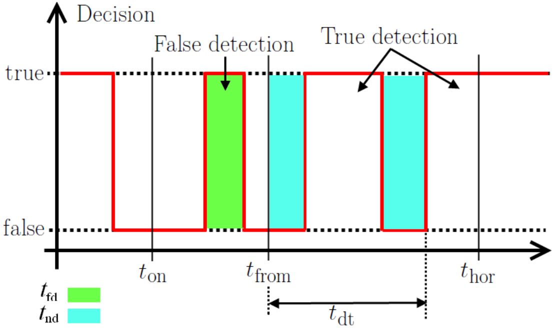
ONERA
THE FRENCH AEROSPACE LAB

Application – tuning of 2 fault-diagnosis schemes



1. Luenberger observer (3 poles) + CUSUM (2 hp) → 5 hp
2. Kalman filter (4 non-zero initial covariance values) + CUSUM (2 hp) → 6 hp

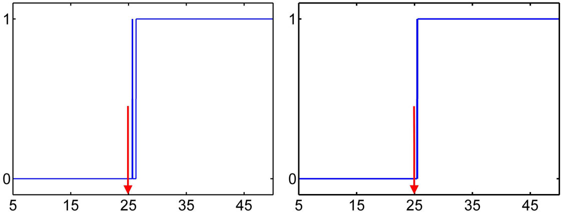
Cost function



$$r_{\text{fd}} = \frac{t_{\text{fd}}}{t_{\text{from}} - t_{\text{on}}},\ r_{\text{nd}} = \frac{t_{\text{nd}}}{t_{\text{hor}} - t_{\text{from}}} \rightarrow y = r_{\text{fd}} + r_{\text{nd}}$$

$$\widehat{\mathbf{x}}_{\text{c}} = \arg \min_{\mathbf{x}_{\text{c}} \in \mathbb{X}_{\text{c}}} y\left(\mathbf{x}_{\text{c}}\right)$$

A sample of numerical results



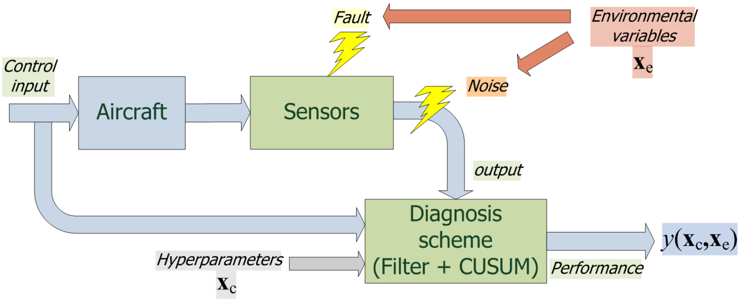
	Observer and CUSUM	Kalman and CUSUM
Ranking	*2*	*1*
False-alarm rate	0	0
Non-detection rate	0.0455	0.0184
Mean number of simulations	102.21	136.14

ONERA THE FRENCH AEROSPACE LAB

Robust tuning

Need for a robust tuning

- Results obtained for fixed conditions of the simulation
- What happens with stronger disturbances, more noise, smaller fault ?
- →Simulation depends on a set of *environmental variables* $\mathbf{x}_\mathrm{e}$



ONERA
THE FRENCH AEROSPACE LAB

Robust tuning – proposed solution

Continuous minimax optimization

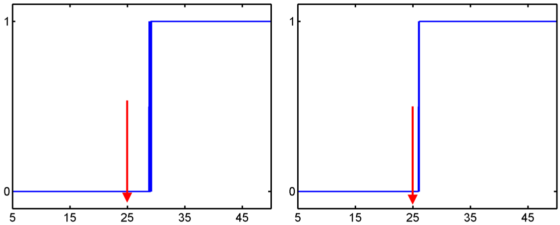
- Search for optimal tuning for worst-case environmental variables

$$\widehat{\mathbf{x}}_{\mathrm{c}}, \widehat{\mathbf{x}}_{\mathrm{e}} = \arg \min_{\mathbf{x}_{\mathrm{c}} \in \mathbb{X}_{\mathrm{c}}} \max_{\mathbf{x}_{\mathrm{e}} \in \mathbb{X}_{\mathrm{e}}} y\left(\mathbf{x}_{\mathrm{c}}, \mathbf{x}_{\mathrm{e}}\right)$$

Sketch of proposed algorithm

- Transform the initial problem into $\begin{cases} \min\limits_{\mathbf{x}_{\mathrm{c}}, \tau} \tau \\ y\left(\mathbf{x}_{\mathrm{c}}, \mathbf{x}_{\mathrm{e}}\right) < \tau, \ \forall \mathbf{x}_{\mathrm{e}} \end{cases}$
- Iterative relaxation :
  1. Draw a new $\mathbf{x}_{\mathrm{e}}$
  2. Find a minimum $\widehat{\mathbf{x}}_{\mathrm{c}}$ for all explored $\mathbf{x}_{\mathrm{e}}$ with EGO
  3. Find a maximum $\widehat{\mathbf{x}}_{\mathrm{e}}$ for $\widehat{\mathbf{x}}_{\mathrm{c}}$ with EGO
  4. Check convergence, repeat if necessary

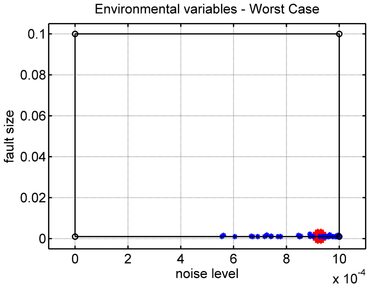
Robust tuning for aircraft fault diagnosis application

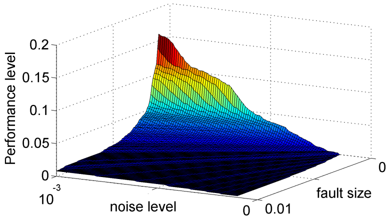


	Observer and CUSUM	Kalman and CUSUM
Ranking	*2*	*1*
Minimax performance	0.114	0.0312
Average number of simulations	168	199

ONERA
THE FRENCH AEROSPACE LAB

Worst-case estimation





Summary and future work

Summary

- Automatic tuning with *Kriging* and *Bayesian Optimization*
- Tuning complete FDI schemes for dynamical systems : simultaneous adjustment of hyperparameters of residual-generation and residual-evaluation strategies
- Robust tuning algorithm in the worst-case sense
- Few runs of the simulation required (20 to 30 per dimension)
- Generic : applicable to many engineering design problems

Future work

- Consider higher-dimensional problems (in both dimensions)
- More complex constraints on the cost function